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Broken promises, competition, and capital allocation in the mutual fund industry[☆]

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ABSTRACT

What characteristics of mutual funds do investors care about? In addition to performance and fees, we show that investors exhibit a clear preference for managers who adhere to the strategies they describe in their prospectuses. Capital flows respond negatively when funds diverge from the average holdings of their text-based strategy peer groups, but positively when they outperform those peer averages. We identify this effect using a novel instrumental variables approach, and show that funds face a delicate trade-off between keeping their promises and outperforming their peers who make similar promises.

1. Introduction

Most fund managers operate according to fixed investment mandates that curtail the types of assets they are permitted to hold (He and Xiong, 2013), implying that institutional demand is ultimately determined by end investors allocating across fund categories. In this view, it is of crucial importance to uncover what characteristics drive investors' allocation decisions and fund product offerings.

The existing literature studying US active equity mutual funds has mostly focused on investors' preference for higher risk-adjusted returns, and documented product segmentation along priced characteristics such as size, value and momentum. In this paper we expand the current understanding of investor preferences and fund styles by taking advantage of the Principal Investment Strategy (PIS) descriptions included in mutual fund prospectuses.[1] We obtain a comprehensive sample of prospectuses from EDGAR (the SEC's Electronic Data Gathering, Analysis, and Retrieval system) for the period 2000–2017. Then, using a simple tool from unsupervised machine learning — the *k-means* algorithm — we distill the text into interpretable *strategy peer groups* (SPGs): clusters of similar descriptions that represent distinct text-based investment styles. SPGs provide a novel taxonomy for the equilibrium outcome between investor demand for fund characteristics and the supply of funds. Quantifying this equilibrium sheds light on which fund characteristics investors desire, and how their preferences shape the Industrial Organization (IO) of the mutual fund industry.

In analyzing the market equilibrium, we first focus on the supply of funds. We show that differences in strategy descriptions across SPGs

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[1] Mandated by the Securities and Exchange Commission, these descriptions are intended to "explain in general terms how the fund's adviser decides what securities to buy and sell … [and] provide investors with essential information about the fund's investment approach and how the fund's portfolio would be managed." (SEC rule S7-10-97).

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reflect significant differences in fund returns, holdings, and strategy features, but not in risk-adjusted performance. Textual differences do not seem to be a mere marketing artifact, but rather reflect a differentiated product offering. The lack of differences in risk-adjusted performance suggests that product differentiation might happen along risk exposures and/or non-priced characteristics. Second, we focus on investor demand by examining their flow responses. We show that investors are aware of SPG boundaries by documenting a significant flow-performance sensitivity for SPG-adjusted returns, of comparable magnitude to that for other commonly used performance measures. Additionally, we show that investors care about the strategy features offered by SPGs, as they react with outflows when funds diverge from their SPG's core strategy, even after controlling for performance. Lastly, we provide evidence for the economic mechanism driving the results: investor preferences for both higher SPG-adjusted performance and adherence to SPG core strategies provide funds with conflicting incentives. This generates a trade-off between SPG-adjusted performance and SPG adherence: when SPG peer groups are crowded in the classic style space (size, value, and momentum), funds that move to a less crowded space by diverging from their SPG's core strategy outperform their SPG peers.

Our full analysis is structured as follows. We first describe the construction of our Strategy Peer Groups, using the *k-means* algorithm.[2] We start by encoding each fund's PIS description as a vector of relative word frequencies. Then, after randomly initializing k *centroid* vectors in the space spanned by the entire corpus of descriptions, each PIS is assigned to the closest centroid by Euclidean distance. Following this assignment, each centroid vector is recomputed as the mean vector of all documents assigned to it. The last two steps are repeated until convergence, resulting in k *clusters*, each with minimal distance between their constituents and the geometric center.[3]

We optimally identify 17 distinct strategies, as shown in Fig. 1. The key features of some strategies are well known to academics and practitioners (e.g. *Large Cap*, *Mid Cap*, *Small Cap*). But most appear to go beyond: some are associated with firm characteristics (*Dividends*; *New Products & Services*; *Competitive Advantage*; *Price-Earnings Ratio*), some with investment philosophies (*Quantitative*; *Fundamental*; *Intrinsic Value*; *Long Term*; *Defensive*; *Tax*), some with secondary asset classes (*Fixed Income*; *Derivatives*), and some with international markets (*Foreign (ADR)*; *Foreign (Emerging Markets)*).[4] In our baseline analysis we adopt the simplifying assumption that, at any given time, funds belong to a single dominant strategy. Hence, our strategy peer groups (SPGs) perfectly overlap with the outcome of the *k-means* algorithm. We then generalize that approach by allowing funds to promise any combination of the above strategies, which identifies customized fund-specific SPGs. All results hold with both methods, as funds tend to have a dominant SPG which explains the majority of the documented effects, consistent with the findings of He and Xiong (2013), who show a tendency towards narrower mandates.

Having determined the structure of *promised* product offerings, we assess whether SPGs reflect an *actual* differentiated product offering. Starting with a narrative approach, we find that the characteristics of fund holdings differ significantly across funds belonging to different SPGs, in a way that is consistent with an intuitive reading of their promised strategies. For instance, funds belonging to the "*Dividend*" SPG hold stocks with the highest dividend yield, less cash and less investment, whereas funds belonging to the "*Long Term*" SPG hold stocks with lower book-to-market ratios, higher intangibles and lower dividend yields.

Next, we build a formal measure of strategy adherence (or, equivalently, strategy divergence). This approach has the advantages of quantifiability and objectivity but requires a simplifying assumption: that divergences from core strategies within each peer group are purely idiosyncratic. If this condition is satisfied, the average portfolio weight vector within each SPG represents its core strategy. Our measure of strategy divergence is therefore the (log-transformed) sum of squared differences between each fund's portfolio weight vector and the average weight vector for all funds in the same SPG.[5] If funds are following their promised strategies, they should diverge less from their own peer group average than from a placebo strategy, i.e., some other peer group average. Indeed, we find that funds' portfolio weights are between 9% and 46% more similar to their own SPG average than the placebo (depending on included controls), confirming that funds generally follow their promised strategies. To show that SPGs capture a novel dimension of product differentiation, the controls include alternative measures of competition (Hoberg et al. (2018), henceforth HKP) and product uniqueness (Kostovetsky and Warner (2020), henceforth KW).

Following standard practice in the literature, we study investor demand for SPGs through their flow responses. A rich body of work has documented flow sensitivity to performance (e.g. Chevalier and Ellison (1997); Sirri and Tufano (1998); Barber et al. (2016); Berk and Van Binsbergen (2016)) and stressed the importance of evaluating funds relative to their direct rivals (e.g., Cohen et al. (2005) and Hoberg et al. (2018)). Combining these insights, we hypothesize that if investors are aware of SPG boundaries and consider funds in the same SPG to be substitute products, we should observe a significant flow-performance sensitivity when benchmarking performance relative to these SPG rivals. Thus we construct SPG-adjusted returns by subtracting the average return of all funds in same textual peer group, and show that this new measure of performance is positively and significantly related to future flows, even when controlling for a wide variety of traditional performance measures, namely: CAPM alpha, Fama–French-Carhart four-factor (FFC4) alpha, Fama and French (2015) five-factor plus momentum (FFC6) alpha, HKP customized peer alpha, and the Daniel et al. (1997) (henceforth, DGTW) characteristic selectivity measure. When all controls are included, the sensitivity of flows to SPG-adjusted performance remains 43% as large as the sensitivity to CAPM alpha, suggesting that investors are aware of SPG boundaries and consider funds belonging to the same SPG to be imperfect substitutes. We note that this perceived substitutability must occur along dimensions that are novel and distinct from traditional priced characteristics, given the traditional performance controls.

To further explore investors' preferences for SPG-specific characteristics, we study their responses when funds diverge from promised strategies. In months following higher strategy divergence, flows as a percentage of TNA are significantly lower, and this result is robust to controlling for both performance and alternative measures of product differentiation (KW and HKP). To analyze the dynamics and full magnitude of the effect, we implement a structural panel Vector

[2] A popular alternative for textual topic modeling is Blei et al. (2003)'s Latent Dirichlet Allocation (LDA), which estimates a posterior distribution over several topics for each document. Although this method yields similar results to k-means if we assign peer groups based on the most probable topic for each fund, we use k-means in our main specifications for two reasons: (i) philosophically, minimizing the distance to a single cluster center is more consistent with our interpretation of average portfolio weights as core strategies; and (ii) empirically, the topics generated by LDA have slightly less clear boundaries (e.g. two very similar topics for *quantitative*, while *small cap* and *large cap* strategies are merged into one topic; see Appendix C).

[3] To determine the number of clusters, we develop two criteria which we call *density* and *stability*. Intuitively, the density criterion requires new clusters to be sufficiently linguistically distinct, and the stability criterion requires most funds to be classified into the same groups across consecutive ks. Our results are not sensitive to the exact number of clusters chosen; see Appendix B.2.

[4] All funds in our sample hold an average of at least 80% of assets in U.S. common stock; however, what funds do with the remaining 20% is sometimes their most distinguishing feature.

[5] The log transformation is applied so that the variable is approximately normally distributed.

(a) Small Cap (b) Mid Cap (c) Large Cap

(d) Dividends (e) Products & Services (f) Competitive Advantage

(g) PE-Ratio (h) Quantitative (i) Fundamental

(j) Intrinsic Value (k) Long Term (l) Defensive

(m) Tax (n) Fixed Income (o) Derivatives

(p) Foreign (EM) (q) Foreign (ADR)

Fig. 1. Strategy Peer Groups: Word clouds for all estimated SPGs using the k-means algorithm with $k = 17$ clusters. These represent the frequency of features (words and bi-grams) in the strategy sections within each SPG. Word sizes are proportional to frequency.

Auto-Regression (SPVAR) model. Orthogonalized divergence shocks are recovered using a Cholesky identification approach (Sims, 1980), with variable ordering based on a slow-moving capital argument. This approach enables us to show that investors' outflows continue for more than 12 months following an initial change in divergence, with a single-month, one-standard-deviation shock leading to a reduction in annual percentage flows equal to 15% of the annual sample mean. Using this framework, we are also able to analyze the dynamics of strategy divergence. Divergence exhibits mean reversion at an unconditional rate of 75% per year, which increases by 12.5% when funds face one-standard-deviation outflows. This result is consistent with a market-led disciplining mechanism holding funds close to their promised strategies, even when legal enforcement would be difficult.

Although the SPVAR approach renders reverse causality unlikely, other forms of endogeneity remain a concern for our analysis. In particular, unobserved fund characteristics or macroeconomic events may be correlated with both strategy divergence and investor flows, resulting in omitted variable bias. To mitigate these concerns, we rely on the fact that our sample excludes industry funds (hence, most funds have a balanced exposure to multiple industries), and identify plausibly exogenous shocks to divergence originating from idiosyncratic industry-specific events. The idea is that large idiosyncratic industry returns — positive or negative — will mechanically change the composition of a fund's portfolio in a way that is uncorrelated with fund attributes or macroeconomic events.[6] Since return-driven shocks affect individual portfolios and SPG averages differently, they will cause funds to involuntarily diverge from their core strategies.

Idiosyncratic industry shocks are computed by regressing returns from each of the Fama–French 10 industry portfolios on a comprehensive factor model (the Fama–French-Carhart six factors). The absolute values of the regression residuals then serve as instruments. In the first stage of the IV regression, we show that there is a strong positive relationship between absolute idiosyncratic industry returns and changes in divergence (F-statistic > 10). Using the fitted values from the first stage, we then show that funds experience outflows starting one quarter after a divergence shock and lasting for at least four quarters. Economically this pattern is reassuring, as investors would likely react with a delay after observing the impact of the shocks on portfolio composition. Due to the time-series nature of the instruments the IV resembles an event study, and in this light it is also encouraging to note that the "no pre-trends" assumption is satisfied: instrumented divergence has no effect on flows prior to the industry shock.

In the OLS and SPVAR regressions, we estimate an average effect across cases where divergence is intentional and cases where it is unintentional. The IV approach, by contrast, allows us to estimate the effect of divergence specifically in cases where it is not confounded by strategic managerial decisions. Thus, the results of our IV regressions likely reflect investors' "pure" preferences for SPG adherence. Based on variation in strategy divergence directly attributable to the industry shocks, a one-standard-deviation increase in fitted changes in divergence results in an annual percentage flow reduction of 0.6% per year, or 25% of the annual sample mean. Note that the magnitude of this result is constrained by the size of the shocks generated by our instrument. Hence, it likely represents a lower-bound for the true magnitude of the typical effect.

Finally, having examined the supply and demand effects of SPGs, we explore a potential economic mechanism driving strategy divergence. As highlighted by our IV approach, there exist scenarios in which divergence happens involuntarily, and investors punish those cases harshly. We could imagine, however, that funds might want to diverge strategically when they identify alpha opportunities and/or when they face high competition from similar funds, despite potential disapproval from investors. To better understand this trade-off, we isolate cases in which divergence is more likely to happen strategically. Relying on HKP's finding that funds with fewer DGTW peers are better able to deliver alpha, we conjecture that changes in divergence which lead funds to move from a high-density DGTW-characteristics space (many HKP peers) to a lower density space (fewer HKP peers) are more likely to be driven by strategic considerations. In these cases we expect increases in divergence to lead to increases in SPG-adjusted performance. Confirming this conjecture, we find that while divergence is generally negatively or insignificantly related to performance, the effect becomes significantly positive when interacted with the strategic divergence dummy. In these cases, increasing divergence from the lower quartile to the upper quartile of its empirical distribution results in funds outperforming their SPG peers by 1.02% (or 56% of the sample standard deviation; the mean is zero by construction).

1.1. Related literature

Our findings relate primarily to the mutual fund IO literature, where we contribute by showing that investor preferences, and the supply of fund styles, are much more fine-grained than what has previously been documented in the literature. Various papers have studied competition in the index fund space,[7] while fewer investigate the active equity space. Those that do, study competition via holdings or return similarities. In this vein, the closest papers to ours are Wahal and Wang (2011), who examine competition among incumbents and new entrants through similarities in overall fund holdings; Li and Qiu (2014), who document that funds reduce competition by differentiating the factor exposures of their portfolios; Hoberg et al. (2018), who identify fund-specific peer groups by computing similarities in exposures to size, value, and momentum; and Kostovetsky and Warner (2020),[8] who find that small and start-up fund families avoid competition by differentiating themselves through more distinctive prospectus text.[9] Adding to this body of work, we show that investors exhibit preferences that go beyond standard measures of performance and priced characteristics (particularly size, value, and momentum), and that funds clearly differentiate their product offerings along these lines. We further show that differences in strategy descriptions reflect real differences in fund behavior rather than pure marketing, and that they are relevant for investors in terms of their specific content, not simply the uniqueness of the text.[10]

We also contribute to the more extensive mutual funds style literature by proposing a novel taxonomy of styles based on textual information in mutual fund prospectuses. The existing literature focuses mostly on return-based (e.g., Sharpe (1988, 1992); Brown and Goetzmann (1997); Hunter et al. (2014)) or holdings-based (e.g., Grinblatt

[6] Effects on flows coming via performance are accounted for using explicit controls.

[7] e.g., Elton et al. (2004); Hortacsu and Syverson (2004); Khorana et al. (2009); Gil-Bazo and Ruiz-Verdú (2009); Stoughton et al. (2011); Sun (2021)

[8] Kostovetsky and Warner (2020) use strategy description excerpts provided by Morningstar, which contain, on average, only the first 70 words of the full strategy text available in EDGAR filings. For comparison, the average length of this section in our dataset is 317 words.

[9] Other related papers include Khorana and Servaes (2012), who study the drivers of fund family market shares by analyzing their marketing expenses and funds' exposure to price-to-book, earnings growth, and market capitalization; Ali et al. (2020), who show that among funds taking advantage of post earnings announcement drift, only those who are able to avoid competition by investing in harder to hold stocks outperform, and Guercio and Reuter (2014), who study funds' incentives to generate alpha based on the competitive pressure they face due to diverse preferences of their target clientele (proxied by distribution channels).

[10] To ensure that our SPGs capture a novel and distinct dimension of competition, we show that there exists a low correlation between KW's and HKP's measures and ours, and we include both of these measures as controls in our analysis.

Table 1
Summary Statistics: This table reports summary statistics for the full matched sample in our dataset (i.e., each observation for which we can assign a prospectus to the fund). For each variable, the table displays the number of available observations (*count*), the mean (*mean*), the standard deviation (*sd*), the minimum (*min*) and maximum (*max*) values, and the 25th (*p25*), 50th (*p50*) and 75th (*p75*) percentiles.

	count	mean	sd	min	p25	p50	p75	max
TNA ($M)	315 190	1209.68	4394.34	5.10	68.70	246.80	908.20	177 462.59
Age (Months)	315 178	178.83	158.20	0.00	78.00	138.00	221.00	1121.00
Expense Ratio (%)	313 724	1.21	0.39	0.28	0.98	1.18	1.42	2.44
Turnover Ratio (%)	313 288	78.78	65.91	4.00	33.35	62.00	102.00	369.00
Flows (%)	314 940	−0.12	3.42	−9.00	−1.50	−0.45	0.74	12.54
Raw Return (Monthly)	315 006	0.61	4.74	−13.96	−1.88	1.04	3.54	12.18
CAPM Alpha (Monthly)	296 110	−0.07	1.86	−5.49	−1.05	−0.10	0.86	5.86
FFC6 Alpha (Monthly)	296 110	−0.09	1.18	−3.57	−0.73	−0.11	0.52	3.72

and Titman (1989); Daniel et al. (1997); Chan et al. (2002); Chan et al. (2009); Hoberg et al. (2018)) style definitions. An exception is Sensoy (2009) who analyzes funds' self disclosed benchmarks in prospectuses, but does not attempt to extract styles from prospectuses' text. These approaches require the ex-ante knowledge of relevant characteristics. Our unsupervised approach instead determines them endogenously, while still providing intuitive strategy descriptions thanks to the data's narrative nature.

We additionally contribute to the vast empirical literature on fund flows by documenting two novel drivers: SPG-adjusted performance and SPG-divergence. Existing work has mostly examined flow responses to performance (e.g. Chevalier and Ellison (1997); Sirri and Tufano (1998); Barber et al. (2016); Berk and Van Binsbergen (2016)), fees (e.g. Barber et al. (2005); Ivković and Weisbenner (2009)), and marketing/product differentiation (e.g. Jain and Wu (2000); Cooper et al. (2005); Reuter and Zitzewitz (2006); Khorana and Servaes (2012); Christoffersen et al. (2013); Kostovetsky and Warner (2020); Roussanov et al. (2021)).

Finally, we contribute to the burgeoning literature analyzing mutual fund mandatory disclosures. We are the first to provide a comprehensive analysis of the full PIS description for active equity mutual funds. Abis (2022) uses the same data, but only to identify quantitative funds. Abis et al. (2022) test a theoretical model of fund disclosure choice and investors' learning; their analysis, though, is conducted *within* fund mandates. Kostovetsky and Warner (2020) construct a textual measure of product differentiation, but do not explore the described strategies. Akey et al. (2021) use PIS text to determine the investment objectives of a different segment of the industry: ETFs and index funds. Krakow and Schäfer (2020) measure textual uniqueness within fund families as a proxy for disclosure informativeness; and Sheng et al. (2021) examine summary risk descriptions.

2. Data and clustering methodology

2.1. Data

To construct our mapping of the mutual fund industry, we combine standard information about mutual fund characteristics, returns and holdings with a novel textual dataset of their "Principal Investment Strategy" descriptions, taken from mandatory disclosures to the SEC (prospectuses). Our combined sample runs from March 2000 to December 2017, covering 2,995 unique funds and 315,190 fund–month observations. Table 1 provides descriptive statistics for the final dataset.

2.1.1. Prospectuses

The SEC requires all mutual fund families to publish prospectuses covering all of their funds. We obtain fund prospectuses from the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) of the SEC. The EDGAR system has been active since 1994, with a 2-year phase-in period. A number of subsequent reforms led to increasing standardization in disclosure formatting. In particular, as detailed in Release No. 33-7684, the SEC began to accept disclosures in HTML format in 2000. Prior to this year, the lack of standardization renders textual analysis much less reliable, and coverage of funds is also much more sparse. Hence, we begin our sample in March (end of Q1) 2000.

Prospectuses are divided into sections, each addressing a different regulatory question. In this paper we focus on a specific section: Principal Investment Strategies (PIS), corresponding to Item 9(c) of the N-1 A mandatory disclosure form.[11] This item requires funds to disclose their main investing methodology, including the types of securities they tend to hold and the primary criteria used in selecting those securities. Funds provide narrative descriptions of their strategies, constrained only by the above requirements and the additional stipulation that they be written in "plain English" (rule 421(d) of the Securities Act).[12]

We construct a comprehensive panel dataset of PIS descriptions by fund–month, which we then merge to the traditional mutual fund datasets. We are able to match 31,695 PIS descriptions to our funds of interest. Prospectuses may be published on any day of the year, and are often published less than once per quarter. Since any material change to the management of the fund must be reported to both the SEC and fund investors, for any month in which PIS is not available, we forward-fill it using the latest available one.

Appendix A provides detailed summary statistics for the PIS corpus utilized in our analysis. We document a large variation in the length, complexity and sentiment of PIS descriptions, suggesting they may contain heterogeneous information about fund strategies.

2.1.2. Fund characteristics and returns

We obtain fund characteristics and returns from the CRSP Survivorship-Bias-Free Mutual Fund dataset. We restrict the sample to equity funds and exclude international funds, sector funds, index funds, and underlying variable annuities. We account for incubation bias by excluding observations dated before the fund's first offer date (Evans, 2010). We also exclude funds with less than $5 million in Total Net Assets (TNA), following Kacperczyk et al. (2008). We then aggregate observations across all share classes of each fund for each time period. This is done by keeping the first offer date of the oldest share class, summing the TNA of all share classes, and averaging all other variables (e.g. fees, returns, turnover, etc.), weighted by lagged TNA. Following Abis (2022), we identify each fund's share classes by constructing a comprehensive fund identifier using the CRSP Class Group identifier, the WFICN identifier in MFLinks, and fund names. This choice is particularly relevant for matching fund returns and characteristic to their holdings. Notably, the MFLinks table excludes many new funds in recent years (Shive and Yun (2013); Zhu (2020)). Finally, we exclude funds for which we have less than 12 months of observations.

2.1.3. Holdings

Fund holdings are obtained by combining the Thomson Reuters (formerly CDA/ Spectrum) Mutual Fund Holdings dataset (from January 2000 to August 2008) and the CRSP Mutual Fund Holdings dataset (from

[11] https://www.sec.gov/files/form-n-1a.pdf
[12] https://www.sec.gov/rules/final/33-7497.txt

September 2008 to December 2017). The date of the switch is chosen to maximize coverage of active equity funds. We drop funds that hold fewer than 10 stocks, and funds that hold, on average, less than 80% of their assets (excluding cash) in common stock (Kacperczyk et al., 2008). When observations are missing or only available quarterly, we forward-fill them to a monthly frequency.[13]

2.1.4. Other

We also use the CRSP monthly security database, Compustat, Fama–French factors and industry portfolios, and the CBOE VIX Index.

2.2. Strategy peer groups

We now describe our methodology for grouping funds into quantifiable and interpretable "Strategy Peer Groups" (SPGs) based on similarities in their PIS text.

2.2.1. Pre-processing

To convert textual data to quantitative data, we use the "bag of words" approach. This procedure yields a list of all words and bi-grams (consecutive two-word combinations) for each document. We remove symbols, standard English stop-words (e.g. "is", "the", "and", etc.), and a list of context-specific stop words.[14] We reduce words to their root using the Porter stemmer algorithm (e.g., "company", "companies", … = "compani").

The second step is to remove boilerplate language, which occurs in most prospectuses and is therefore less informative. This step reduces classification noise. To do this, we aggregate unique word stems found in any of the PIS sections into a corpus, then compute the frequency of all 4-grams (4 word combinations) in this corpus. For each document, we remove any 4-gram with a full-corpus frequency above the 0.1th percentile (this procedure removes 601 4-grams). We further remove single words and bi-grams that appear in more than 30% of PIS sections and in fewer than 5%. The remaining words and bi-grams are the "features" utilized in the clustering algorithm.

In the third step, we represent the entire corpus as a single matrix, whose columns are linguistic terms (words and bi-grams) and whose rows are individual PIS sections. Each element in this matrix is the frequency of a particular feature in a particular PIS section, scaled by the number of sections in which that feature appears. This matrix is known as the term frequency–inverse document frequency, or *tfidf*, matrix.

2.2.2. Clustering

We use the *k-means* algorithm to group PIS sections by textual similarity. We choose this algorithm for its simplicity, and because its outcome naturally aligns with our measurement of core strategies as peer group average portfolio weights.[15]

K-means takes as inputs: the *tfidf* matrix, the desired number of clusters, and a tolerance parameter. The goal of the algorithm is to minimize the total Euclidean distance between the center of each cluster (called the "centroid") and all observations assigned to that cluster. In the context of textual analysis, the Euclidean distance is computed as follows:

$$\sqrt{\sum_{r=1}^{R} \|x_r - x_r^C\|^2}, \tag{1}$$

where x_r is the *tfidf* value for feature r in a specific document and x_r^C is the corresponding value in the cluster centroid. R is the total number of features. Centroids are initialized randomly in the vector space of all documents, then updated using an iterative process. In each iteration, each document is assigned to the closest centroid (i.e., with the smallest Euclidean distance), after which the centroid is redefined as the mean *tfidf* vector of all documents assigned to it. This process continues until the Euclidean distance between cluster centroids in two consecutive iterations is smaller than the specified tolerance level.[16]

The key hyper-parameter is the number of clusters, k. The optimal number varies depending on the true structure of the data. To find this optimum, we run the algorithm independently for consecutive $k = [10, 20]$, then compare outcomes according to two criteria:

1. *Stability*. A robust approach should not be very sensitive to the number of clusters chosen. The majority of PIS sections should be jointly categorized into the same cluster across consecutive ks. This should hold for any two consecutive ks.
2. *Density*. When moving from k to $k+1$, the new cluster generated should be sufficiently distinct from existing ones. This provides an optimal stopping point, beyond which additional clusters are redundant.

We systematically quantify the above concepts as follows. First, we define the cross-tab matrix as the number of observations falling in cluster i under k and cluster j under $k+1$, such as:

$$CrossTab_{(i,j)} = \#\ clustered\ as\ i\ under\ k\ and\ j\ under\ k+1.$$

If we treat $k+1$ as the ground truth, and k as the predicted value, for any combination (i, j), the denominator of its precision is the sum for all j given i, and the denominator of its recall is the sum for all i given j. Formally, define precision and recall as:

$$Precision_{(i,j)} = \frac{CrossTab_{(i,j)}}{\sum_{i=1}^{K} CrossTab_{(i,j)}}; \quad Recall_{(i,j)} = \frac{CrossTab_{(i,j)}}{\sum_{j=1}^{K+1} CrossTab_{(i,j)}}.$$

Intuitively, a large $Precision_{(i,j)}$, means that observations classified as i under k, are likely to be classified as j under $k+1$. Similarly, a large $Recall_{(i,j)}$, means that observations classified as j under $k+1$, are likely to be classified as i under k. We combine those two criteria into an $Fscore$ matrix indicating their harmonic mean. Due to the characteristic of the harmonic mean, if $Fscore_{(i,j)}$ is large, $Precision_{(i,j)}$ and $Recall_{(i,j)}$ are both expected to be large, and cluster i under k is likely to be in line with cluster j under $k+1$:

$$Fscore_{(i,j)} = 2 \cdot \frac{Precision_{(i,j)} \cdot Recall_{(i,j)}}{Precision_{(i,j)} + Recall_{(i,j)}}.$$

We finally transform the $Fscore_{(i,j)}$ matrix into a $Stability_{(i,j)}$ matrix by substituting scores with 1 if they are greater than a threshold (we currently use 0.5), 0 otherwise. All 1s indicate matched clusters across consecutive runs k and $k+1$.

Next, we define $Dist$ as the Eucledian distance between the centroids of any pair of clusters under k and k+1 as: $Dist_{(i,j)} = \|C_i^k - C_j^{k+1}\|^2$; where C_i^k indicates the centroid of *tfidf* vector of cluster i under k, and C_j^{k+1} indicates the centroid of *tfidf* vector of cluster j under k+1. A small distance between two centroids indicates that the underlying clusters are likely to be similar in meaning. Hence, we transform the $Dist_{(i,j)}$

[13] Monthly holdings are already available for or 42% of the sample; 90% of the data is forward-filled for at most 1 quarter in total; and 99% is forward-filled for at most 2 quarters in total. Forward-filling is restricted to a maximum of 1 year.

[14] The full list of removed words, after stemming, is as follows: advis, alloc, asset, averag, bar, billion, chart, class, compani, describ, equiti, fmr, fund, iii, inform, invest, least, manag, may, might, money, mutual, net, nyse, object, page, portfolio, potenti, price, princip, prospectu, rang, reason, risk, russel, s&p, secur, sharehold, shown, state, stock, strategi, style, subadvis, total, unit, varieti, year.

[15] It is possible to construct peer groups using other popular models such as Latent Dirichlet Allocation (LDA). In that case, core strategies could be defined by using the highest weighted topic for each fund. This procedure gives similar results to k-means clustering. See Appendix C.

[16] For a more detailed description of the k-means algorithm, see Appendix B.1.

matrix into the $Density_{(i,j)}$ matrix by substituting distances with 1 if they are lower than a threshold (we currently use 0.2), 0 otherwise. All 1s indicate matched clusters across consecutive runs k and $k+1$.

We start by inspecting the $Stability_{(i,j)}$ matrix for $(k, k+1) = (10, 11)$. For the $stability$ criterion to be satisfied we must have that: (1) all rows of $Stability_{(i,j)}$ sum to at least 1; that means that all clusters in $k = 10$ are matched to at least 1 cluster in $k = 11$. (2) Columns should sum to at most 1; that means that all clusters in $k = 11$ are matched to at most one cluster in $k = 10$. Any column whose sum is zero is considered to be a new cluster. Note that it is possible for a cluster in k to be matched into 2 clusters in $k+1$, that would be the case if a cluster representing a broad category is split into two meaningfully different sub-clusters. To verify that newly generated clusters are sufficiently distinct from existing ones we next inspect the $Density_{(i,j)}$ matrix for $(k, k+1) = (10, 11)$. For the density criterion to be satisfied we must have that for any newly generated cluster in $k+1$ the sum of the corresponding column in the $Density_{(i,j)}$ matrix should equal 0 (i.e., the centroid vector for that cluster should be meaningfully different from any centroid vector already present in k). If both conditions are satisfied we proceed to analyzing the $Stability$ and $Density$ matrices for $(k, k+1) = (11, 12)$. We repeat the above steps until the $Density$ criterion fails. That allows us to establish that the optimal number of clusters in our setting is 17.[17]

2.2.3. Clusters as text-based styles

Centroids identified through this methodology should be interpreted as distinct text-based *promised* strategies. Although strategies are represented by a full distribution over words and bi-grams, the labels and key terms shown in Fig. 1 are a useful short-hand to indicate the features that are most distinctive of each. The key features of some strategies are commonly known by academics and in the industry (*Large Cap*, *Mid Cap*, *Small Cap*). But most represent novel dimensions: some are associated with firm characteristics (*Dividends*, *New Products & Services*, *Competitive Advantage*, *Price-Earnings Ratio*); some with investment philosophies (*Quantitative*, *Fundamental*, *Intrinsic Value*, *Long Term*, *Defensive*, *Tax*); some with secondary asset classes (*Fixed Income*, *Derivatives*); and some with international markets (*Foreign (ADR)*, *Foreign (Emerging Markets)*).

K-means assigns each PIS section to one centroid, implicitly assuming that each strategy description has a dominant strategy; i.e., that the spatial distribution of funds is concentrated around centroids. We adopt two methods to assign funds to Strategy Peer Groups (SPGs). First, we take k-means assignments to represent SPGs; i.e., we study funds' *dominant* promised strategies. Then, we generalize SPG definitions by allowing funds to promise a weighted combination of the identified strategies (a fund's *promise vector*). That approach yields fund-specific SPGs, defined as the set of funds with the most similar *promise vectors*. In both approaches the 2,995 funds of interest are assigned to an SPG for every month they are active between March 2000 and December 2017. All of the paper's results are robust to utilizing either implementation. Hence, for simplicity of exposition, we first report results based on the simplified method, while generalized results are reported in Section 3.4.

Fig. 2 shows that the relative size of SPGs varies over time in terms of both the number of funds and TNA. Panel 1 of Fig. 3 shows the frequency of assignment to each SPG; Panel 2 shows that funds tend to be assigned to the same SPG over time. 1,087 funds are assigned to only one SPG throughout their lives, the majority of funds is assigned to a maximum of 5, and only a small number is assigned to more (that may be the result of estimation noise). We do not constrain the cluster estimation to group together PIS sections from the same fund. Hence, the time-series stability of the assignment further confirms the robustness of our approach.

[17] Since the stability criterion is generally satisfied for any consecutive ks, our results are not very sensitive to the choice of k. Appendix B.2 shows that our main result holds for $k = [14, 20]$.

3. Empirical analysis

3.1. Supply of funds

To better understand the nature of the uncovered strategies, and to ascertain if this *promised* product differentiation lines up with *actual* differences in implementation, we start with a narrative analysis. We ask whether fund characteristics, risk-factor loadings, performance, and holdings attributes line up with an intuitive reading of strategy descriptions. This exercise necessarily involves a subjective component. Hence, it should be intended as purely descriptive. In Section 3.1.1 we provide evidence based on objective similarity measures.

For each variable, and for each SPG, we implement a regression analysis which allows us to estimate the average difference in that variable for the SPG of interest and all other SPGs (holding other characteristics, family membership, and month constant). Appendix D explains in detail that regression strategy, reports a detailed set of results, and provides a discussion of the key characteristics of all 17 SPGs. In the discussion below, we highlight the most striking attributes of a few selected SPGs.

Dividends. The "Dividends" group arguably has the most straightforward strategy and the clearest ex-ante expectations for investors: funds in this SPG should try to maximize dividend distributions. Accordingly, we find that these funds hold stocks with (by far) the highest dividend yield among all SPGs. The funds implementing this strategy tend to charge lower fees and have lower turnover ratios. The companies they hold are typical high-dividend firms: they are larger and older, have lower investment, and R&D expenses, and hold less cash (plausibly due to higher payout ratios). Portfolios are tilted towards high-dividend industries such as Utilities, Telecoms, and Banks; and tilted away from the Tech industry.

Long term. Funds in this SPG claim to be searching for long term investment opportunities, or companies with long term growth potential. In the data, funds implementing this strategy tend to be older and have lower turnover ratios. The stocks they hold have lower than average book-to-market ratios, both at the fund level and at the stock level (indicting a growth style tilt). They tend to avoid mature industries such as Utilities and Banks. Instead, they hold companies with higher intangibles (which includes capitalized R&D), higher cash, and lower dividend yields (greater retained earnings, typically used to grow the firm).

New products & services. Funds in this SPG focus on companies with new or innovative product lines, and new or rapidly changing technologies. Consistent with this focus, funds in this SPG tend to avoid stable industries such as utilities, telecoms, and banks, while holding a significantly greater fraction of stocks from innovative industries such as technology and pharmaceuticals (drugs). The funds implementing this strategy charge higher fees and have higher turnover ratios. The firms they hold have higher levels of investment and R&D expenditure, higher asset growth, and lower dividend yield, as would be expected for companies introducing new products and services.

It is clear from the above descriptions, and by inspecting the full Tables in Appendix D, that each of these strategies has a multi-faceted implementation. Indeed, they imply differential exposures to various risk-factors, as well as differences in other fund and holdings features. For instance, both the *Long Term* and the *New Products & Services* strategies have a growth tilt, but they achieve that objective differently: *Long Term* funds have a low turnover ratio, *New Products & Services* funds have a high one. *New Products & Services* funds hold younger firms with higher asset growth and R&D expenditures, and a greater than average exposure to the Tech and Drugs industries, while *Long Term* funds do not.

A natural next question is whether SPGs significantly differ in risk-adjusted performance. Appendix Table D.9 shows that this is generally

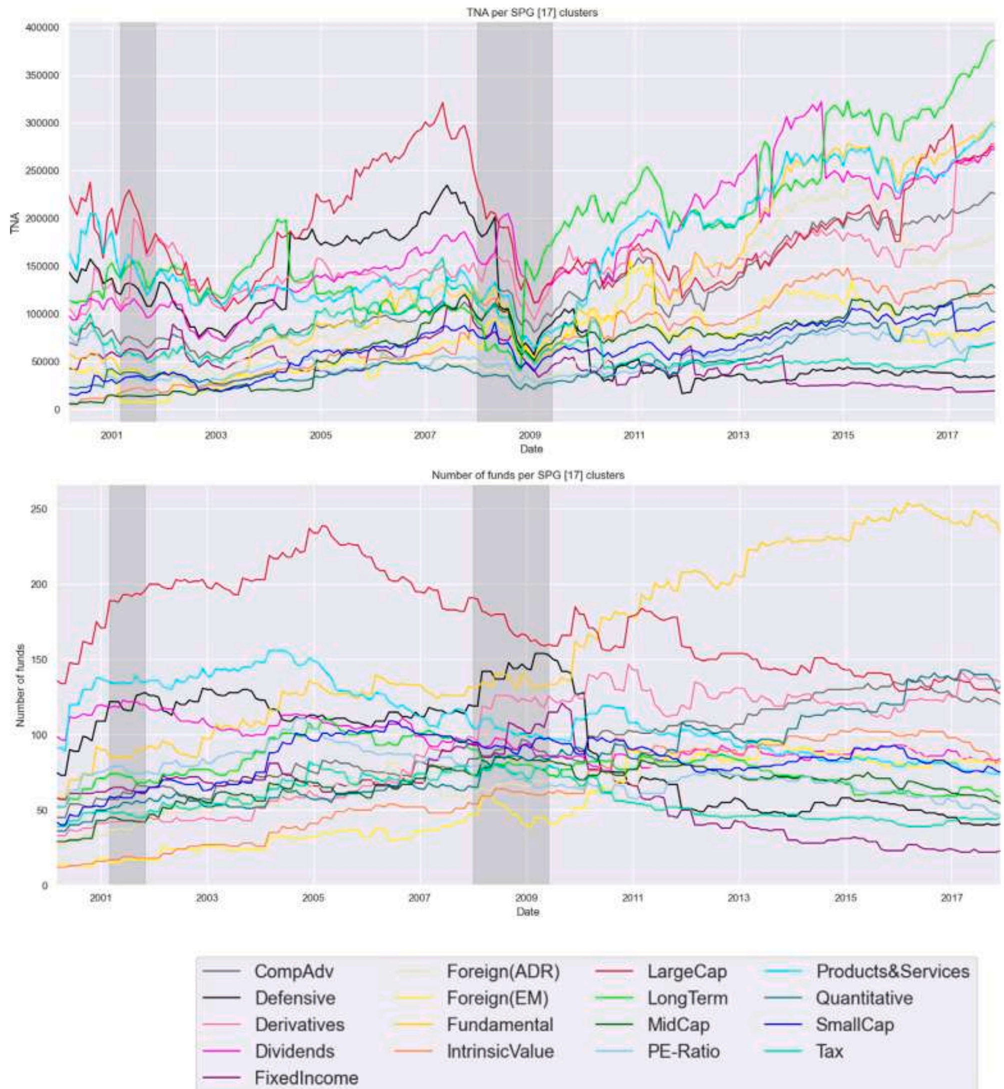


Fig. 2. TNA by SPG Over Time: Panel 1 displays the cumulative TNA managed by funds in different SPGs between January 2000 and December 2017. Panel 2 displays the number of funds assigned to the different SPGs between January 2000 and December 2017.

not the case. An intuitive alternative explanation for the documented product differentiation is that funds cater to investors with different preferences for risk-exposures and/or for non-priced characteristics. For instance, investors who prefer income to capital gains might choose *Dividend* funds.[18] Similarly, among investors looking for exposure to the growth factor, those with a longer horizon might prefer *Long Term* funds while those with a shorter horizon might prefer *New Products & Services* ones.

3.1.1. Divergence from core strategies

In this section, we construct a general measure of strategy divergence that does not depend on subjective interpretations of the text. The underlying assumption is that the average holdings of the funds in each SPG are representative of the group's core strategy—in other words, we assume that individual fund divergences are purely idiosyncratic and cancel out over many funds in a group. Then, the *core strategy* of each SPG is measured as the mean portfolio weight vector across all funds in that group, and an individual fund's divergence from the core strategy is measured by the distance of its holdings from this mean vector. For each month in our sample, we compute this distance relative to each fund's own assigned SPG, and relative to the average of other SPGs. If funds are following their promised strategies, we should observe smaller divergences from their own group average. Formally:

$$Divergence_{j,t}^{G_{j,t}} = \sum_{i=1}^{N_t^j} \left(w_{i,t}^j - \bar{w}_{i,t}^{G_{jt}} \right)^2 \quad (2)$$

for $G = [SPG, \widetilde{SPG}]$, where $SPG_{j,t}$ is the SPG of fund j at time t, and $\widetilde{SPG}_{j,t}$ represents all groups other than $SPG_{j,t}$. $w_{i,t}^j$ is the weight on stock i in fund j's portfolio in month t, and $\bar{w}_{i,t}^{G_{j,t}}$ is the average weight on stock i at time t for all funds belonging to group $G_{j,t}$. We log-transform divergence so that it is approximately normally distributed.

To test whether funds generally adhere to the strategies described in their prospectuses (which lead them to be categorized into a particular SPG) we run the following regression:

$$Divergence_{j,t} - \widetilde{Divergence}_{j,t} = \alpha + \lambda' X_{j,t} + \eta_{f,t} + \varepsilon_{j,t}. \quad (3)$$

[18] e.g., Allen et al. (2000); and Hartzmark and Solomon (2019) document investor preferences for high dividends, motivated by taxation or behavioral reasons, respectively.

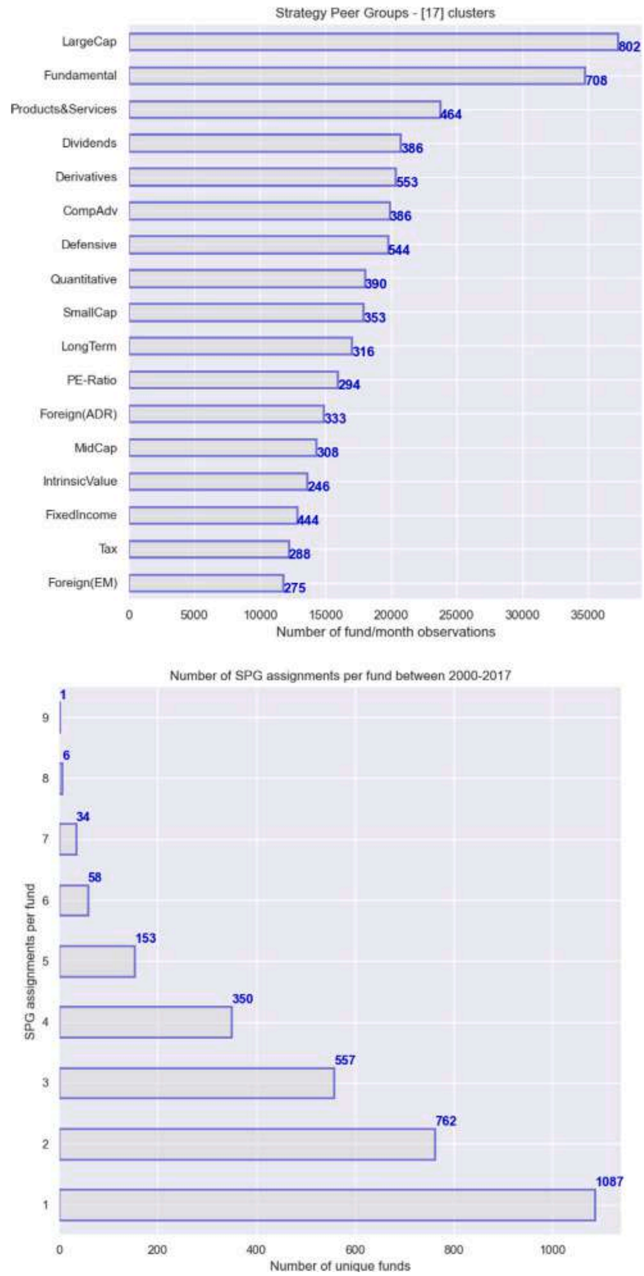


Fig. 3. SPG Assignments Per Fund: Panel 1 shows the number of fund-month observations assigned to each of the SPGs using the k-means algorithm with 17 clusters. The number next to each bar indicates the unique number of funds assigned to each SPG at some point in their lifetimes. Panel 2 shows the number of different SPG assignments that unique funds receive throughout their lives.

The coefficient of interest is $\hat{\alpha}$, which estimates the difference between within-group $Divergence$ and outside-group $\widetilde{Divergence}$ when all control variables are equal to their mean values (all controls are demeaned). The control variable vector, $X_{j,t}$, contains the log of total net assets (TNA), the log of fund age, the fund's expense and turnover ratios, monthly percentage flows, and monthly flow volatility for fund j in month t. $\eta_{f,t}$ are fund family × month fixed effects. Standard errors are clustered by fund and month. Hence, a negative and significant $\hat{\alpha}$ should be interpreted as a lower mean in SPG-divergence *within* SPGs than *outside*, between funds in the same month and fund family, after controlling for fund-level characteristics.

The top Panel of Table 2 reports the estimated $\hat{\alpha}$s in the third column, while the first two columns show the average divergences

Table 2
SPG Divergence - Validation: This table reports mean divergence of funds from the average holdings of their own peer group (Column 1), mean placebo divergence from the average holdings of other peer groups (Column 2), and the difference between these two estimates (Column 3) (see Section 3.1.1). Throughout the table, averages are estimated controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, fund flow volatility, and family-month fixed effects. In the second row, we additionally control for funds' holdings divergence based on Daniel et al. (1997) characteristics peer groups, the log of the number of Hoberg et al. (2018) fund peers, and the Kostovetsky and Warner (2020) uniqueness measure. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	(1) Within SPG	(2) Outside SPG	(3) Difference
Baseline	−4.790***	−4.360***	−0.430***
	(−443.16)	(−348.65)	(−50.54)
R2	0.347	0.374	0.278
N	266 803	266 803	266 803
Add. Controls	−2.015***	−1.086***	−0.929***
	(−47.44)	(−25.48)	(−23.21)
R2	0.566	0.700	0.326
Obs	264 089	264 089	264 089
Controls	Yes	Yes	Yes
FE	Family-Month	Family-Month	Family-Month
Cluster	Fund+Month	Fund+Month	Fund+Month

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

relative to the fund's own SPG (within) and relative to other SPGs (outside), respectively. Column 3 shows that divergence is on average 8.98% lower within the SPG than outside it,[19] and all results are significant at the 1% level.[20]

These results imply that funds allocate their capital more similarly to the average fund in their own SPG. Thus we conclude that, on average, *promised* product differentiation translates into *actual* differences in product offering. This interpretation does not depend on the average level of distance within any particular group, as long as funds with high in-group distance still have higher distance with respect to funds outside of the group.[21]

A remaining concern is that SPG-divergence might be capturing a simple transformation of other product differentiation measures previously documented in the literature. In particular, SPG centroids might be conceptually similar to centroids obtained by sorting funds based on terciles of market capitalization, book-to-market, and past returns of the stocks they hold (DGTW-peers).[22] Hence, we construct peer groups based on that alternative methodology and compute divergence based on those clusters, following Eq. (3). As HKP have shown, though, competition in DGTW space is driven by the crowdedness of the strategy space in the proximity of a fund's location. For that reason, we additionally compute HKP's fund-specific peer groups and proxy for the degree of competition using the number of HKP peers and its natural logarithm. Finally, it is plausible that SPG divergence could be capturing a general drive towards strategy uniqueness, in a conceptually similar way to KW's uniqueness measure. Hence, we also reproduce it.

[19] Portfolio weight divergences are always negative due to the log transformation.

[20] Note that the large t-statistics are due to the fact that the reported coefficients are regression intercepts.

[21] We acknowledge that our measure is limited by how well portfolio weights can capture all aspects of fund strategies. The $\hat{\alpha}$ coefficient could be biased towards zero if we miss a major axis of commonality for a particular strategy (e.g., we do not observe derivative positions for funds in the *Derivatives* SPG).

[22] The 9 main Morningstar categories for U.S. Equity funds are nested within the 27 DGTW peer groups.

Table 3
SPG Divergence - Correlations: This table reports the monthly correlations of our SPG Divergence measure with other measures of mutual fund competition and product differentiation used in the literature: the Hoberg et al. (2018) number of customized characteristics-based peers (HKP Peers) and its natural logarithm (HKP Log Peers); the Kostovetsky and Warner (2020) uniqueness measure; and an alternative divergence measure based on Daniel et al. (1997) characteristics peer groups. SPG Divergence is the log sum of squared differences between the fund's portfolio weights and the average weights for funds in the same Strategy Peer Group. DGTW Divergence is constructed in the same way but with respect to average portfolio weights among funds whose holdings are in the same Daniel et al. (1997) size, book-to-market, and past return terciles. See Section 3.1.1 for further details.

	Divergence		HKP	
	SPG	DGTW	Peers	Log Peers
DGTW Divergence	0.628***			
HKP Peers	−0.123***	−0.146***		
Log HKP Peers	−0.203***	−0.242***	0.829***	
KW Uniqueness	0.126***	0.120***	0.028***	−0.018***
N	315 190			

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3 shows the correlation among SPG-divergence, DGTW-divergence, HKP-peers, and KW-uniqueness. We observe a small positive correlation of 12.6% between SPG-divergence and KW-uniqueness; a small negative correlation of (−20.3%) −12.3% between SPG-divergence and (log) HKP-peers; and a much higher positive correlation of 62.8% between SPG-divergence and DGTW-divergence. The higher correlation with DGTW-divergence is not surprising, as both measures are constructed as distances between holdings vectors. Given those correlations, the bottom Panel of Table 2 repeats the analysis in Eq. (3) by adding those variables to the controls vector (X). In this case, the difference increases substantially: divergence is 46.1% lower with respect to funds' own assigned SPGs, suggesting that our measure is capturing a novel dimension of product differentiation.

In Appendix E we allow for more stringent controls by comparing funds pairwise. That analysis yields similar conclusions: any pair of funds is more likely to have lower divergence and similar moments in future return distribution if they belong to the same SPG.

3.2. Investor demand

In this section we examine investors' demand for SPGs by studying their flow responses to SPG-adjusted performance and SPG-divergence.

3.2.1. Fund flows and SPG-adjusted performance

Given our analysis of the supply of funds, it is plausible that SPG-level product differentiation might reflect investor preferences for risk-exposures and/or other non-priced characteristics distinctive of each SPG. If that was the case, investors should be aware of SPG boundaries and should view funds within the same SPG as imperfect substitutes.

An extensive academic literature has documented investors' preference for higher active returns and their flow-performance sensitivity (e.g. Chevalier and Ellison (1997); Sirri and Tufano (1998); Barber et al. (2016); Berk and Van Binsbergen (2016)). If investors prefer higher active returns, while simultaneously having a preference for other SPG features, we should observe a significant flow-performance sensitivity when benchmarking a fund's return against the average return of other funds in the same SPG. To test that hypothesis we build a measure of SPG-adjusted performance as follows:

$$SPG\ Alpha = R_{j,t} - \bar{R}^{SPG}_{t_{j,t}} \tag{4}$$

where $R_{j,t}$ is the annual net of fee return of fund j from month $t-11$ to month t; and $\bar{R}^{SPG}_{t_{j,t}}$ is the average annual net of fee return from month $t-11$ to month t, of funds belonging to the same SPG as fund j in month t. Table 4 displays the correlations between SPG Alpha and other performance measures commonly used in the literature.

We then run the following regression:

$$Flow_{j,t+1} = \alpha + \beta SPG\ Alpha_{j,t} + \gamma' Performance_{j,t} + \lambda' X_{j,t} + \eta_{f,t} + \varepsilon_{j,t}. \tag{5}$$

where $Flow_{j,t+1}$ represents fund flows at time $t+1$ (one month ahead), measured as the percentage change in total net assets not due to returns. $SPG\ Alpha_{j,t}$ is the SPG-adjusted performance for fund j in month t, as defined in Eq. (4). $Performance_{j,t}$ contains other common measures of performance, namely: CAPM, FFC4, and FFC6 alphas;[23] and HKP and DGTW peer-adjusted returns. All returns and alphas are net of fees. $X_{j,t}$ contains fund-level control variables (log TNA; log age; expense ratio; turnover ratio) for fund j in month t. Since capital flows are heavily influenced by distribution channels common to funds in the same family, and given the impact of overall market conditions (e.g., aggregate outflows during recessions) that may affect different families in different ways, all specifications include fund family×month fixed effects, represented by $\eta_{f,t}$. Standard errors are clustered by fund and month. A positive and significant $\hat{\beta}$ would indicate a significant flow-performance sensitivity towards SPG-adjusted performance.

Column 1 of Table 5 shows the outcome of that regression, when excluding the vector of additional $Performance$ controls. As expected, we observe a positive and significant (at the 1% level) $\hat{\beta} = 0.116$. To better understand the economic magnitude of this result, and to assess its incremental explanatory power, Column 2 of Table 5 reports the same results when adding other standard performance controls. The statistical significance of $\hat{\beta}$ is unchanged (1% level), while its point estimate becomes $\hat{\beta} = 0.015$. Despite other alphas absorbing much of the variation, SPG alpha remains incrementally relevant to investors: to put the coefficient into perspective, it represents 43% of the incremental effect of CAPM alpha, 29% of that of FFC4 alpha, 60% of that of FFC6 alpha, 200% of that of DGTW-adjusted returns, and 22% of that of HKP peer-adjusted returns.

These results suggests that investors are aware of SPG boundaries and consider products within them to be imperfect substitutes. Combining those insights with the lack of differences in risk-adjusted performance across SPGs, provides preliminary evidence of investor preferences for other characteristics of SPGs, beyond risk-adjusted performance.

3.2.2. Fund flows and SPG divergence

To more formally study investors' preferences for SPG core strategies, we study their flow responses to SPG-divergence. If investors have a preference for risk exposures or other non-priced features of SPGs, we should observe that they punish funds with outflows when their *implemented* strategy diverges from the *promised* one.

To test this hypothesis, we use the measure of SPG-divergence, constructed as per Eq. (2). To facilitate discussion of magnitudes, we standardize the measure to have mean zero and variance 1. We then examine the relationship between fund flows and SPG-divergence, controlling for fund characteristics, past performance, and fund family membership, which are already known to drive flows, by running the following regression:

$$Flow_{j,t+1} = \alpha + \beta Divergence_{j,t} + \gamma SPG\ Alpha_{j,t} + \lambda' X_{j,t} + \eta_{f,t} + \varepsilon_{j,t+1}, \tag{6}$$

where $Flow_{j,t+1}$ represents fund flows at time $t+1$ (one month ahead); *Divergence* is *within*-SPG divergence (Eq. (2)) for fund j in month t;

[23] All alphas are computed at a monthly frequency by subtracting monthly fund returns from a beta-adjusted factor return portfolio, where the betas are estimated using rolling 24-month regressions. We then aggregate the monthly alphas up to the annual frequency. Note that we do not include Berk and van Binsbergen (2015)'s value added measure in this regression as our goal is to understand investor responses. Value-added is a measure of fund manager skill in the presence of decreasing returns to scale, while investors only care about the returns they will experience on their own portfolios.

Table 4
SPG Alpha - Correlations: This table reports the correlations of monthly SPG-adjusted performance (SPG Alpha) with various other standard performance measures: Daniel et al. (1997) characteristic selectivity measure (DGTW Alpha); Hoberg et al. (2018) customized peer alpha (HKP Alpha); CAPM Alpha, Fama–French-Carhart 4-Factor Alpha (FFC4 Alpha), and Fama–French-Carhart 6-Factor Alpha (FFC6 Alpha). All performance measures are computed net of fees. See Section 3.1.1 for further details.

	SPG Alpha	DGTW Alpha	HKP Alpha	CAPM Alpha	FFC4 Alpha
DGTW Alpha	0.566***				
HKP Alpha	0.750***	0.619***			
CAPM Alpha	0.756***	0.513***	0.607***		
FFC4 Alpha	0.557***	0.452***	0.593***	0.641***	
FFC6 Alpha	0.495***	0.408***	0.534***	0.576***	0.892***
N	315 006				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5
Fund Flows, SPG Divergence, and Performance: This table shows regressions of one-month-ahead net fund flows (% of TNA) on SPG Divergence, SPG Alpha, various other measures of one-year past performance, and controls for fund characteristics (omitted for brevity), competition, and product differentiation (see Section 3.2.2). SPG Alpha is the fund's return relative to the average of all funds in the same text-based Strategy Peer Group (SPG). SPG Divergence is the log sum of squared differences between the fund's portfolio weights and the average weights for funds in the same SPG. DGTW Divergence is constructed in the same way but with respect to funds in the same Daniel et al. (1997) characteristics terciles. HKP Peers is the number of fund competitors according to Hoberg et al. (2018), and HKP Alpha is the fund's return relative to these competitors. The dummies Low Comp and Med Comp indicate the bottom and middle terciles (by month) of the distribution of HKP Peers. KW Uniqueness is the Kostovetsky and Warner (2020) measure of textual prospectus uniqueness. All specifications include fund-family × month fixed effects, and standard errors are two-way clustered by fund and month.

	(1)	(2)	(3)	(4)	(5)
SPG Divergence			−0.049***	−0.060***	−0.055***
			(−2.63)	(−3.20)	(−2.96)
DGTW Divergence				0.027	0.027
				(1.59)	(1.60)
KW Uniqueness				−0.043*	−0.041
				(−1.71)	(−1.63)
Log HKP Peers				−0.036**	
				(−2.11)	
SPG Alpha	0.116***	0.015***	0.116***	0.013**	0.012**
	(22.03)	(2.91)	(22.07)	(2.40)	(2.20)
CAPM Alpha		0.035***		0.035***	0.036***
		(7.32)		(7.42)	(7.70)
FFC4 Alpha		0.052***		0.053***	0.052***
		(5.93)		(5.95)	(5.94)
FFC6 Alpha		0.025***		0.024***	0.024***
		(3.43)		(3.20)	(3.21)
DGTW Alpha		0.007**		0.007**	0.007**
		(2.05)		(2.05)	(2.22)
HKP Alpha		0.068***		0.071***	0.060***
		(12.27)		(12.53)	(7.61)
Low Comp					0.142***
					(3.17)
Med Comp					0.120***
					(3.38)
Low Comp × HKP Alpha					0.011
					(1.49)
Med Comp × HKP Alpha					0.016**
					(2.25)
R2	0.320	0.336	0.320	0.336	0.336
Obs	239,751	239,751	239,751	237,178	239,486

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

$SPG\ Alpha$ is SPG-adjusted performance (Eq. (4)); $X_{j,t}$ contains fund-level controls (log TNA; fund age; expense ratio; turnover ratio) for fund j in month t; $\eta_{f,t}$ are family×month fixed effects. Standard errors are clustered by fund and month. A negative and significant $\hat{\beta}$ would indicate outflows when a fund's portfolio diverges from that of its SPG's average.

Column 3 of Table 5 reports the results without additional controls. As expected, $\hat{\beta}$ is negative and significant at the 1% level. Although the single-month magnitude appears modest — on average, a one-standard-deviation increase in *SPG-Divergence* leads to a decrease in next-month flows of 0.05% — the effect grows over time and is substantially greater in the long run, as we show in Sections 3.2.3 and 3.2.4. Furthermore, as we discuss in Section 3.3, SPG divergence can occur for a variety of reasons, both accidental and deliberate. In equilibrium, the estimated coefficient reflects an average of these effects and thus will be driven towards zero, whereas Section 3.2.4 shows that the magnitude is much greater when divergence is not a conscious choice by the fund manager. Lastly, it is worth keeping in mind that our measure of SPG adherence is necessarily noisy, which also potentially biases the coefficient towards zero.

The effect of $SPG\ Alpha$ on flows ($\hat{\gamma}$) remains positive and significant, highlighting the dual preference of investors for higher SPG-adjusted returns and lower SPG divergence.

To explore the robustness of these results, in Column 4 of Table 5 we add to the controls vector all additional performance measures included in Column 3; as well as DGTW-divergence, KW-uniqueness and log(HKP-peers) (constructed as in Section 3.1.1). This alleviates concerns that the effect of divergence on flows might be driven by SPGs' correlation with omitted measures of performance, competition, or product differentiation. In this specification, $\hat{\beta}$ remains statistically significant at the 1% level, while its economic magnitude increases: a one-standard-deviation increase in *SPG-Divergence* leads to a decrease in next-month flows of 0.06%. To ascertain that SPG-divergence is capturing a truly distinct effect from HKP's measures, we further refine our analysis by substituting log(HKP-peers) with dummies for funds in the bottom and mid terciles of HKP-peers, as well as the interaction between those dummies and HKP Alpha. Column 5 of Table 5 reports those results, showing a similar economic and statistical significance of $\hat{\beta} = 0.055$.

Taken together, these results indicate that the effect of SPG-divergence on flows is driven by investor preferences that are novel and distinct from the preference for higher risk-adjusted performance. However, questions remain about the magnitude of the effect, which we address in our subsequent analysis. The joint significance of SPG-adjusted performance and SPG-divergence in driving flows, suggests that the dual nature of investor preferences is distinct and the two effects need not necessarily go in the same direction. We study this trade-off more in depth in Section 3.3, when investigating the economic mechanism driving divergence.

3.2.3. Dynamics of investor and fund responses

In this section we explore the dynamic interrelationships among our main variables of interest. We have shown that investors respond negatively to funds' divergence from their core strategies and positively to higher peer-adjusted returns, but our interpretation of these results may be confounded by endogenous feedback effects in a complex equilibrium system. For instance, rational fund managers may also anticipate or respond to investors' responses, and fund performance may depend on prior managerial actions and investor flows. To capture these intertemporal feedback effects in a more disciplined way, we consider a structural panel vector autoregression (SPVAR) model.

Structural panel vector autoregression. The L-order structural equation we would like to estimate is:

$$y_{j,t}A_0 = \sum_{l=1}^{L} y_{j,t-l}A_l + x_{j,t}B + \alpha_j + \varepsilon_{j,t}, \tag{7}$$

where $y_{i,t}$ is an N-vector of endogenous variables for fund j in month t; $x_{j,t}$ is a vector of exogenous control variables; A_0 through A_L and B are coefficient matrices; α_j are fund-level fixed effects;[24] and $\varepsilon_{j,t}$ is a vector of independent structural shocks driving each of the endogenous variables, distributed as $N(0, I)$. The endogenous vector $y_{i,t}$ contains SPG divergence (measured at the beginning of month t), SPG alpha (measured from t to $t+1$), percentage fund flows (measured from t to $t+1$), and the multiplicative interaction between divergence and flows. Including the interaction term allows the autoregressive coefficients for divergence to depend on flows, and vice versa. The exogenous vector $x_{j,t}$ contains other standard performance measures—HKP, and DGTW peer-adjusted returns, and CAPM, FFC4, and FFC6 alphas (measured from $t-12$ to $t-1$)—as well as fund characteristics—log age, log TNA, expense ratio, and turnover ratio (measured as of the beginning of month t).

This framework permits simultaneous estimation of several key intertemporal relationships: (i) the *long-run* effects of divergence and performance on flows (Section 3.2.2 considers investor responses only one month ahead); (ii) the time-series properties of divergence; (iii) the feedback effects of flows on future divergence; and (iv) the effects of divergence and flows on future performance.

Contemporaneous relationships among the endogenous variables are represented by the matrix A_0, which is not directly observable. We also cannot directly observe the structural shocks $\varepsilon_{j,t}$. Fortunately, well-documented market frictions combined with variable timings imply a natural causal ordering that allows us to first estimate the reduced-form model,

$$y_{j,t} = \sum_{l=1}^{L} y_{j,t-l}\tilde{A}_l + x_{j,t}\tilde{B} + \tilde{\alpha}_j + \nu_{j,t}, \tag{8}$$

where $\nu_{j,t} \sim N(\omega, \Omega)$, and then identify the structural coefficients via Cholesky decomposition of the reduced-form residual variance–covariance matrix $\hat{\Omega}$ (Sims, 1980). Specifically, we set $\hat{A}_0\hat{A}_0{}' = \hat{\Omega}$, which yields estimates $\hat{A}_l = \tilde{A}_l\hat{A}_0^{-1}$, $\hat{B} = \tilde{B}\hat{A}_0^{-1}$, $\hat{\alpha}_i = \tilde{\alpha}_j\hat{A}_0^{-1}$, and $\hat{\varepsilon}_{j,t} = \hat{\nu}_{j,t}\hat{A}_0^{-1}$. Our identification strategy thus depends crucially on the following ordering of variables and equations:

1. SPG divergence is causally ordered first (i.e., last in $y_{j,t}$, due to the lower-triangular form of $\hat{A}_0$), allowing the orthogonalized divergence shocks ($\hat{\varepsilon}_{j,t}^{Div}$) to affect all variables contemporaneously, while other shocks can only affect divergence with a lag. This assumption is true by construction, since divergence is recorded at the *beginning* of month t while the other variables are recorded *during* month t.
2. The interaction between divergence and flows is causally ordered second (second-last in $y_{j,t}$). The divergence component of the orthogonalized interaction shocks ($\hat{\varepsilon}_{j,t}^{Div\times Flow}$) can affect all other variables contemporaneously but the flow component cannot affect divergence contemporaneously, again by construction due to variable timing.
3. Fund flows are causally ordered third (third-last in $y_{j,t}$): orthogonalized flow shocks ($\hat{\varepsilon}_{j,t}^{Flow}$) can affect only flows and performance contemporaneously (the latter could occur due to flow-induced trading as fund managers seek to deploy new capital or meet redemptions). For the same reason as above, flow shocks cannot immediately affect divergence or its interaction.
4. SPG alpha is causally ordered last (first in $y_{j,t}$), implying that orthogonalized performance shocks ($\hat{\varepsilon}_{j,t}^{Alpha}$) can affect all other variables only with a lag. This is mechanically true for divergence as discussed above, and it is justifiable for flows due to market frictions, particularly slow-moving capital (Mitchell et al. (2007), Duffie (2010)).

Following Hansen (1982), Holtz-Eakin et al. (1988), Arellano and Bover (1995), and Abrigo and Love (2016), we estimate the model using feasible generalized method of moments (GMM) after applying a forward orthogonal deviation (FOD) transformation to the data to absorb fund fixed effects,[25] while the untransformed variables are used as GMM instruments.[26] Estimation results are reported as orthogonalized impulse-response functions (IRFs), derived from the infinite-order vector moving average (VMA) representation of Eq. (7):

$$\begin{aligned} IRF_0 &= I_N; \\ IRF_k &= \sum_{i=1}^{k} IRF_{k-1}\hat{A}_k \quad \forall k > 0 \end{aligned} \tag{9}$$

[24] We use fund fixed effects as we are interested in estimating within-fund time-series dynamics.

[25] This methodology delivers consistent and efficient estimates of the reduced-form coefficient matrices for fixed T (number of months) as $J \to \infty$ (number of funds), which is sensible in our setting. Alvarez and Arellano (2003) prove consistency also for $T \to \infty$, but under conditions that do not hold in our setting.

[26] The optimal weighting matrix is derived from the expected squared moment condition $E[Z'\hat{\nu}\hat{\nu}'Z]$, where Z is the stacked matrix of instrument observations and ν is the stacked matrix of reduced-form residuals.

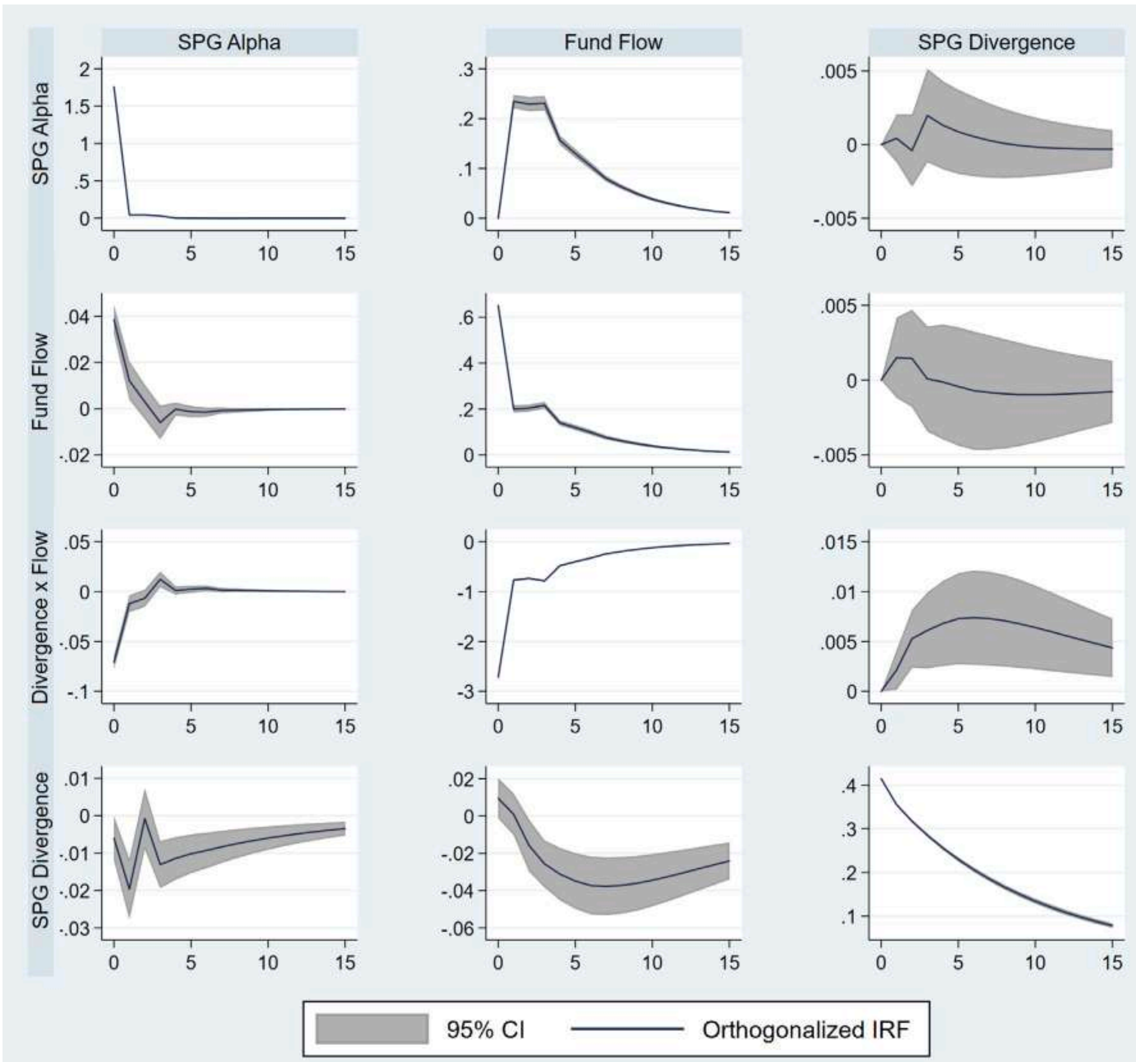


Fig. 4. SPVAR Impulse Response Functions: This figure plots orthogonalized impulse response functions for all endogenous variables in the structural panel VAR described in Section 3.2.3. In the figure arrangement, rows correspond to impulses and columns to responses. Responses of the interaction between $SPGDivergence$ and $Flow$ are not shown for brevity. Structural identification is via Cholesky decomposition, and variables are causally ordered from bottom to top in the figure. Shaded regions indicate 95% confidence intervals, computed via bootstrapping (Lütkepohl, 2005).

IRF confidence intervals are computed by bootstrapping from the reduced-form residuals (Lütkepohl, 2005), retaining their estimated covariance structure. To select the number of lags L we rely on the coefficient of determination (R^2), as the model is just-identified and thus information criteria are unavailable (Abrigo and Love, 2016).

Note that this identification strategy says nothing about the ultimate source of the structural shocks, only that they are orthogonal to each other. Shocks to divergence could arise from strategic managerial decision making, from flow-induced trading, from return-driven changes in portfolio composition, or from shifts in the core strategy of the peer group. Several of these sources may be driven by macroeconomic events or unobserved fund/manager characteristics that could potentially also affect flows. Thus, while the SPVAR approach is informative for establishing intertemporal feedback relationships and ruling out reverse causality, omitted variable bias remains a concern. We address this concern in Section 3.2.4 using an instrumental variables identification strategy.

Results. Fig. 4 displays the orthogonalized impulse response functions (IRFs). Each row of the figure shows responses to a different structural shock (rows are arranged in reverse causal order), and each column shows the responses of a different endogenous variable. Since the interaction term between SPG divergence and flows is not itself an outcome of interest, we omit its responses for the sake of brevity. The impulses are positive one-standard-deviation realizations of the structural errors $\hat{v}_{j,t}\hat{A}_0^{-1}$.

The first notable result, which can be seen in the bottom right panel of Fig. 4, is that SPG divergence is strongly mean-reverting over time. After an initial shock raises divergence by just over 40% of its unconditional standard deviation, the effect declines to 10% after twelve months, implying a mean reversion rate of 0.75 per year. Rather than funds having the freedom to move permanently to different strategy spaces, their portfolio weights appear to be anchored to the core strategies of their peer groups. This finding further validates the salience of SPGs in explaining fund manager behavior, and suggests that funds are responsive to market or regulatory forces pushing them to keep their promises. Given the many possible drivers of divergence (see discussion in previous subsection), it would be practically impossible for a fund to adhere perfectly to the peer group average even if such adherence were the goal. Thus, the speed at which mutual funds revert towards the average is potentially as important as the level of divergence itself.

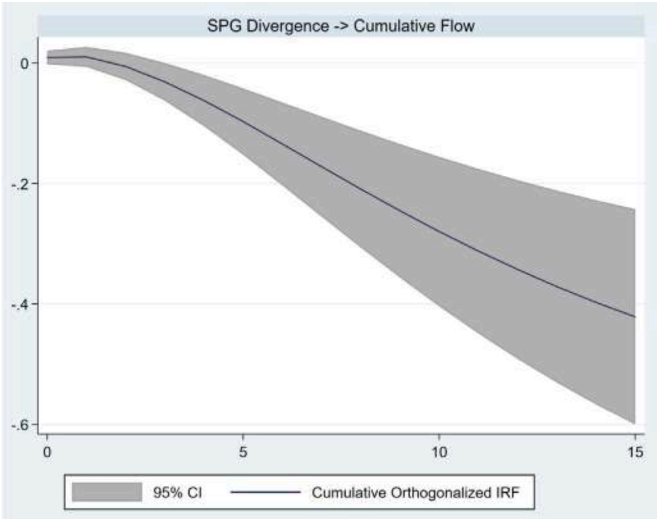


Fig. 5. SPVAR Cumulative Flow Response: This figure plots the cumulative response of fund flows to the orthogonalized SPG divergence shock in the structural panel VAR described in Section 3.2.3. Shaded regions indicate 95% confidence intervals, computed via bootstrapping (Lütkepohl, 2005).

If market discipline is a factor driving fund manager behavior, we hypothesize that the future evolution of divergence should be influenced by investors' flow responses. Specifically, we expect strategy mean reversion to be faster if the initial divergence shock results in higher outflows. Including the interaction of divergence and subsequent flows as an endogenous variable allows us to test this hypothesis. As shown in the third row of the final column in Fig. 4, the interaction effect is significant and positive from month $t + 1$ onwards, peaking in month 6 at a value of 0.0075. That indicates that mean reversion speed increases when flows are negative, or conversely that divergence remains higher for longer relative to its pre-shock level if flows are positive.

To illustrate the magnitude of the effect, consider a large shock that shifts divergence two standard deviations above its mean. Then, if monthly flow is one standard deviation below its mean following the divergence shock (−3.37% in the regression sample), divergence will be $0.0075 \times 2 \times -3.37 \approx 0.05$ closer to its long-run mean after six months than if flow was at its mean—or an increase in mean-reversion speed of 12.5%. These results are in line with a market-led disciplining mechanism, whereby flow responses keep funds' *actual* strategies close to the *promised* ones, even when that would be difficult to achieve through legal enforcement.

The main finding from Section 3.2.2 — that SPG divergence negatively affects flows — is confirmed in the bottom row and second column of Fig. 4. Compared to the OLS methodology, orthogonalizing the divergence shock results in the estimation of a delayed flow effect: the response is initially insignificant, and only becomes significantly negative in the second month after the shock. This delay is consistent with investor inattention or slow moving capital. The magnitude of the response continues to increase through month six, possibly as more investors become aware of the fund's promise-breaking, before gradually decaying towards zero. Fig. 5 plots the cumulative flow response: a one-standard-deviation increase in divergence results in a reduction in percentage flows of about 0.35% over the course of a year (about 15% of the unconditional mean of 2.35% in the regression sub-sample).[27]

Several other results are also of secondary interest. The dynamics of the flow-performance relationship are shown in Column 2, Row 1 of Fig. 4: the impact of SPG-adjusted performance on flows persists for over a year following the initial shock.[28] Fund flow shocks have a contemporaneously positive effect on SPG Alpha which lasts into the first post-shock month (Column 1, Row 2), consistent with flow-induced trading. Finally, SPG divergence shocks have a lasting negative impact on future fund performance. We will return to the relationship of divergence and fund performance in Section 3.3.

3.2.4. Identification

Instrumental variables. To mitigate the concern that unobserved fund attributes could be correlated with both SPG divergence and fund flows, resulting in omitted variable bias, we employ a novel instrumental variables strategy. The key underlying idea is that SPG divergence can change *mechanically* when some subset of a funds' portfolio holdings experiences extreme returns. Provided the fund's holdings are not initially identical to the SPG core strategy (confirmed in Table 2), the re-weighting caused by large positive or negative returns will have differing effects on the fund's portfolio and the SPG average portfolio, potentially increasing their distance. To exploit this effect for identification, we then require a source of extreme stock returns that is plausibly unrelated to both fund and investor behavior.

Following this logic, we propose the use of (absolute) idiosyncratic industry returns as instruments for changes in SPG divergence. After subtracting compensation for aggregate risk exposures (using the FFC6 factor model), industry return residuals should be driven almost entirely by specific shocks to narrow sectors of the economy, and thus should be approximately orthogonal to the macroeconomic shocks that drive aggregate mutual fund flows. Moreover, because our sample explicitly excludes sector funds, and industry returns only affect part of a fund's portfolio, they are less likely to be correlated with unobserved fund or manager attributes. We also control directly for observable fund performance (SPG, HKP, and DGTW peer-adjusted returns; and CAPM, FFC4, and FFC6 factor model alphas) as well as fund characteristics (log TNA, log age, expense ratio, and turnover ratio). In some specifications we also control for the VIX Index, to account for common volatility shocks that may drive both absolute industry return residuals and fund flows.

In sum, our instruments are valid if: (1) *Relevance*: absolute industry return residuals significantly predict changes in SPG divergence; and; (2) *Exogeneity*: (i) risk adjustment using a standard asset pricing model is sufficient to separate industry-specific news from economy-wide shocks; (ii) industry-specific news does not affect flows via channels other than SPG divergence, fund alphas, or common volatility shocks.

Although it is impossible to prove that the exogeneity condition is satisfied, we submit that (i) and (ii) are reasonable assumptions. First, we use a comprehensive factor model that enjoys much empirical success in the asset pricing literature. Second, it seems unlikely that idiosyncratic events affecting narrow industries without any corresponding effects on the market (or small stocks, value stocks, profitable stocks, stocks with low investment or high past returns) should directly drive mutual fund flows across the entire market, unless through their effects on fund performance, which is controlled for in our regressions, or funds' portfolio composition. By using an idiosyncratic shock to instrument for a more general effect, our approach is similar in spirit to the granular instrumental variables strategy of Gabaix and Koijen (2021). Even if the above assumptions do not hold universally, the IV approach should be closer to random assignment than ordinary least squares.

We estimate the effect of SPG divergence on future fund flows using a two-stage least squares (2SLS) procedure. The first stage is as follows:

$$DivgDiff_{j,t} = \iota_j + \sum_{n=1}^{N} \delta_n \tilde{I}_{n,t} + \gamma' X_{j,t} + \varepsilon_{j,t}, \tag{10}$$

[27] Note that this figure differs from the average reported in the full-sample statistics (Table 1).

[28] This result holds for any standard performance measure, as we confirm in unreported results.

Table 6

IV - First Stage: This table reports estimated coefficients and F-statistics from the first stage of an instrumental variables regression of future fund flows on first-differences of SPG Divergence. SPG Divergence differences (the dependent variable in the first stage regression) is instrumented using absolute idiosyncratic industry returns (i.e., residuals from the Fama–French-Carhart six factor model) for the Fama–French 10 industry portfolios. Included exogenous control variables are fund characteristics, yearly lagged performance, competition and product differentiation measures (see description of Table 5). Column 1 omits the control variables to illustrate the relevance of the excluded instruments alone, and is therefore is not used in the second stage regressions. Columns 2 through 5 are used in the second stage regressions. Columns 2 and 4 use the full sample of observations, while Columns 3 and 5 omit the dotcom crash years of 2000-01 and the financial crisis of 2008-09. Columns 4 and 5 also control for the VIX Index. All specifications include fund fixed effects, and standard errors are clustered by fund. See Section 3.2.4 for further details.

	(1)	(2)	(3)	(4)	(5)
Consumer Durables	0.039	0.085**	0.036	0.123***	0.044
	(1.09)	(2.29)	(0.82)	(3.26)	(0.97)
Consumer NonDur	0.260***	0.253***	0.054	0.257***	0.059
	(3.37)	(3.27)	(0.65)	(3.31)	(0.70)
Manufacturing	0.328***	0.295**	0.350***	0.391***	0.360***
	(2.89)	(2.55)	(2.78)	(3.36)	(2.87)
Energy	0.071*	0.061	0.153***	0.019	0.143***
	(1.75)	(1.50)	(3.21)	(0.47)	(2.96)
High Tech	0.295***	0.341***	0.516***	0.384***	0.526***
	(3.81)	(4.40)	(6.37)	(4.97)	(6.49)
Telecoms	0.148***	0.157***	0.224***	0.203***	0.233***
	(2.63)	(2.77)	(3.68)	(3.55)	(3.76)
Wholesale/Retail	−0.194***	−0.243***	−0.370***	−0.277***	−0.373***
	(−2.60)	(−3.20)	(−4.15)	(−3.64)	(−4.17)
Healthcare	0.243***	0.236***	0.404***	0.271***	0.412***
	(3.90)	(3.74)	(5.47)	(4.24)	(5.48)
Utilities	−0.224***	−0.205***	−0.125**	−0.221***	−0.126**
	(−5.06)	(−4.64)	(−2.50)	(−4.98)	(−2.53)
Other	−0.084	−0.064	−0.268*	0.003	−0.255
	(−0.67)	(−0.51)	(−1.71)	(0.02)	(−1.63)
VIX Index				−0.069***	−0.015
				(−7.90)	(−1.22)
Controls	No	Yes	Yes	Yes	Yes
Sample	All	All	No Crash	All	No Crash
F-Statistic	10.13	67.59	62.56	69.31	60.27
Obs	271,708	271,708	230,404	271,708	230,404

t statistics in parentheses; * p < 0.10, ** p < 0.05, *** p < 0.01.

where $DivgDiff_{j,t}$ is the first difference of SPG divergence within funds, ι_j is a fund-specific intercept and the vector $X_{j,t}$ contains performance controls, VIX levels, and fund characteristics. Using the estimated coefficients from Eq. (10), we compute fitted values of the dependent variable, $\widehat{DivgDiff}$ (we use first differences because return shocks affect changes in portfolio holdings rather than levels). Note the variation in $\widehat{DivgDiff}$ is mostly time-series variation, as the instruments are the same for all funds (only the control variables differ).[29] The interpretation of the first-stage fitted values is therefore the average change in SPG divergence, across all funds, that is driven by idiosyncratic industry shocks.[30] In this way, the IV results resemble an event study following an exogenous shock.

Finally, we estimate the second stage regression:

$$Flow_{j,t+1:t+k} = \iota_j + \beta \widehat{DivgDiff}_{j,t} + \gamma' X_{j,t} + \varepsilon_{j,t}, \qquad k = 1, \ldots, 12 \qquad (11)$$

where $Flow_{j,t+1:t+k}$ is the cumulative flow to fund j from months $t+1$ to $t+k$. In addition to cumulative future flows, we also estimate variants of Eq. (11) with contemporaneous and past flows on the left hand side. If our instruments do in fact capture exogenous shocks to SPG divergence, we would expect there to be no effects on past flows. Similarly, if our assumptions (i) and (ii) hold, we should also not see any contemporaneous effects on flows. Throughout the analysis, due to the variation in our instruments being exclusively time-series in nature, we can include only fund-level fixed effects and cluster standard errors at the fund level.

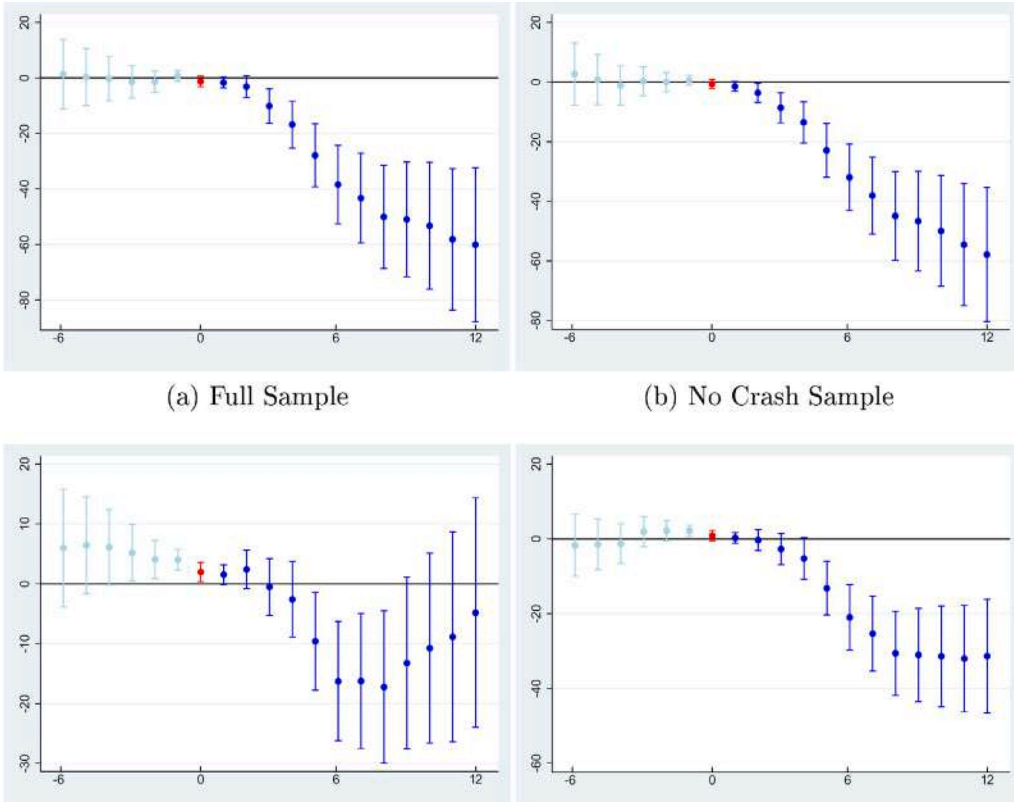
Results. The first-stage coefficients (Eq. (10)) are reported in Table 6. The first column shows a variant of the regression omitting all controls, to illustrate the relevance of the instruments (importantly, the fitted values from this column are *not* used in the second stage). The F-statistic of this regression is above the standard rule-of-thumb of 10 (10.13) and, as hypothesized, the majority of the coefficients are positive and significant. In other words, increasing the magnitude of idiosyncratic shocks that affect only part of funds' portfolios also generally results in a greater positive change in SPG divergence. These conclusions continue to hold if we include fund-specific control variables (particularly past performance) in Column 2, where the F-statistic rises considerably (to 67.59).

As shown in Columns 3-5, we employ two strategies to further reduce the likelihood that our instruments capture unobserved macroeconomic variation. First, as in Columns 3 and 5, we run the regression in a sub-sample that excludes two major events that primarily affected a single industry—the bursting of the Dotcom bubble during 2000–2001, which mainly affected tech firms; and the financial crisis of 2008–2009, which was driven by financial firms. We are extremely conservative in excluding two full years for each event. Second, in Columns 4 and 5, we add the VIX index as a control to capture common volatility shocks. Encouragingly, the first stage results are similar across the different specifications, confirming that the relevance condition is satisfied.[31] Intuitively, the VIX is relevant only in the full sample, and does not affect portfolio compositions outside of the crisis periods. The last specification (Column 5) is therefore the most likely to satisfy assumption (ii) of the endogeneity condition. Unlike in Sections 3.2.2 and 3.2.3,

[29] Due to the time-series nature of the instruments we can only include fund-level fixed effects. For the same reason, standard errors are clustered at the fund level.

[30] We use changes in SPG divergence because they correspond to changes in stock prices, i.e., returns.

[31] We are unable to run tests of over-identifying restrictions in this setting, as they are invalid in the presence of sample heterogeneity, which is clearly the case for mutual fund panel data (Angrist and Pischke, 2009).



(a) Full Sample

(b) No Crash Sample

(c) Full Sample + VIX Control

(d) No Crash Sample + VIX Control

Fig. 6. IV Regression Second Stage Coefficients: In this figure we plot point estimates and 95% confidence intervals from an instrumental variables regression of cumulative fund flows on changes in SPG divergence, where divergence changes are instrumented using absolute idiosyncratic industry returns. Stocks are classified into Fama–French 10 industry portfolios, and idiosyncratic returns are computed by subtracting estimated FFC six-factor model benchmarks. The regression includes exogenous controls for fund performance (SPG Alpha; Hoberg et al. (2018) Alpha; FFC 6-factor Alpha), fund characteristics (log TNA; log age; expense ratio; turnover ratio), competition (Hoberg et al. (2018) customized peer alpha and log number of peers), product differentiation (Kostovetsky and Warner (2020) uniqueness), and fund fixed effects. Panels (c) and (d) also include the VIX Index as an additional control. Panels (a) and (c) use the full sample, while panels (b) and (d) omit the years 2000-01 and 2008-09. Light blue indicates lagged cumulative flows (from months $t-k$ to t), red indicates contemporaneous (month t) flows, and dark blue indicates future cumulative flows (from months t to $t+k$). The bars are 95% confidence intervals, and standard errors are clustered at the fund level. See Section 3.2.4 for further details.

where the variation in SPG divergence may be driven by many factors including strategic managerial considerations, the variation in the fitted values from these regressions is more likely to be unintentional on the part of fund managers.

The second stage coefficients are plotted in Fig. 6 for various cumulative flow horizons. Starting with the baseline full-sample case without a VIX control (panel a; corresponding to the first stage in Column (2) of Table 6), flows are unaffected by fitted changes in divergence for up to six months prior to the idiosyncratic shock. This result is necessary (though not sufficient) for our identifying assumptions to hold. Consistent with a delayed investor response, flows are also unaffected contemporaneously and for two months following the shock. Then, in month three, they begin to respond negatively and continue to do so in each subsequent month. By month twelve, the cumulative coefficient is −60. Since fitted divergence has a standard deviation of 0.01, a one-SD shock results in an annual percentage flow response of 0.6%, or approximately 25% of its annual mean in the regression subsample (2.35%).[32] Note that the magnitude of this result is constrained by the size of the shocks generated by our instrument. Hence, it likely represents a lower-bound for the true magnitude of the typical effect.

Removing the Dotcom crash and the global financial crisis from the data does not attenuate the results significantly (panel b; corresponding to Column 3 of Table 6), suggesting that the instruments are not driven entirely by the largest macroeconomic events affecting particular industries during our sample period. Adding the VIX as a control (panel c; corresponding to Column 4 of Table 6) introduces substantial noise in the estimation, but the significance of the results nonetheless holds (for at least eight months after the shock). Finally, adding the VIX in the restricted sample (panel d; corresponding to Column 5 of Table 6) no longer increases estimation variance, and the effect on flows remains steadily significant after twelve months. Although the coefficient magnitude is halved compared to the baseline.

Overall, the results presented in this section increase our confidence that fund investors are responding to fund strategy divergence and not some unobserved attribute of the fund, the fund manager, or the macroeconomic environment.

3.3. Economic mechanism

In this section, we delve deeper into the economic mechanism driving divergence. Section 3.2.1 highlighted the dual preference of investors for SPG-adjusted performance and SPG-adherence. If all funds were skilled, and divergence only happened for strategic motives, we would expect funds to diverge from their promised strategy only when that would increase SPG-adjusted performance. If this is the case, we should observe a positive relationship between divergence and future performance. As highlighted by our IV strategy, though, there can be scenarios in which divergence happens involuntarily. Additionally, unskilled fund managers might diverge to exploit alpha opportunities but be unsuccessful in their attempts. Hence, the net effect of divergence on

[32] Note that this figure differs from the average reported in the full-sample statistics (Table 1).

Table 7

Future Performance and SPG Divergence: This table reports coefficients from regressions of future ($t+1$ to $t+12$) fund performance on SPG Divergence, as well as controls for lagged ($t-11$ to t) performance, fund characteristics, competition, and product differentiation (see description of Table 5). Performance variables are SPG-adjusted returns (SPG Alpha), CAPM Alpha, and Fama–French-Carhart six-factor alpha (FFC6 Alpha). All specifications include fund fixed effects, and standard errors are two-way clustered by fund and month. See Section 3.3 for further details.

	SPG Alpha		CAPM Alpha		FFC6 Alpha	
	(1)	(2)	(3)	(4)	(5)	(6)
SPG Divergence	−0.021	−0.079	−0.144**	−0.077	−0.095***	−0.084**
	(−0.41)	(−1.49)	(−2.52)	(−1.41)	(−2.78)	(−2.30)
DGTW Divergence		0.009		−0.127***		−0.031
		(0.18)		(−2.62)		(−0.94)
KW Uniqueness		−0.014		0.121		−0.036
		(−0.20)		(1.52)		(−0.73)
Low Comp		1.340***		0.448*		0.349***
		(5.24)		(1.86)		(2.76)
Med Comp		1.221***		0.634***		0.387***
		(6.65)		(3.46)		(3.45)
Lagged SPG Alpha	0.043*	0.038	−0.166***	−0.202***	−0.003	−0.021
	(1.75)	(1.01)	(−5.45)	(−5.65)	(−0.27)	(−1.64)
Lagged HKP Alpha		0.008		0.062*		−0.002
		(0.23)		(1.88)		(−0.07)
Low Comp × HKP Alpha		−0.019		−0.011		0.046**
		(−0.83)		(−0.52)		(2.51)
Med Comp × HKP Alpha		−0.025		−0.009		0.029*
		(−1.26)		(−0.46)		(1.89)
Other Lagged Alphas	No	Yes	No	Yes	No	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.298	0.306	0.385	0.387	0.370	0.371
Obs	211,014	210,764	211,014	210,764	211,014	210,764

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

future performance is unclear. To explore that relationship empirically, we run the following regression:

$$Performance_{j,t+12} = \alpha + \beta Divergence_{j,t} + \theta' C_{j,t} + \lambda' X_{j,t} + \eta_{f,t} + \epsilon_{j,t} \quad (12)$$

where $Performance_{j,t+12}$ is the annualized net of fees SPG, $CAPM$ or $FFC6\ Alpha$ for fund j over the period ($t+1$ to $t+12$); $Divergence_{j,t}$ is *within*-SPG divergence (as in Eq. (2)) for fund j in month t. $C_{j,t}$ contains competition controls (DGTW-divergence, KW-uniqueness, HKP-peers controls) for fund j in month t.[33] $X_{j,t}$ contains fund-level controls (log TNA; fund age; expense ratio; turnover ratio) for fund j in month t. $\eta_{f,t}$ are family×month fixed effects. Standard errors are clustered by fund and month. The coefficient of interest is $\hat{\beta}$—as previously discussed, there is no clear economic prediction for the sign of the result.

Table 7 reports the outcome of those regressions. Regardless of how we measure performance, divergence is *not* significantly positively related to future performance (on the contrary, point estimates are often negative and sometimes significantly so). That is not surprising, as those regressions do not distinguish between strategic or involuntary motives for divergence. Instead, they provide an average estimate across all scenarios.

To better understand the relationship between *strategic* divergence and performance, we need to isolate cases in which divergence likely happens for strategic reasons. To do so, we utilize HKP's findings. HKP show that funds with fewer DGTW peers face lower competition and are better able to achieve higher future performance. Hence, we conjecture that divergence which leads funds to move to a lower density DGTW-space (i.e., a space with fewer HKP peers) is likely to be driven by strategic motives. If so, in those cases we would expect increases in divergence to lead to increases in SPG-adjusted performance.

To test that hypothesis we construct a dummy variable that takes a value of 1 when divergence is likely to happen strategically, and 0 otherwise. We isolate those cases by imposing two conditions. First, we require the number of HKP peers at $t-1$ to be in the top tercile; i.e., ex-ante competition should be high for funds to be incentivized to move to a less crowded space. Second, we require changes in divergence and changes in the number of HKP peers between $t-1$ and t to go in opposite directions; i.e., there should be a trade-off between SPG-divergence and the degree of competition funds face.

We then run the following regression:

$$\begin{aligned} \Delta Performance_{j,t+12} =& \alpha + \beta \Delta Divergence_{j,t} + \delta Strategic_{j,t} + \\ & \zeta \Delta Divergence_{j,t} \times Strategic_{j,t} + \theta' \Delta C_{j,t} + \\ & \gamma' Performance_{j,t-1} + \lambda' X_{j,t} + \eta_{f,t} + \epsilon_{j,t}. \end{aligned} \quad (13)$$

where $\Delta Performance_{j,t+12}$ is the change in annualized net of fees SPG, $CAPM$ or $FFC6\ Alpha$ for fund j between the periods ($t-11$ to t), and ($t+1$ to $t+12$). $\Delta Divergence_{j,t}$ is the change in *within*-SPG divergence for fund j between months $t-1$ and t. $Strategic_{j,t}$ is the dummy identifying whether the divergence of fund j between $t-1$ and t is likely strategic; $\Delta Divergence_{j,t} \times Strategic_{j,t}$ is the interaction between $\Delta Divergence_{j,t}$ and $Strategic_{j,t}$. $\Delta C_{j,t}$ contains changes in competition controls (DGTW-divergence, and KW-uniqueness) for fund j between months $t-1$ and t, as well as their interaction with $Strategic_{j,t}$.[34] $Performance_{j,t-1}$ contains controls for past annualized net of fee HKP, SPG, $CAPM$ or $FFC6\ Alpha$ for the period ($t-23$ to $t-12$). $X_{j,t}$ contains fund-level controls (log TNA; fund age; expense ratio; turnover ratio) for fund j in month t. $\eta_{f,t}$ are family×month fixed effects. Standard errors are clustered by fund and month.

The coefficients of interest are $\hat{\beta}$, and $\hat{\zeta}$. $\hat{\beta}$ identifies the unconditional effect of changes in divergence on changes in performance. Similarly to the prior specification, we cannot provide a clear prediction for the direction of this effect. $\hat{\zeta}$, instead, identifies the incremental effect of changes in divergence on changes in performance, when divergence likely happens for strategic reasons. The overall effect in those cases is given by $\hat{\beta}+\hat{\zeta}$. We expect that overall effect ($\hat{\beta}+\hat{\zeta}$) to be positive and statistically significant.

[33] In order to provide the most stringent set of competition controls, for what regards HKP-peers we add dummies for the bottom and medium terciles of the number of HKP-peers as well as the interaction between those dummies and $HKP\ Alpha$. That is the specification utilized by HKP in their performance regressions.

[34] We cannot add controls based on HKP-peers as they are collinear with the $Strategic$ dummy, which already accounts for the interaction between HKP's result and ours.

Table 8

Strategic SPG Divergence: This table reports coefficients from regressions of changes in annual fund performance (month $t+1$ to $t+12$ minus month $t-11$ to t) on changes in SPG Divergence, a dummy variable ($Strategic$) indicating that divergence changes are more likely to be strategic rather than involuntary, and the interaction between these variables. $Strategic$ equals 1 when Hoberg et al. (2018) competition at time $t-1$ is high, and changes in SPG Divergence have the opposite sign to changes in the number of HKP peers. The regressions also control for fund characteristics, lagged ($t-23$ to $t-12$) performance, changes in DGTW divergence and Kostovetsky and Warner (2020) uniqueness, and the interaction of the IO variables with the $Strategic$ dummy. All specifications include family-month fixed effects, and standard errors are two-way clustered by fund and month. See Section 3.3 for further details.

	(1) SPG Alpha	(2)	(3) CAPM Alpha	(4)	(5) FFC6 Alpha	(6)
SPG Divg. Diff.	−0.044	−0.155**	−0.080	−0.129*	−0.020	−0.026
	(−0.58)	(−2.13)	(−1.09)	(−1.81)	(−0.46)	(−0.57)
Strategic		−0.075		0.099		−0.040
		(−0.33)		(0.44)		(−0.38)
Strategic × SPG Divg. Diff.		0.927***		0.357		0.055
		(3.28)		(1.52)		(0.41)
DGTW Divg. Diff.	−0.032	−0.033	−0.039	−0.045	−0.003	−0.002
	(−0.94)	(−0.89)	(−1.05)	(−1.13)	(−0.11)	(−0.06)
KW Unique Diff.	0.042	0.054	0.054	0.056	−0.048	−0.058
	(0.36)	(0.40)	(0.41)	(0.36)	(−0.75)	(−0.74)
Strategic × DGTW Divg. Diff.		−0.024		0.050		−0.013
		(−0.19)		(0.41)		(−0.16)
Strategic × KW Unique Diff.		−0.088		−0.013		0.074
		(−0.30)		(−0.04)		(0.39)
Lagged HKP Alpha	0.066	0.066	0.130***	0.130***	0.028**	0.028**
	(1.58)	(1.60)	(4.38)	(4.36)	(2.02)	(2.03)
Lagged SPG Alpha	−0.044	−0.045				
	(−0.92)	(−0.93)				
Lagged CAPM Alpha			−0.087**	−0.087**		
			(−2.54)	(−2.52)		
Lagged FFC6 Alpha					−0.164***	−0.164***
					(−11.12)	(−11.14)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.289	0.289	0.374	0.374	0.346	0.346
Obs	182,690	182,690	182,690	182,690	182,690	182,690

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 reports the outcome of those regressions. In line with Table 7's results, the unconditional effect ($\hat{\beta}$) is negative or insignificant in all specifications. The effect of the interaction between changes in divergence and the *Strategic* dummy ($\hat{\zeta}$), instead, is positive and statistically significant (at the 1% level) when measuring performance using changes in $SPG\ Alpha$ specifically (Column 2). As expected, the combined effect in these cases $(\hat{\beta} + \hat{\zeta}) = -0.155 + 0.927 = 0.772$ is overwhelmingly positive. Increasing divergence from the lower quartile to the upper quartile of its empirical distribution would result in the average fund outperforming its SPG peers by 1.02%, or 56% of the sample standard deviation (since the mean change in SPG alpha is zero by construction, the relevant comparison is the sample standard deviation).

The estimate of $\hat{\zeta}$ is not statistically significant in any other specification; i.e., it is only significant when measuring changes in performance using $SPG\ Alpha$. This is in line with the expected economic mechanism. As previously highlighted, the characteristics driving SPG product differentiation are unrelated to funds' ability to generate risk-adjusted performance. Hence, if all funds remained close to their SPG's core strategy, that location would likely become crowded in an HKP-sense. When that happens, funds that strategically diverge in order to move to a less crowded space are able to beat their SPG-peers. As more funds diverge, the trade-off between SPG adherence and SPG-adjusted performance would become less advantageous, leading to mean-reversion towards SPG core strategies. Funds cannot fully anticipate other funds' behavior or overall equilibrium outcomes, as divergence can also happen for non-strategic reasons.

The results in this section are consistent with the hypothesized trade-off faced by fund managers between SPG adherence and SPG Alpha. However, the results are open to interpretation, and we consider this analysis to be suggestive rather than conclusive. Further research along this dimension would be a fruitful topic for future research.

3.4. Generalized SPG assignments

All results presented so far rely on the assumption that funds' promises contain one *dominant* strategy. This implies that the spatial distribution of strategy descriptions is concentrated around k-means centroids. If instead many funds were close to cluster boundaries, we might erroneously assign a high divergence to these boundary funds that are actually close to implementing their promised strategy. To exclude this alternative interpretation, we generalize SPG assignment by allowing funds to offer a combination of the 17 strategies identified by the k-means algorithm.

Similarly to HKP, we locate each fund in a multi-dimensional space based on its exposure to different strategy dimensions. HKP consider 3 dimensions in their main results: size, value, and momentum characteristics of funds' holdings. We adopt a similar methodology in a 17-dimensional space by identifying each fund with a vector of weights on each SPGs' core strategy. To compute weights we first identify the features of each centroid that are most indicative of that SPG's core strategy. We do so by curtailing the centroid vector to the top 1% of most frequent terms.[35] For each prospectus we then compute the percentage of top-terms of each SPG centroid which are present in its text, weighted by their *tfidf* score. Finally, we normalize those percentages to sum to one for each prospectus' 17-dimensional vector, which we define as the fund's *"promise vector"*. Finally, we identify fund-specific sets of SPG-peers by taking pairwise Euclidean distances between funds' promise vectors, and utilizing the same cut-off as HKP to identify the boundaries of each peer set (i.e., the average number of peers in Lipper fund categories).

The columns of Fig. 7 report the average *promise vector* for funds that were originally assigned to each of the 17 strategies. Reassuringly,

[35] Results are robust, but noisier, if choosing higher cut-offs up to at least 10%.

Table 9
Promise-Weighted Divergence - Correlations: This table reports correlations among various generalized versions of our SPG Divergence measure, constructed as the log sum of squared differences between the fund's portfolio holdings vector and the weighted average holdings of funds in the top x most relevant strategy peer groups (SPGs). The weights on the SPG holdings vectors are given by the fund's "promise vector", constructed from the fraction of *relevant* words for each SPG that appear in the fund's prospectus strategy description (see Section 3.4).

	SPG Divg.	Weighted SPG Divg.			
	Single SPG	Top 2	Top 3	Top 5	Top 10
Weighted Divg. (Top 2)	0.799***				
Weighted Divg. (Top 3)	0.786***	0.977***			
Weighted Divg. (Top 5)	0.770***	0.959***	0.987***		
Weighted Divg. (Top 10)	0.757***	0.947***	0.977***	0.994***	
Weighted Divg. (All SPGs)	0.755***	0.946***	0.976***	0.994***	1.000***
N	315 190				

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	LC	FA	LT	PE	T	PS	FI	FE	Div.	Def.	MC	SC	Q	IV	CA	FU	Der.
Large Cap (LC)	0.13	0.05	0.04	0.07	0.06	0.07	0.05	0.05	0.04	0.03	0.06	0.06	0.05	0.03	0.04	0.05	0.04
Foreign ADR (FA)	0.05	0.32	0.03	0.05	0.02	0.04	0.05	0.06	0.04	0.02	0.03	0.04	0.04	0.05	0.05	0.05	0.07
Long Term (LT)	0.06	0.03	0.20	0.06	0.05	0.05	0.03	0.03	0.02	0.02	0.04	0.05	0.04	0.03	0.05	0.05	0.02
PE-Ratio (PE)	0.07	0.03	0.06	0.19	0.03	0.05	0.02	0.03	0.06	0.02	0.03	0.04	0.05	0.05	0.06	0.06	0.03
Tax (T)	0.05	0.04	0.07	0.04	0.37	0.03	0.05	0.03	0.07	0.03	0.03	0.05	0.05	0.02	0.03	0.03	0.05
Products & Services (PS)	0.06	0.04	0.04	0.06	0.05	0.24	0.02	0.06	0.03	0.03	0.04	0.06	0.03	0.04	0.08	0.06	0.04
Fixed Income (FI)	0.04	0.05	0.06	0.03	0.04	0.04	0.37	0.07	0.10	0.09	0.03	0.04	0.04	0.02	0.02	0.03	0.08
Foreign EM (FE)	0.04	0.08	0.05	0.03	0.03	0.03	0.04	0.31	0.04	0.02	0.04	0.04	0.04	0.05	0.04	0.05	0.05
Dividends (Div.)	0.07	0.04	0.04	0.05	0.04	0.03	0.10	0.04	0.31	0.02	0.03	0.03	0.04	0.03	0.04	0.05	0.04
Defensive (Def.)	0.05	0.05	0.06	0.04	0.06	0.06	0.09	0.05	0.05	0.50	0.03	0.04	0.03	0.03	0.03	0.04	0.05
Mid Cap (MC)	0.06	0.04	0.04	0.05	0.03	0.05	0.01	0.04	0.02	0.03	0.37	0.06	0.05	0.03	0.04	0.05	0.03
Small Cap (SC)	0.05	0.03	0.04	0.05	0.03	0.06	0.02	0.03	0.02	0.01	0.06	0.26	0.05	0.05	0.04	0.04	0.04
Quantitative (Q)	0.06	0.04	0.04	0.06	0.03	0.03	0.01	0.03	0.03	0.02	0.04	0.04	0.24	0.04	0.02	0.10	0.06
Intrinsic Value (IV)	0.05	0.03	0.06	0.05	0.04	0.04	0.03	0.04	0.04	0.04	0.04	0.05	0.05	0.39	0.08	0.06	0.04
Competitive Advantage (CA)	0.06	0.03	0.05	0.06	0.04	0.07	0.02	0.04	0.03	0.03	0.04	0.04	0.04	0.05	0.28	0.08	0.04
Fundamental (FU)	0.06	0.04	0.05	0.07	0.03	0.05	0.01	0.03	0.04	0.02	0.04	0.05	0.09	0.06	0.06	0.15	0.05
Derivatives (Der.)	0.04	0.07	0.05	0.04	0.06	0.05	0.07	0.07	0.05	0.06	0.03	0.04	0.07	0.03	0.03	0.05	0.26

Fig. 7. SPG Promise Weights: This figure shows the average "promise weight" for each Strategy Peer Group (along the rows) among funds assigned primarily to the SPGs listed along the columns. Promise weights are constructed from the fraction of *relevant* words for each SPG that appear in the fund's prospectus strategy description (see Section 3.4).

the dominant strategy in each average promise vector is always consistent with the dominant strategy that had been assigned utilizing the simplified approach, with average weights ranging from 13% for funds originally assigned to the $LargeCap$ SPG, to 50% for those originally assigned to the Tax SPG. Additionally, none of the other strategies appears to be co-dominant.

Next, we compute SPG-divergence and SPG-adjusted performance based on the generalized approach. To compute SPG-divergence, we first construct a tailored reference portfolio for each fund, as the weighted average of each SPG's average portfolio, weighted by the fund's *promise vector*. We then compute divergence equivalently to Eq. (2), but substituting $\bar{w}_{i,t}^{G_{jt}}$ with the weights in each stock i in the reference portfolio of fund j at time t. Finally, we compute SPG-adjusted performance by subtracting from each fund's return the average return of its tailored SPG-peers. This procedure is repeated monthly, but, just like the single-cluster SPG assignment, it is sticky as PIS sections vary slowly over time.

For SPG Divergence, we repeat the above procedure in x-dimensional spaces, for $x\ in\ [2,3,5,10]$, by considering only the x SPGs with the greatest weight in each fund's 17-dimensional promise vector; i.e., we construct x-dimensional promise vectors, which we normalize to sum to 1.

Table 9 reports the correlation of SPG-divergence constructed using the simplified method (1-strategy assignment per fund-month) with the generalized versions (up to 17 weighted strategy assignments per fund-month). Correlations are always very high. There is a 79.9% correlation between the single-strategy assignment and the 2-strategy assignment; that correlation only drops to 75.5% when allowing up to 17-strategy assignments.

Table 10
Customized SPG Alpha - Correlations: This table reports the correlation between our baseline measure of SPG-adjusted performance (SPG Alpha), and an alternative measure based on the average performance of customized "promise peers" (Promise Peer Alpha). Promise Peer Alpha is constructed by applying the Hoberg et al. (2018) peer identification methodology to the vector of funds' textual loadings on our 17 strategy peer groups (see Section 3.4).

	SPG Alpha
Promise Peer Alpha	0.941***
N	315 006

Table 10 reports the correlation between SPG-adjusted performance based on a single dominant SPG, and the generalized version based on funds with similar promise vectors. For SPG-adjusted performance the correlation is still 94% when comparing the construction based on the single-strategy assignment to that based on the 17-strategy assignment.

Finally, we replicate our core results in 2/3/5/10/17-dimensional spaces. First, in Table 11 we confirm that investors have a dual preference for higher SPG-adjusted performance but lower SPG-divergence. All specifications are based on Eq. (6), and are equivalent to Column 4 of Table 5, with the only difference that SPG-divergence and $SPG\ Alpha$ are computed based on 1/2/3/5/10/17-dimensional spaces. Coefficients $\hat{\beta}$ and $\hat{\gamma}$ are almost identical across specification, both statistically and economically (even if t-stats drop with the number

Table 11

Flows, Divergence, and Performance (Promise-Weighted): This table repeats the analysis of future flows, SPG Divergence, and SPG Alpha from Column 4 of Table 5, but using the generalized versions of these measures based on funds' "promise vectors" (i.e., the weighted fraction of relevant words from each SPG that are found in the fund's prospectus strategy description). See Section 3.4 for additional details.

	(1) Single	(2) Top 2	(3) Top 3	(4) Top 5	(5) Top 10	(6) All
SPG Divergence	−0.060***	−0.062***	−0.058***	−0.060***	−0.057***	−0.058***
	(−3.20)	(−3.01)	(−2.73)	(−2.75)	(−2.61)	(−2.63)
SPG Alpha	0.013**	0.015***	0.016***	0.016***	0.015***	0.015***
	(2.40)	(2.73)	(2.77)	(2.75)	(2.65)	(2.65)
DGTW Divergence	0.027	0.031*	0.029	0.030*	0.028	0.029
	(1.59)	(1.77)	(1.63)	(1.66)	(1.55)	(1.57)
KW Uniqueness	−0.043*	−0.044*	−0.043*	−0.043*	−0.043*	−0.043*
	(−1.71)	(−1.73)	(−1.71)	(−1.70)	(−1.70)	(−1.70)
Log HKP Peers	−0.036**	−0.041**	−0.041**	−0.042**	−0.042**	−0.042**
	(−2.11)	(−2.36)	(−2.34)	(−2.39)	(−2.40)	(−2.40)
HKP Alpha	0.071***	0.069***	0.069***	0.069***	0.069***	0.069***
	(12.53)	(12.25)	(12.06)	(12.02)	(12.07)	(12.07)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.336	0.337	0.336	0.336	0.336	0.336
Obs	237,178	237,178	237,178	237,178	237,178	237,178

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of dimensions). Second, in Fig. 8 we confirm the dynamics of the relationship between divergence and flows. Row 1 of Fig. 8 reproduces the two key panels of the SVAR baseline result from Fig. 4, which show respectively that flows decrease following a shock to divergence, and that mean-reversion in divergence is accelerated by outflows. Rows 2-4 of Fig. 8 report the same two panels when constructing measures based on 2/5/17-dimensional spaces. Impulse response functions are almost identical across specifications. Third, Fig. 9 confirms that the IV results hold with multi-dimensional SPG assignments. Panel 1 of Fig. 9 reports the second stage of the 2SLS baseline approach (as in Panel 1 of Fig. 6). Panels 2-4 report the same analysis when constructing measures based on 2/5/17-dimensional spaces. Results are economically similar across specifications, while confidence intervals widen with the number of dimensions.

These results lead us to conclude that our original assumption was reasonable. Indeed, it appears that funds do have a *dominant* strategy and investor flows seem to respond predominantly to SPG-divergence and SPG-adjusted performance based on that dominant dimension. That conclusion is in line with the findings of He and Xiong (2013), who show a tendency towards narrower mandates. Indeed, from a "market-disciplining" perspective, it would be more complex for investors to determine the correct weighting of different strategies from PIS text and hold funds accountable to their promises, leaving more room for manipulation. Hence, it is reasonable that in equilibrium we would observe funds with narrower mandates, while investors can still combine different funds into an overall portfolio that can accommodate preferences over multiple SPG strategies.

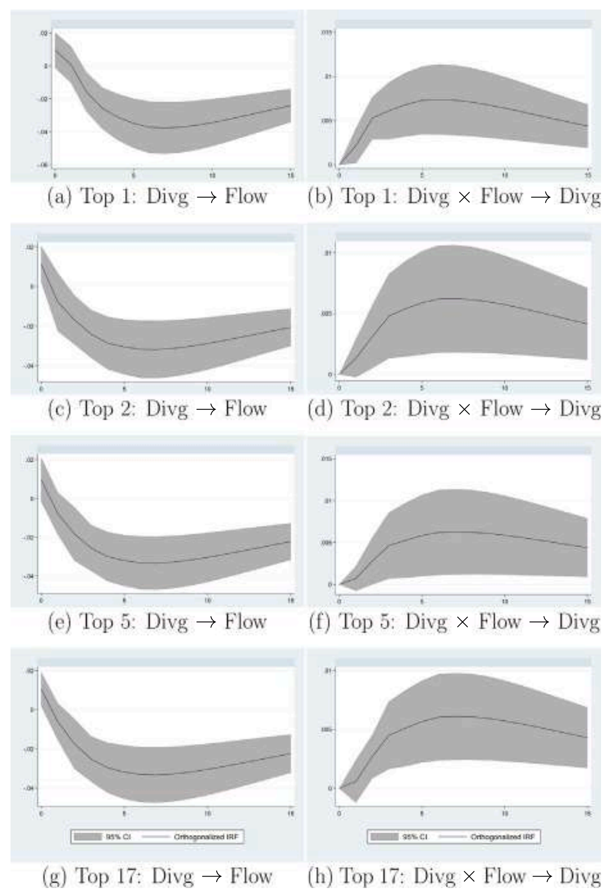


Fig. 8. Promise-Weighted SPGs - SPVAR IRFs: In this figure we repeat the analysis from Fig. 4 but using generalized versions of our SPG Divergence measure, constructed as the log sum of squared differences between the fund's portfolio holdings vector and the weighted average holdings of funds in the top x most relevant strategy peer groups (SPGs). The weights on the SPG holdings vectors are given by the fund's "promise vector", constructed from the fraction of *relevant* words for each SPG that appear in the fund's prospectus strategy description (see Section 3.4).

4. Conclusion

In this paper we investigate the characteristics sought by U.S. mutual fund investors by examining the strategy descriptions in their prospectus documents. We use unsupervised machine learning to group together funds with similar strategy descriptions and use these to infer aggregated portfolios that correspond to different fund strategies. Each of the resulting 17 *strategy peer groups (SPGs)* capture distinct and interpretable approaches to investment, most of which go beyond the standard size-value axis widely used to measure fund styles.

To answer the question of whether funds follow their promised strategies, we compute fund-level divergences from the core strategy of each SPG and find that funds are on average closer to the core strategies of their own peer groups than to others. We then document a market discipline effect that operates via investors' net capital flows. Controlling for performance and other fund characteristics, flows are lower for funds that diverge more from the core strategy of their SPG. The investor response is persistent, lasting up to twelve months after the initial divergence. Investors also chase SPG-adjusted returns independently of standard factor model alphas, with similar levels of predictive power. We show that funds are responsive to the disciplinary

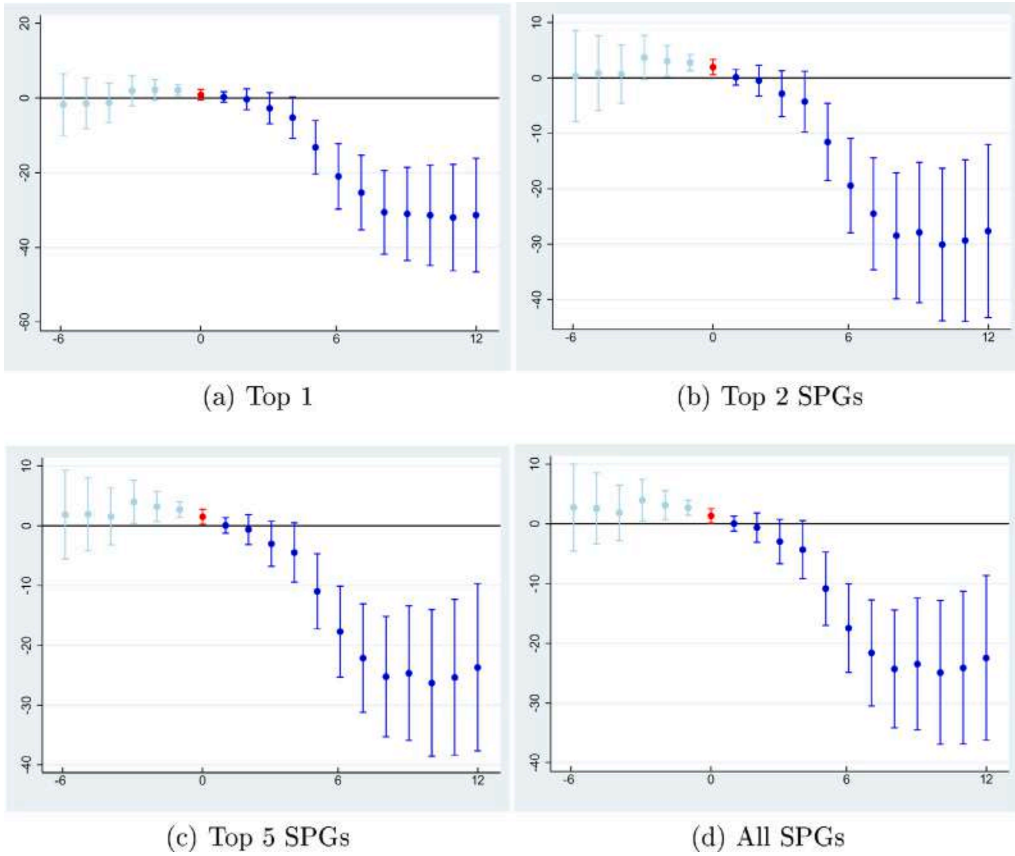


Fig. 9. Promise-Weighted SPGs - IV Second Stage: In this figure we repeat the analysis from Fig. 6 but using generalized versions of our SPG Divergence measure, constructed as the log sum of squared differences between the fund's portfolio holdings vector and the weighted average holdings of funds in the top x most relevant strategy peer groups (SPGs). The weights on the SPG holdings vectors are given by the fund's "promise vector", constructed from the fraction of *relevant* words for each SPG that appear in the fund's prospectus strategy description (see Section 3.4).

effect of fund flows. Strategy divergence mean-reverts over time, and does so at a faster rate following months in which funds diverged more from their core strategies *and* experienced outflows.

To overcome concerns of omitted variable bias, we implement a novel instrumental variables identification strategy based on idiosyncratic shocks to portfolio composition coming from narrow industry sectors. Finally, we document a plausible economic mechanism driving our results. When funds diverge from their peer groups in order to move to a less crowded strategy space, they earn higher SPG-adjusted returns. However, in the absence of these strategic considerations, diverging results in negative or insignificant effects on performance. Our results uncover a diverse fund strategy landscape that was previously unknown from traditional analyses of holdings and returns.

CRediT authorship contribution statement

Simona Abis: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anton Lines:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

AbisLinesMutualFundStrategyDescriptions(Originaldata) (Mendeley Data) AbisLinesMFPromisesReplicationPacket(Originaldata) (Mendeley Data).

Appendix A. Prospectuses summary statistics

In this section we provide detailed summary statistics about the corpus of PIS sections utilized in the paper.

Fig. A1 displays the cross-sectional distribution of PIS word counts, which show wide variation from as few as 20 to as many as 1500. This figure also indicates that the complete PIS sections are much longer than the excerpts provided by Morningstar (average word counts of 70 for Morningstar versus 306 in our sample), examined previously by KW.

We also observe significant variation in the textual sentiment and textual complexity of these sections. Panel 1 of Fig. A2 shows the distribution, across fund–month observations, of the Flesch-Kincaid grade level complexity measure (Kincaid et al., 1975). Panel 2 displays the same distribution for the Flesch reading ease measure (Flesch, 1948). These measures are based on the relative number of total words to total sentences (average sentence length) and the relative number of total syllables to total words (average word syllable length) in a given text. They are calibrated to indicate, respectively, the number of years of schooling required to comprehend the text (panel 1) and a standardized readability index on a range of $[0, 100]$ (panel 2). The figure shows that there exists a large dispersion in the complexity (readability) of

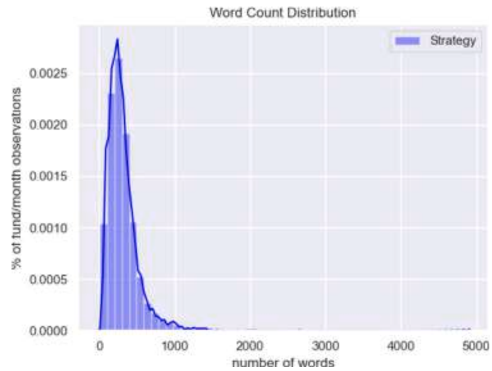


Fig. A1. Distribution of word count for Strategy Sections: Pooled distribution of the number of words contained in of all fund–month observations, for PIS sections.

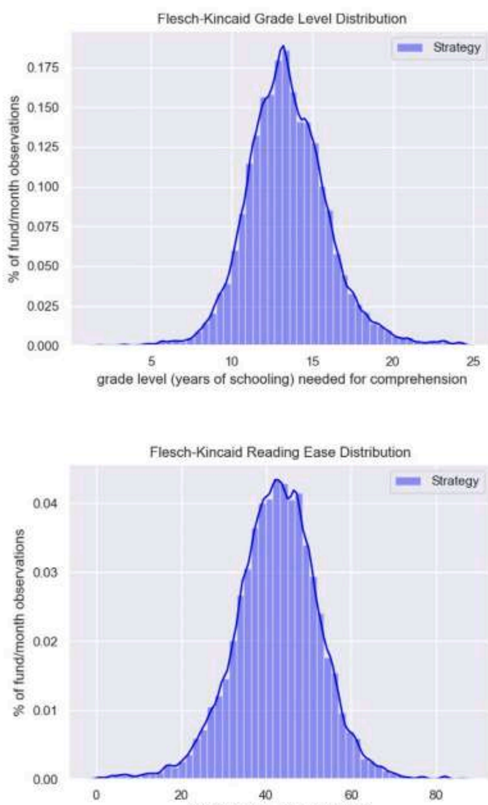


Fig. A2. Distribution of Complexity for Strategy Sections: Panel 1 displays the pooled distribution of the Flesch-Kincaid grade level complexity measure across all fund–month observations, for PIS sections. This measure indicates the number of years of schooling required in order to comprehend each section. Panel 2 displays the same distribution for the Flesch-Kincaid reading ease measure. This measure indicates, on a scale of $[1, 100]$, how easily a section can be read (a higher score indicates lower complexity). Both measures are based on the relative number of total words to total sentences (average sentence length) and the relative number of total syllables to total words (average word length) contained in each section.

these sections, with most sections requiring between 5 to 25 years of schooling (with a mean of 13.7), or a reading ease score between 10 and 80.

Finally, we use the Loughran and McDonald dictionaries of *positive*, *negative*, *uncertainty* and *litigious* words to measure sentiment. These dictionaries are adapted to account for specific characteristics of financial language (Loughran and McDonald, 2011). Fig. A3 shows the distribution of the frequency of *positive* (panel 1), *negative* (panel 2), *uncertainty* (panel 3) and *litigious* (panel 4) words for all pooled fund–month strategy descriptions. Here we also observe large cross-sectional variation in the sentiment of strategy sections.

These descriptive statistics suggest that the narrative descriptions in fund prospectuses may contain relevant and heterogeneous information about their strategies.

Appendix B. K-means

B.1. *The algorithm*

The K-Means algorithm takes as inputs the *tfidf* matrix, the number of desired clusters (k) and a tolerance threshold (τ). The algorithm is initialized by choosing k points in the vector space (centroids). Points are deliberately chosen to be far from each other in order to minimize the likelihood of converging to a local minimum. Each chosen point represents a features vector of same length as the number of chosen features (10,000), whose elements exist in $[0, 1]$. Then the following steps are repeated until the pre-defined tolerance is reached:

1. Calculate the euclidean distance between the vectors representing each document (rows of the tfidf matrix) and each of the k centroid vectors as follows:

$$\sum_{r=1}^{R} \|x_r - x_r^C\|^2 \tag{B.1}$$

where x_r is the frequency assigned to feature r in a specific document and x_r^C is the frequency assigned to feature r in a cluster's centroid. R is the total number of features.

2. Assign each document to the closest centroid (form clusters)
3. Generate new centroids (features vectors) by taking the item-by-item average of the feature vectors of all documents assigned to the same cluster
4. Calculate the euclidean distance between the centroids at iteration n and those at iteration $n + 1$.
   - If the largest distance is greater than the tolerance level τ, repeat all steps
   - Otherwise exit the loop and return the formed clusters (convergence)

We ran the above algorithm with different specifications for the user defined parameters (k and τ). All runs are independent (use different seeds). Despite the possibility of K-means reaching a local optimum, in our setting, the procedure is robust to changes in initial parameters (see discussion in Appendix B.2). In the main specification we use the default value for τ in Python's scikit-learn implementation: 0.0001. We use 17 clusters for the determination of the SPGs.

B.2. *Robustness to choice of k*

To further verify the validity of our methodology and the stability of assignment when changing the number of clusters (k), Table B.1 replicas our main result in Table 5 using alternative numbers of SPGs from 14 to 20. All specifications are based on Eq. (6), and are equivalent to Column 4 of Table 11, aside for the number of chosen clusters in the k-means implementation. We confirm the dual preference of investors for higher SPG-adjusted performance and lower SPG-divergence. Coefficients $\hat{\beta}$ and $\hat{\gamma}$ are both statistically and economically significant across specifications. Reassuringly, the effect of SPG-divergence on future flows is largest in magnitude for $k = 17$.

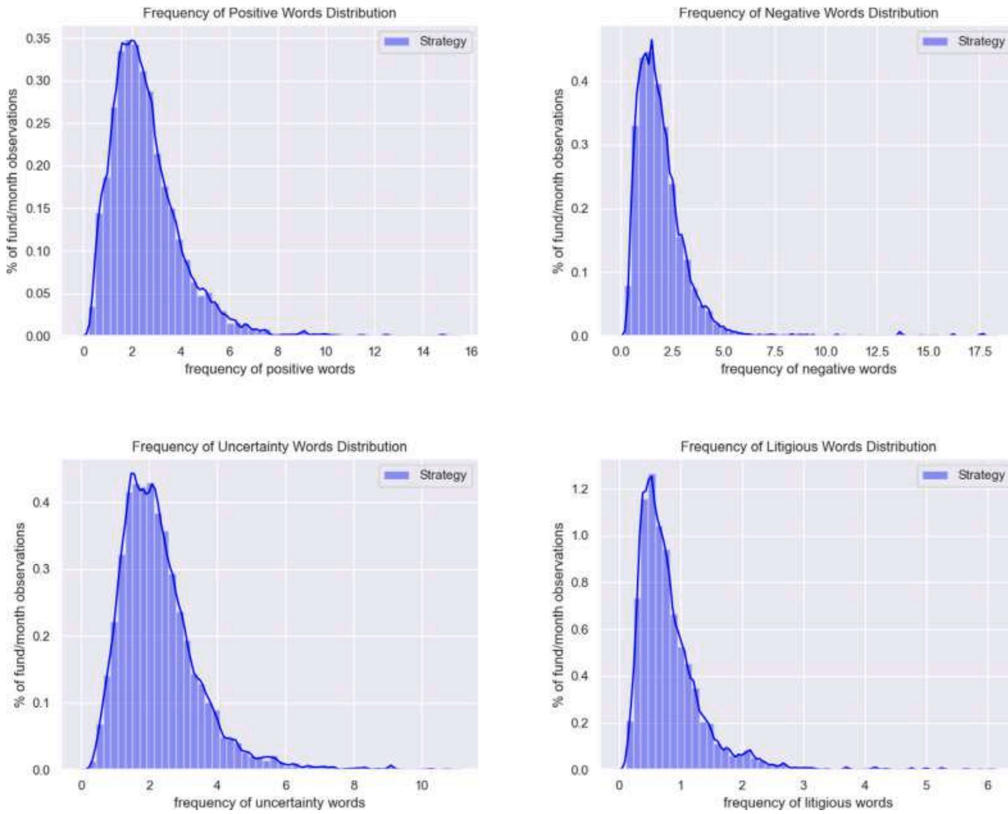
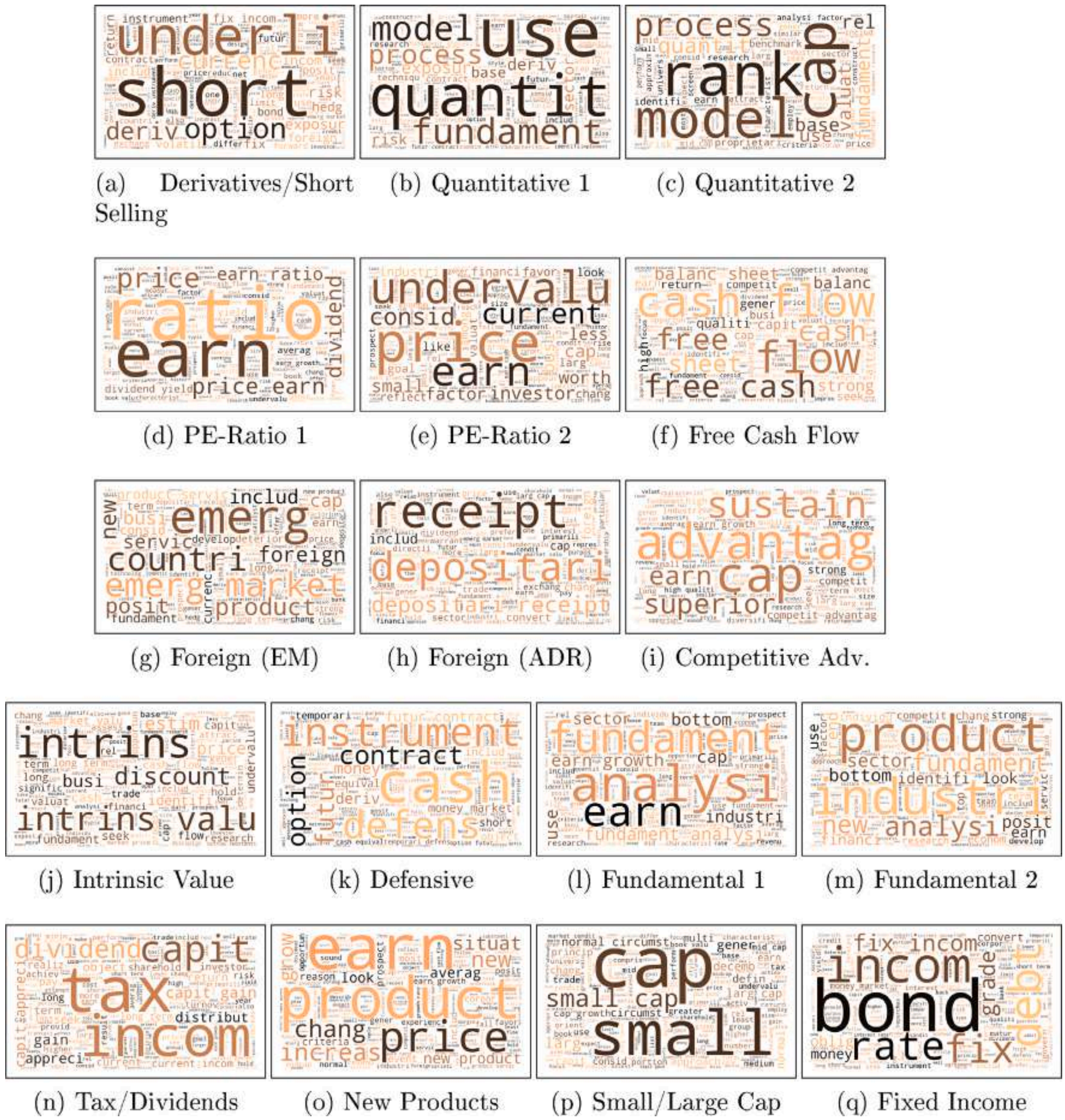


Fig. A3. Frequency of Positive, Negative Uncertainty and Litigious Words in Strategy Sections: Panel 1 displays the distribution of the frequency of *positive* words for all fund–month observations. Panel 2 displays the distribution for *negative* words, Panel 3 for *uncertainty* words and Panel 4 for *litigious* words. The frequency of words per PIS is obtained by computing the percentage of the total number of words in each section that appear in the Loughran-McDonald *positive*, *negative*, *uncertainty* or *litigious* dictionaries. These dictionaries are adapted to account for specific characteristics of financial language (Loughran and McDonald (2011)).

Table B.1
Flows, Divergence, and Performance (Alternative Clustering): This table repeats the analysis of future flows, SPG Divergence, and SPG Alpha from Column 4 of Table 5, but using alternative numbers of Strategy Peer Groups from the K-Means Algorithm.

	Number of clusters					
	14	15	16	18	19	20
SPG Divergence	−0.064***	−0.070***	−0.069***	−0.053***	−0.055***	−0.048***
	(−3.76)	(−4.04)	(−4.03)	(−3.05)	(−3.16)	(−2.83)
DGTW Divergence	0.034*	0.037**	0.035**	0.026	0.027	0.023
	(1.92)	(2.09)	(2.04)	(1.53)	(1.54)	(1.32)
KW Uniqueness	−0.044*	−0.044*	−0.043*	−0.043*	−0.043*	−0.043*
	(−1.74)	(−1.74)	(−1.71)	(−1.71)	(−1.69)	(−1.70)
Log HKP Peers	−0.038**	−0.038**	−0.037**	−0.036**	−0.035**	−0.035**
	(−2.22)	(−2.21)	(−2.15)	(−2.08)	(−2.07)	(−2.04)
SPG Alpha	0.013**	0.013**	0.012**	0.013**	0.012**	0.012**
	(2.42)	(2.40)	(2.39)	(2.42)	(2.37)	(2.37)
CAPM Alpha	0.035***	0.036***	0.036***	0.035***	0.036***	0.036***
	(7.42)	(7.43)	(7.45)	(7.42)	(7.42)	(7.44)
FFC4 Alpha	0.053***	0.053***	0.053***	0.053***	0.053***	0.053***
	(5.96)	(5.94)	(5.94)	(5.96)	(5.95)	(5.96)
FFC6 Alpha	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(3.20)	(3.22)	(3.23)	(3.21)	(3.20)	(3.18)
DGTW Alpha	0.007**	0.007**	0.007**	0.007**	0.007**	0.007**
	(2.04)	(2.06)	(2.05)	(2.01)	(2.03)	(2.03)
HKP Alpha	0.071***	0.071***	0.071***	0.071***	0.072***	0.071***
	(12.52)	(12.53)	(12.53)	(12.57)	(12.59)	(12.53)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.337	0.337	0.337	0.336	0.336	0.336
Obs	237,178	237,170	237,178	237,162	237,162	237,092

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.



(a) Derivatives/Short Selling (b) Quantitative 1 (c) Quantitative 2

(d) PE-Ratio 1 (e) PE-Ratio 2 (f) Free Cash Flow

(g) Foreign (EM) (h) Foreign (ADR) (i) Competitive Adv.

(j) Intrinsic Value (k) Defensive (l) Fundamental 1 (m) Fundamental 2

(n) Tax/Dividends (o) New Products (p) Small/Large Cap (q) Fixed Income

Fig. C1. LDA Topics: Word clouds for $k = 17$ topics estimated by applying Latent Dirichlet Allocation to fund strategy descriptions. The word clouds represent the distribution of features (words and bi-grams) for each topic. Word sizes are proportional to frequency.

Appendix C. Alternative clustering: LDA

Latent Dirichlet Allocation (Blei et al., 2003) is commonly used for textual topic modeling in the finance and economics literatures (see the recent survey in Loughran and McDonald (2020)). The reader may wonder why we use k-means clustering instead of the more common LDA. In practice, the results of the two methodologies are fairly similar, as can be seen in Fig. C1. This figure shows the topic word clouds resulting from an application of LDA with prior topic probability $Dir(1/k)$ and prior word probability $Dir(1/N)$, where k is the number of topics and N is the number of terms (words and bi-grams) in the corpus. For comparison with our *k-means* results, we choose $k = 17$.

Despite the similarities, k-means is more suited to our particular application because it explicitly generates maximum differences between groups, whereas LDA seeks to maximize the likelihood of a generative model, even if the resulting topics are fairly similar. Fig. C1 illustrates this problem with LDA: there are two “Quantitative” topics, two “Fundamental” topics, and two “PE-Ratio” topics, with quite similar word distributions. On the other hand, topics that are separated by k-means are sometimes merged by LDA: e.g. “Tax” and “Dividends”; and “Small Cap” and “Large Cap”.

Another issue with LDA is that it is much less stable than k-means. The example in Fig. C1 would not be reproducible by re-running the algorithm, whereas k-means, even with different random seeds, delivers similar clusters every time it is run on the same data.

Finally, one advantage of LDA, in principle, is that it estimates a distribution over topics for each document. In the context of fund strategies, it would be useful to have the ability to assign multiple strategies to the same fund. In practice, however, due to the short length of the PIS descriptions (about 300 words, on average), over 90% of funds have virtually all of their weight in a single topic. The relatively short documents may also be the reason why LDA is less stable in our setting.

Table D.1

Fund Attributes by SPG: This table reports *differences* between average fund attributes within a particular Strategy Peer Group (SPG) and the average across all other SPGs. Coefficients are estimated in separate regressions of the dependent vars (log of fund age, log of TNA, expense ratio, and turnover ratio) on dummies for each SPG (see Appendix D). Also shown are the *overall* averages across the full sample. We include month and fund family fixed effects. Standard errors are two-way clustered by fund and month.

	ln(TNA)	ln(Age)	Expenses	Turnover
Large Cap	−0.0268 (−0.69)	0.0382 (1.52)	−0.0255** (−2.19)	−4.658** (−2.33)
Fundamental	0.0151 (0.33)	−0.0400 (−1.47)	0.00132 (0.12)	2.480 (0.97)
Products & Services	0.0876 (1.61)	0.0365 (1.17)	0.0586*** (4.09)	8.583** (2.57)
Dividends	0.0447 (0.68)	0.0279 (0.69)	−0.0676*** (−4.27)	−10.60*** (−3.90)
Derivatives	−0.0441 (−0.76)	−0.0261 (−0.66)	−0.0346** (−2.42)	13.94*** (4.25)
Comp. Advantage	0.0784 (1.07)	−0.00135 (−0.04)	0.0377** (2.09)	−0.761 (−0.24)
Defensive	0.123** (2.21)	−0.0464 (−1.32)	−0.0289** (−2.13)	−3.678 (−1.09)
Quantitative	−0.251*** (−3.75)	−0.116*** (−3.20)	−0.0713*** (−3.90)	27.24*** (6.11)
Small Cap	0.00894 (0.13)	−0.104*** (−3.05)	0.0725*** (3.88)	1.201 (0.37)
Long Term	0.103 (1.61)	0.102*** (2.67)	0.0365* (1.90)	−11.01*** (−4.18)
PE-Ratio	−0.0275 (−0.36)	0.0813** (2.04)	0.0126 (0.71)	−2.328 (−0.65)
Foreign (ADR)	−0.0438 (−0.69)	−0.0406 (−1.04)	−0.0254 (−1.46)	−1.840 (−0.59)
Mid Cap	−0.104 (−1.27)	0.0168 (0.42)	0.0276 (1.37)	4.676 (1.36)
Intrinsic Value	0.0239 (0.27)	0.000798 (0.01)	0.0399** (2.44)	−18.96*** (−7.20)
Fixed Income	0.0841 (1.42)	0.0612* (1.66)	0.00454 (0.26)	3.322 (0.88)
Tax	−0.105 (−1.11)	−0.0154 (−0.33)	−0.00645 (−0.29)	−11.38** (−2.59)
Foreign (EM)	−0.0168 (−0.17)	0.0607 (1.26)	−0.00695 (−0.32)	−7.608** (−2.44)
Overall	5.545*** (325.90)	4.898*** (472.54)	1.224*** (278.75)	81.29*** (99.19)
Obs	288,012	288,012	288,012	288,012

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D. Full narrative analysis

As a supplement to our quantitative findings on core strategy divergences, we conduct a narrative analysis of each strategy peer group (SPG), asking whether its implementation lines up with an intuitive reading of the strategy descriptions. This exercise necessarily involves a subjective component, and reasonable readers may disagree with some of our choices. We try to avoid overly detailed inferences and instead focus on broad observations that we believe are less likely to be controversial. This narrative exercise is intended to act as a sanity check on, and to provide context for, the objective similarity measures examined in Section 3.1.1. The exercise also has independent descriptive value, as the active equity investment landscape in the United States has not previously been examined in this way.

For each fund, we compile fund attributes, performance statistics, risk-factor loadings, average industry composition, and average stock characteristics weighted by the percentage of assets invested in each stock. The fund attributes are log TNA, log age, expense ratio, and turnover ratio. The performance measures are rolling 24-month six-factor alphas ((Fama and French, 2015) plus momentum) and six-factor value-added (Berk and van Binsbergen, 2015). For risk-factor loadings, we again use the five Fama–French factors plus momentum. For industry composition, we use the Fama–French 48 industries. The stock characteristics are subdivided into five categories: (i) "traditional" characteristics (market beta, market capitalization, book-to-market ratio, past year's stock return, investment, and profitability); (ii) balance sheet variables (current assets, inventories, non-performing assets, PP&E, intangible assets, asset growth, cash and equivalents, current liabilities, deferred taxes, long-term debt, and leverage ratio); (iii) income statement variables (operating income, earnings growth, and R&D expenditures); (iv) market variables (dividend yield, equity issuance, equity repurchases, Amihud illiquidity, and firm age). Furthermore, we compute the following portfolio characteristics: percentage of holdings in ADRs (American Depository Receipts); percentage of holdings that are foreign incorporated; percentage of holdings in common stock; percentage of holdings in cash; and number of different stocks in the

Table D.2
Risk Factor Exposures by SPG: This table reports *differences* between funds' loadings on the Fama and French (2015) five factors plus momentum within a particular Strategy Peer Group (SPG) and the average across all other SPGs. Coefficients are estimated in separate regressions of fund loadings (estimated from prior 12 months' daily returns) on dummies for each SPG (see Appendix D). Also shown are the *overall* averages across the full sample. We control for (demeaned) log age, log assets, expense and turnover ratio, fund flows, flow volatility, as well as month fund and family fixed effects. Standard errors are two-way clustered by fund and month.

	Market beta	SMB beta	HML beta	MOM beta	RMW beta	CMA beta
LargeCap	−0.00302	−0.0357**	−0.00561	0.00182	−0.00575	−0.00825
	(−0.65)	(−2.57)	(−0.64)	(0.46)	(−0.89)	(−1.28)
Fundmntl	0.00153	0.0309*	0.0101	0.00476	−0.0130*	−0.00954
	(0.32)	(1.90)	(1.01)	(1.08)	(−1.71)	(−1.29)
ProdServ	0.0194***	0.0601***	−0.0653***	0.0298***	−0.0764***	−0.0391***
	(2.77)	(3.18)	(−6.34)	(5.16)	(−7.20)	(−4.67)
Dividends	−0.0203**	−0.179***	0.0863***	−0.0420***	0.105***	0.106***
	(−2.54)	(−11.13)	(7.95)	(−7.38)	(11.05)	(10.44)
Deriv	−0.0305***	−0.0472***	0.00147	−0.00753	0.00763	0.0110
	(−3.65)	(−2.75)	(0.15)	(−1.35)	(0.86)	(1.34)
CompAdv	0.00610	−0.0171	−0.0985***	0.0170**	−0.0604***	−0.0622***
	(0.92)	(−0.74)	(−7.67)	(2.53)	(−5.31)	(−5.18)
Defensive	−0.0119*	−0.0373**	0.00344	−0.00717	0.00265	0.0115
	(−1.90)	(−2.57)	(0.36)	(−1.35)	(0.30)	(1.28)
Quantit	0.00603	−0.0385	0.0361***	0.0158***	0.0790***	0.0238***
	(0.88)	(−1.65)	(3.06)	(2.76)	(9.18)	(2.71)
SmallCap	0.0205***	0.372***	0.0402***	0.00406	−0.00438	−0.0135**
	(2.91)	(19.48)	(3.22)	(0.79)	(−0.43)	(−1.98)
LongTerm	0.00944	−0.0176	−0.0375***	0.000236	−0.0144	−0.0373***
	(1.15)	(−0.82)	(−2.75)	(0.04)	(−1.29)	(−3.43)
PE-Ratio	0.00556	0.00966	0.0423***	−0.00407	0.0364***	0.0206**
	(0.75)	(0.38)	(3.23)	(−0.53)	(3.23)	(2.11)
Foreign(ADR)	0.00985	−0.00703	−0.0145	0.0129**	−0.0130	−0.0271**
	(1.24)	(−0.30)	(−1.03)	(2.37)	(−1.09)	(−1.97)
MidCap	0.00935	−0.00812	−0.0272**	0.00937	−0.0136	0.0190*
	(1.30)	(−0.47)	(−2.10)	(1.61)	(−1.27)	(1.88)
IntrValue	−0.00306	−0.0716***	0.0675***	−0.0485***	0.0260**	0.0360***
	(−0.34)	(−3.14)	(5.34)	(−7.40)	(2.17)	(3.09)
FixedInc	−0.0154	−0.0125	0.00391	−0.0202***	−0.0160	0.0115
	(−1.64)	(−0.72)	(0.37)	(−3.60)	(−1.50)	(1.14)
Tax	0.00110	−0.0615**	−0.0139	0.00367	0.0135	0.00345
	(0.17)	(−2.14)	(−1.13)	(0.67)	(1.19)	(0.36)
Foreign(EM)	−0.00647	0.0294	−0.0160	0.0106	−0.0335***	−0.0351***
	(−0.79)	(1.09)	(−1.05)	(1.55)	(−3.00)	(−2.82)
Overall	0.980***	0.222***	−0.00637*	0.0307***	−0.0542***	−0.0319***
	(970.75)	(34.85)	(−1.85)	(21.39)	(−20.49)	(−13.29)
Obs	285,996	285,996	285,996	285,996	285,996	285,996

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

portfolio. All variables are normalized by subtracting the full-sample mean and dividing by the standard deviation.

As highlighted in Section 3.1, for each of the above variables, and for each SPG, we run the following regression:

$$Y_{j,t} = \alpha + \beta I_{j,t}^{SPG_{j,t}} + \gamma X_{j,t} + \eta_t + \iota_{j\in f} + \varepsilon_{j,t}, \tag{D.1}$$

where $Y_{j,t}$ is the variable of interest for fund j at time t; η_t and $\iota_{j\in f}$ denote fixed effects for month t and membership of fund j in family f, respectively; $I_{j,t}^{SPG_{j,t}}$ is an indicator variable equal to 1 if fund j belongs to the SPG of interest at time t, and 0 otherwise; and $X_{j,t}$ is a vector of demeaned fund-level control variables (the natural logarithms of fund age and TNA, expense ratio, turnover ratio, net fund flows, and flow volatility; when $Y_{j,t}$ is one of these fund-level characteristics, it is excluded from the control vector). Because all independent variables are demeaned, α can be interpreted as the mean of the characteristic of interest when $I_{j,t}^{SPG_{j,t}} = 0$ (i.e. when fund j does not belong to the SPG of interest at time t). The β coefficient then indicates the average difference between the characteristic for the SPG of interest and all other SPGs (holding other characteristics, family membership, and month constant).

In the discussion below, we highlight the most striking (and statistically significant) attributes of each SPG. The full breakdown for all of the above attributes is provided in Tables D.1 through D.8.

Large cap, mid cap, and small cap. The obviously relevant attributes for peer groups based on company size are SMB beta, average market capitalization, and average firm age. Accordingly, we find that funds in the *Large Cap* SPG have significantly lower SMB betas, and hold significantly older firms with larger average market cap. The SMB beta of the *Mid Cap* SPG is not significantly different from other funds, but average firm age and market cap are smaller. The *Small Cap* SPG has both a higher SMB beta (highest among all SPGs) and a much lower average firm age and market cap (lowest among all SPGs).

Intrinsic value. Funds in this SPG invest in companies trading at a discount to perceived intrinsic value. This is the closest SPG to a typical "value" strategy, and as such is reflected in higher than average HML

Table D.3
Industry Exposures by SPG: This table displays *differences* in average industry exposures between funds in each Strategy Peer Group (SPG) and the average across all other SPGs. These differences are estimated in separate regressions of fund-level industry exposures on dummy variables for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month. Industries are the Fama–French 48 industries—a selected sample is displayed for brevity.

	Util	Telcm	Hshld	Oil	Banks	Tech	Drugs
LargeCap	−0.23**	−0.16	0.05	−0.28	−0.05	0.00	−0.05
	(−2.29)	(−1.07)	(0.98)	(−1.12)	(−0.16)	(1.38)	(−0.20)
Fundamental	0.22	−0.34**	−0.08	0.37	0.57	0.00	−0.18
	(1.58)	(−2.54)	(−1.47)	(1.12)	(1.64)	(0.81)	(−0.64)
ProductsServices	−0.68***	−0.46**	−0.08	−0.36	−2.77***	0.01***	0.99**
	(−6.04)	(−2.04)	(−1.38)	(−0.96)	(−6.33)	(3.43)	(2.51)
Dividends	1.71***	1.83***	0.11*	0.31	4.09***	−0.02***	−0.27
	(8.89)	(7.95)	(1.79)	(1.02)	(7.44)	(−5.91)	(−0.83)
Derivatives	0.14	0.37**	−0.00	−0.02	0.04	0.00	0.01
	(0.96)	(2.16)	(−0.01)	(−0.06)	(0.10)	(0.73)	(0.03)
CompAdvantage	−0.87***	−0.61***	0.35***	−1.33***	−1.18***	0.01*	1.15***
	(−7.75)	(−3.58)	(3.94)	(−3.77)	(−2.86)	(1.86)	(2.78)
Defensive	0.03	0.16	−0.02	0.07	0.87*	−0.00	−0.56*
	(0.23)	(0.84)	(−0.33)	(0.21)	(1.81)	(−0.53)	(−1.85)
Quantitative	0.25	0.41**	−0.09*	0.63*	1.19***	0.00	−0.37
	(1.63)	(2.43)	(−1.67)	(1.74)	(2.63)	(0.08)	(−1.19)
SmallCap	−0.24**	−1.53***	−0.12*	2.62***	−1.41***	−0.01***	0.32
	(−2.01)	(−9.00)	(−1.79)	(4.37)	(−3.11)	(−2.69)	(0.61)
LongTerm	−0.55***	−0.19	0.10	−0.52	−1.35***	0.00	0.93*
	(−2.69)	(−0.76)	(1.03)	(−1.14)	(−2.66)	(1.08)	(1.81)
PERatio	0.39**	−0.13	0.03	0.26	0.79	−0.00	−0.99***
	(2.49)	(−0.65)	(0.26)	(0.56)	(1.36)	(−1.25)	(−2.91)
Foreign(ADR)	−0.51**	−0.28	−0.19**	0.54	0.20	0.00	0.38
	(−2.07)	(−1.12)	(−2.46)	(1.18)	(0.40)	(0.10)	(1.13)
MidCap	0.43**	−0.39**	−0.07	−1.83***	−2.75***	−0.00	−1.57***
	(2.29)	(−2.07)	(−0.91)	(−4.61)	(−5.99)	(−1.20)	(−4.42)
IntrinsicValue	0.14	1.87***	0.02	−1.57***	1.91***	−0.00	−0.57
	(0.77)	(3.52)	(0.18)	(−3.25)	(3.41)	(−0.01)	(−1.63)
FixedIncome	0.19	0.14	−0.06	0.13	0.21	0.00	0.49
	(1.34)	(0.54)	(−0.78)	(0.35)	(0.44)	(0.03)	(0.99)
Tax	−0.41*	0.28	0.12	1.28**	0.37	0.00	0.66
	(−1.95)	(1.07)	(1.24)	(2.14)	(0.73)	(0.91)	(1.29)
Foreign(EM)	−0.17	−0.08	−0.13	−0.60	−0.54	0.00	−0.55*
	(−0.80)	(−0.29)	(−1.43)	(−1.01)	(−1.04)	(1.16)	(−1.70)
Obs	288,012	288,012	288,012	288,012	288,012	288,012	288,012

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

betas at the fund level, as well as higher than average book-to-market ratio at the stock level. The "discount to intrinsic value" attribute may also be reflected in the fact that these funds buy firms with higher share repurchases, potentially indicating undervaluation.

Long term. Funds in this SPG claim to be searching for long term investment opportunities, or companies with long term growth potential. In the data, funds implementing this strategy tend to be older and have lower turnover ratios. The stock they hold have lower than average book-to-market ratios, both at the fund level and at the stock level (indicting a growth style tilt). They tend to avoid mature industries such as Utilities and Banks. Instead, they hold companies with higher intangibles (which includes capitalized R&D), higher cash, and lower dividend yields (greater retained earnings, typically used to grow the firm).

Fixed income. The *Fixed Income* SPG is distinguished by an emphasis on bonds as a secondary asset class. Consistent with this emphasis, we find funds in this SPG to have the lowest percentage of holdings in common stock, and the highest holdings in cash.

Derivatives:. Funds in this SPG discuss the use of derivatives (particularly options and futures) and short selling to enhance their portfolio return. Unfortunately, we do not observe derivative positions in our dataset and are thus unable to validate this SPG using the narrative/descriptive approach.

Quantitative. Funds in this group are significantly younger and smaller, with higher turnover ratio and lower expense ratio. This confirms the findings of Abis (2022), who identifies quantitative funds using a different methodology (supervised machine learning). We also expect *Quantitative* funds to make greater use of trend-following strategies and hold stocks of more companies at a time, signifying their greater information-processing capabilities. Both of these expectations are validated by the data: funds in this SPG have higher momentum betas and hold stocks of more companies than other funds.

Fundamental. The *Fundamental* SPG is comprised of funds that engage in bottom-up, fundamental research on individual companies. As such, we would not expect any particular tilts in industry composition, risk factor loadings or stock characteristics. Funds in this peer group can be seen as generic traditional investment managers. Consistent with this

Table D.4
Traditional Stock Characteristics by SPG: This table reports *differences* between various average stock characteristics within a particular Strategy Peer Group (SPG) and the average across all other SPGs. The differences are estimated in separate regressions of fund-level average stock characteristics on dummy variables for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	MarketBeta	MarketCap	BookToMkt	Momentum	Investment	Profitability
LargeCap	−0.942**	7.372**	−0.0126	−0.935	−0.492	0.552
	(−2.03)	(2.47)	(−0.13)	(−1.03)	(−0.75)	(0.60)
Fundmntl	0.618	−4.409	0.113	1.562*	−0.296	−0.715
	(1.17)	(−1.36)	(1.09)	(1.68)	(−0.55)	(−0.73)
ProdServ	0.843	−14.96***	−0.337***	6.930***	2.542***	4.726***
	(1.09)	(−3.82)	(−3.01)	(4.27)	(2.73)	(4.17)
Dividends	−2.774***	38.89***	0.763***	−10.61***	−2.195***	−7.378***
	(−4.28)	(10.74)	(5.60)	(−6.48)	(−3.80)	(−7.89)
Deriv	0.796	7.771**	0.118	−1.397	0.502	−1.820
	(0.99)	(2.08)	(1.02)	(−1.13)	(0.63)	(−1.34)
CompAdv	−0.0285	6.995	−0.817***	3.233**	−0.420	7.258***
	(−0.04)	(1.40)	(−5.50)	(2.31)	(−0.53)	(5.79)
Defensive	−0.825	5.265	0.0531	−2.519**	−0.530	0.341
	(−1.25)	(1.64)	(0.56)	(−2.27)	(−0.87)	(0.32)
Quantit	−0.247	9.875**	0.0675	1.021	−2.325***	−0.447
	(−0.38)	(2.22)	(0.56)	(0.73)	(−4.68)	(−0.41)
SmallCap	2.153**	−68.46***	0.350*	5.071***	5.652***	−2.402
	(2.41)	(−18.03)	(1.76)	(3.36)	(4.45)	(−1.46)
LongTerm	0.626	5.138	−0.408***	0.562	0.912	2.421
	(0.72)	(1.11)	(−2.63)	(0.38)	(0.77)	(1.56)
PERatio	−0.236	−2.696	0.0336	−1.647	−0.569	−1.198
	(−0.27)	(−0.51)	(0.26)	(−1.02)	(−0.62)	(−0.84)
Foreign(ADR)	1.428*	1.856	−0.0654	3.049**	0.460	1.518
	(1.71)	(0.39)	(−0.34)	(2.23)	(0.70)	(1.10)
MidCap	0.249	−12.88***	−0.156	0.335	−1.184**	3.009**
	(0.35)	(−3.40)	(−0.69)	(0.29)	(−2.30)	(2.45)
IntrValue	−1.332	13.17***	0.287**	−7.736***	−2.803***	−3.813***
	(−1.26)	(2.81)	(2.04)	(−6.64)	(−3.58)	(−2.94)
FixedInc	0.114	2.770	0.101	−2.037*	−0.132	−3.458**
	(0.13)	(0.70)	(0.89)	(−1.69)	(−0.15)	(−2.39)
Tax	1.240	18.27***	0.0109	1.271	−0.348	−1.022
	(1.40)	(3.08)	(0.06)	(0.72)	(−0.30)	(−0.64)
Foreign(EM)	−1.173	−10.12*	−0.204	1.690	0.466	0.610
	(−1.27)	(−1.93)	(−1.62)	(1.35)	(0.83)	(0.41)
Obs	288,012	288,012	288,012	288,012	288,012	288,012

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

intuition, we do not observe large differences between funds in this SPG and funds outside this SPG.

Defensive. In general, "defensive" strategies can mean either safer asset classes or defensive industries—the word cloud indicates that this SPG focuses on the former, specifically money market and other short term securities. The text generally permits managers to use these cash-like securities to reduce risk in adverse market conditions. In line with this objective, our results show that these funds hold a smaller fraction of their assets in common stock. The funds also have a lower than average market beta.

Tax. This SPG is characterized by tax-management strategies that explicitly aim to reduce the tax burden to the end investor through lower distributions. This strategy is difficult to assess using the simple characteristics we report in this paper, as it depends on the timing of sales relative to accrued capital gains. We note, however, that the *Tax* SPG holds much less of its assets in cash than other funds, which may correlate with lower taxable distributions.

Dividends. The "Dividends" group arguably has the most straightforward strategy and the clearest ex-ante expectations for investors: funds in this SPG should try to maximize dividend distributions. Accordingly, we find that these funds hold stocks with (by far) the highest dividend yield among all SPGs. The funds implementing this strategy tend to charge lower fees and have lower turnover ratios. The companies they hold are typical high-dividend firms: they are larger and older, have lower investment, and R&D expenses, and hold less cash (plausibly due to higher payout ratios). Portfolios are tilted towards high-dividend industries such as Utilities, Telecoms, and Banks; and tilted away from the Tech industry.

PE ratio. The use of the price-earnings ratio in security valuation is the common theme among funds in this SPG, who claim to look for companies whose prices are low relative to the prices implied by PE multiples for similar firms. This SPG also contains funds who use the PE ratio to identify "value" firms (i.e., those with low PE ratios). This is consistent with our finding that funds in this SPG have higher than average HML betas (though not higher book-to-market ratios at the stock level). Overall, our analysis for this SPG is limited.

Table D.5
Balance Sheet Variables by SPG: This table reports *differences* between average balance sheet characteristics of fund holdings within a particular Strategy Peer Group (SPG) and the average across all other SPGs. These differences are estimated in separate regressions of the dependent variables on dummies for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	CurrAsts	Invent.	NonPrfAst	PP&E	Intang.	AstGrw	Cash
LargeCap	−0.05	0.47	−0.46	−1.42	0.78	−0.24	−0.23
	(−0.03)	(0.59)	(−1.40)	(−1.33)	(0.60)	(−0.52)	(−0.18)
Fundmntl	−0.72	0.26	1.10**	1.03	−1.75	0.66	−0.79
	(−0.49)	(0.42)	(2.53)	(0.89)	(−1.27)	(1.12)	(−0.55)
ProdServ	13.88***	−0.95	−0.96**	−1.27	5.25***	4.15***	11.83***
	(7.54)	(−1.27)	(−2.28)	(−0.84)	(3.48)	(4.85)	(6.07)
Dividends	−20.09***	−2.83***	0.98**	1.72	−4.54***	−6.18***	−14.61***
	(−12.05)	(−3.30)	(2.53)	(1.33)	(−3.24)	(−7.37)	(−9.32)
Deriv	−2.20	−0.24	−0.42	0.77	−2.87*	−1.14**	−0.72
	(−1.35)	(−0.30)	(−0.79)	(0.67)	(−1.73)	(−1.99)	(−0.40)
CompAdv	8.99***	−0.03	−1.94***	−6.17***	9.09***	2.22***	8.13***
	(4.43)	(−0.03)	(−3.61)	(−3.82)	(4.53)	(3.01)	(3.59)
Defensive	−2.00	0.27	1.44*	−2.50*	0.21	−0.86	−1.80
	(−1.23)	(0.25)	(1.86)	(−1.76)	(0.14)	(−1.33)	(−1.11)
Quantit	−5.96***	2.74***	−0.03	0.44	−8.78***	−2.63***	−5.30***
	(−3.53)	(3.59)	(−0.06)	(0.37)	(−4.94)	(−4.34)	(−3.38)
SmallCap	13.13***	2.24**	1.77***	6.30***	−11.08***	3.15***	9.17***
	(6.27)	(1.99)	(2.92)	(3.62)	(−5.93)	(3.19)	(3.85)
LongTerm	4.57**	1.24	−1.61***	−2.40	4.83**	1.21	4.83**
	(2.04)	(1.13)	(−3.35)	(−1.31)	(2.40)	(1.49)	(2.04)
PERatio	−4.20*	2.80**	0.92*	2.58	−2.46	−0.56	−5.80***
	(−1.94)	(2.48)	(1.69)	(1.38)	(−1.35)	(−0.63)	(−3.04)
Foreign(ADR)	1.51	−0.55	−0.22	−0.08	0.18	2.23***	2.40
	(0.73)	(−0.67)	(−0.36)	(−0.05)	(0.10)	(2.97)	(1.22)
MidCap	1.16	0.10	−2.35***	3.32*	13.10***	−0.27	−5.31***
	(0.64)	(0.11)	(−4.78)	(1.94)	(6.06)	(−0.37)	(−3.11)
IntrValue	−9.28***	−2.65**	1.24	−4.22**	5.47**	−3.82***	−5.77***
	(−4.61)	(−2.34)	(1.50)	(−2.08)	(2.10)	(−5.41)	(−2.63)
FixedInc	−2.16	−1.80*	1.11*	1.20	−3.80**	−0.41	−0.58
	(−1.12)	(−1.74)	(1.76)	(0.81)	(−2.19)	(−0.47)	(−0.30)
Tax	−4.10*	−1.27	−0.64	1.34	−4.68**	0.31	−1.24
	(−1.88)	(−1.22)	(−1.41)	(0.61)	(−2.38)	(0.36)	(−0.56)
Foreign(EM)	3.09	−1.90	−0.15	−0.11	2.36	1.39**	3.53*
	(1.37)	(−1.58)	(−0.22)	(−0.06)	(0.97)	(1.98)	(1.69)
Obs	288,012	288,012	288,012	288,012	288,012	288,012	288,012

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

New products & services. Funds in this SPG focus on companies with new or innovative product lines, and new or rapidly changing technologies. Consistent with this focus, funds in this SPG tend to avoid stable industries such as utilities, telecoms, and banks, while holding a significantly greater fraction of stocks from innovative industries such as technology and pharmaceuticals (drugs). The funds implementing this strategy charge higher fees and have higher turnover ratios. The firms they hold have higher levels of investment and R&D expenditure, higher asset growth, and lower dividend yield, as would be expected for companies introducing new products and services.

Competitive advantage. According to the text, the two defining attributes of this SPG are companies with a sustainable competitive advantage and those with a strong balance sheet. Consistent with both of these attributes, we find that funds in this SPG tend to hold companies with higher than average profitability (highest among all SPGs) and companies with lower levels of debt (lowest among all SPGs) and lower leverage.

Foreign. The two *Foreign* SPGs — *Emerging Markets (EM)* and *American Depository Receipts (ADR)* — represent quite different strategies. While the former is explicitly focused on buying stocks of foreign companies, usually in emerging markets, the latter strategy appears to simply indicate a larger investment opportunity set, where funds are permitted (but not required) to hold ADRs. The characteristics data are consistent with this interpretation: *Foreign (EM)* funds hold a higher fraction of both ADRs and foreign-incorporated firms in their portfolios, compared to all other funds. However, there are no significant differences for *Foreign (ADR)* funds.

While we are not able to measure every relevant characteristic associated with the various strategies — derivative and bond positions, for example — we do not find any inconsistencies among the large set of characteristics that we *are* able to measure, and in most cases the measured characteristics directly affirm the text. Overall, we conclude that fund characteristics are broadly consistent with the investment approaches described in the text.

Table D.6
Additional Balance Sheet and Income Statement Variables by SPG: This table reports *differences* between average characteristics of fund holdings within a particular Strategy Peer Group (SPG) and the average across all other SPGs. These differences are estimated in separate regressions of the dependent variables on dummies for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	CurrLiab	Levrg	DefTax	LTDebt	OperInc	EarnGrw	R&D
LargeCap	0.97	0.02	2.02	−2.76***	−2.22	−0.17	0.04
	(1.14)	(0.06)	(1.21)	(−3.16)	(−1.25)	(−0.80)	(0.03)
Fundmntl	−1.44*	−0.65*	−1.32	−0.10	1.60*	0.07	−1.91*
	(−1.68)	(−1.75)	(−0.72)	(−0.10)	(1.74)	(0.31)	(−1.79)
ProdServ	4.69***	−2.33***	−7.74***	−2.71**	−2.20	−0.13	6.07**
	(4.62)	(−5.01)	(−3.80)	(−2.34)	(−1.54)	(−0.38)	(2.52)
Dividends	−5.69***	2.82***	19.86***	2.89***	2.92***	0.28	−4.13***
	(−5.78)	(6.16)	(9.05)	(2.62)	(4.17)	(1.08)	(−3.70)
Deriv	−0.22	0.43	3.52*	−0.09	−2.94	0.14	−1.34
	(−0.22)	(0.91)	(1.69)	(−0.10)	(−0.83)	(0.62)	(−1.20)
CompAdv	4.39***	−1.24**	1.08	−5.62***	−0.18	0.25	−0.59
	(4.43)	(−2.31)	(0.40)	(−4.40)	(−0.11)	(0.63)	(−0.35)
Defensive	−0.50	0.88**	−3.04	−0.77	−0.48	0.11	−0.04
	(−0.50)	(2.11)	(−1.28)	(−0.69)	(−0.36)	(0.31)	(−0.02)
Quantit	0.99	2.15***	7.89***	0.67	4.33***	0.19	−3.40***
	(0.90)	(4.70)	(3.61)	(0.64)	(3.46)	(0.72)	(−3.48)
SmallCap	−2.31*	−2.58***	−19.50***	3.13**	−4.85**	−0.74	7.54**
	(−1.93)	(−4.79)	(−9.93)	(2.05)	(−2.17)	(−1.64)	(2.48)
LongTerm	1.65	−0.09	2.44	−0.59	0.19	0.04	2.51
	(1.29)	(−0.16)	(0.95)	(−0.31)	(0.21)	(0.11)	(0.97)
PERatio	−2.02	−0.05	−0.46	−0.34	1.50	−0.22	−0.76
	(−1.41)	(−0.08)	(−0.17)	(−0.28)	(1.64)	(−0.67)	(−0.38)
Foreign(ADR)	−0.08	−1.09**	2.00	−0.97	0.08	0.18	0.99
	(−0.06)	(−2.05)	(0.69)	(−0.71)	(0.10)	(0.62)	(0.49)
MidCap	3.05**	−0.17	−10.15***	5.48***	1.59**	0.21	−2.10**
	(2.45)	(−0.33)	(−4.57)	(4.34)	(2.04)	(0.51)	(−2.24)
IntrValue	−2.48*	3.05***	4.55*	4.72**	4.98	−0.75	−4.99***
	(−1.89)	(3.43)	(1.72)	(2.44)	(1.56)	(−1.16)	(−2.98)
FixedInc	−1.46	0.29	−3.03	3.33*	−0.16	−0.46	0.98
	(−1.23)	(0.60)	(−1.32)	(1.88)	(−0.15)	(−1.45)	(0.49)
Tax	−1.07	0.53	8.05**	−2.32	0.30	0.51	1.05
	(−0.77)	(0.90)	(2.48)	(−1.59)	(0.16)	(1.49)	(0.35)
Foreign(EM)	−0.13	−0.37	−6.30**	1.58	−1.56	0.65	−0.68
	(−0.09)	(−0.69)	(−2.14)	(1.18)	(−1.32)	(1.13)	(−0.71)
Obs	288,012	288,012	288,012	288,012	288,012	288,012	288,012

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.7

Security Market Characteristics by SPG: This table reports *differences* between average market characteristics of securities held by funds within a particular Strategy Peer Group (SPG) and the average across all other SPGs. These differences are estimated in separate regressions of the dependent variables on dummies for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	DivYield	Issuance	Repurchase	Illiquid	FirmAge
LargeCap	−0.23*	0.03	2.36**	0.00	5.49**
	(−1.74)	(0.07)	(2.29)	(0.33)	(2.05)
Fundmntl	−0.16	0.17	−1.75	−0.00	−5.21
	(−1.14)	(0.43)	(−1.39)	(−0.33)	(−1.64)
ProdServ	−0.74***	−1.49***	−4.91***	−0.00*	−23.29***
	(−4.03)	(−3.63)	(−3.59)	(−1.92)	(−6.36)
Dividends	3.48***	3.01***	5.07***	0.01**	61.97***
	(10.00)	(6.35)	(4.07)	(2.40)	(15.40)
Deriv	0.36	0.10	1.90	−0.00	8.23**
	(1.52)	(0.20)	(1.29)	(−1.28)	(2.16)
CompAdv	−0.83***	−1.32**	−3.60**	−0.01**	−11.85***
	(−4.34)	(−2.12)	(−2.08)	(−2.48)	(−2.72)
Defensive	0.27*	0.55	1.93*	0.00	2.11
	(1.70)	(1.23)	(1.69)	(0.39)	(0.70)
Quantit	0.12	2.23***	11.79***	0.01**	17.54***
	(0.69)	(3.43)	(6.83)	(2.14)	(4.19)
SmallCap	−1.06***	−2.82***	−19.07***	−0.01**	−53.29***
	(−6.26)	(−4.53)	(−11.80)	(−1.98)	(−16.02)
LongTerm	−0.66**	0.71	−1.07	−0.00	−3.30
	(−2.35)	(1.32)	(−0.71)	(−0.35)	(−0.74)
PERatio	0.01	−0.05	−0.21	0.00	9.79*
	(0.07)	(−0.09)	(−0.12)	(0.77)	(1.96)
Foreign(ADR)	−0.46**	0.24	1.14	0.00	−4.14
	(−1.97)	(0.40)	(0.68)	(0.69)	(−0.80)
MidCap	−0.58**	−1.42**	0.18	−0.00	−18.66***
	(−2.33)	(−2.08)	(0.12)	(−0.68)	(−4.78)
IntrValue	0.49*	0.18	10.80***	−0.00	15.32***
	(1.94)	(0.24)	(5.00)	(−0.42)	(3.08)
FixedInc	0.36	−0.35	0.51	0.01	3.34
	(1.36)	(−0.50)	(0.38)	(1.47)	(0.84)
Tax	0.11	1.79***	4.87**	−0.00	17.78***
	(0.45)	(2.65)	(2.32)	(−1.42)	(3.22)
Foreign(EM)	−0.50*	−1.61**	−6.02***	−0.00	−20.42***
	(−1.93)	(−2.32)	(−3.02)	(−1.19)	(−4.12)
Obs	288,012	288,012	288,012	288,012	288,012

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.8

Holdings Characteristics by SPG: This table reports *differences* between average fund holdings characteristics for a particular Strategy Peer Group (SPG) and the average across all other SPGs. These differences are estimated in separate regressions of the dependent variables on dummies for each SPG (see Appendix D), controlling for fund age, log assets, expense ratio, turnover ratio, monthly fund flows, monthly fund flow volatility, and month as well as fund family fixed effects. All non-binary independent variables are demeaned. Standard errors are two-way clustered by fund and month.

	ADR%	ForeignInc	NumStocks	Cash%	CommStk%
LargeCap	−0.02 (−0.38)	0.06 (0.34)	−2.05 (−0.66)	2.45 (1.00)	4.48* (1.71)
Fundmntl	−0.09 (−1.15)	0.06 (0.24)	−2.61 (−0.98)	0.64 (0.28)	2.05 (0.72)
ProdServ	−0.00 (−0.05)	0.15 (0.49)	−1.42 (−0.71)	−2.34 (−0.82)	7.48** (2.24)
Dividends	0.95*** (6.40)	0.37 (1.39)	−6.47* (−1.75)	−4.02 (−1.30)	−23.36*** (−4.80)
Deriv	0.02 (0.23)	0.18 (0.67)	3.52 (0.99)	2.23 (0.55)	−5.59 (−1.09)
CompAdv	−0.03 (−0.31)	0.13 (0.47)	−13.55*** (−5.61)	0.98 (0.22)	8.85* (1.81)
Defensive	0.11 (1.17)	0.39* (1.68)	−3.48* (−1.67)	3.40 (1.00)	−9.22** (−2.36)
Quantit	−0.65*** (−7.95)	−1.81*** (−7.54)	18.93*** (4.89)	−15.44*** (−4.23)	25.16*** (6.67)
SmallCap	−0.36*** (−4.26)	−0.88*** (−2.91)	40.14*** (4.79)	3.45 (1.15)	−3.90 (−1.12)
LongTerm	0.02 (0.20)	−0.22 (−0.72)	−11.17* (−1.91)	−1.33 (−0.33)	7.61* (1.66)
PERatio	−0.22** (−2.08)	−0.34 (−1.03)	−4.50 (−1.30)	−1.03 (−0.24)	7.39* (1.73)
Foreign(ADR)	0.03 (0.18)	0.46 (1.45)	−4.18** (−2.02)	−3.89 (−1.32)	4.31 (1.09)
MidCap	−0.20 (−1.32)	0.51 (1.49)	−6.47 (−1.54)	−3.47 (−1.37)	6.19* (1.86)
IntrValue	0.10 (0.67)	0.50 (1.62)	−13.87*** (−7.47)	3.66 (0.84)	−12.79** (−2.01)
FixedInc	−0.09 (−0.87)	−0.03 (−0.10)	−1.43 (−0.65)	21.33*** (4.40)	−26.77*** (−4.04)
Tax	0.12 (0.84)	−0.29 (−0.94)	15.03 (1.62)	−12.45*** (−3.34)	11.11** (2.54)
Foreign(EM)	0.46*** (3.30)	1.08*** (2.60)	−8.30** (−2.13)	7.60* (1.81)	−16.74** (−2.01)
Obs	288,012	288,012	288,012	275,825	275,825

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table D.9

Fund Performance by SPG: This table reports *differences* between average fund alphas within a particular Strategy Peer Group (SPG) and the average across all other SPGs. Coefficients are estimated in separate regressions of the dependent vars (log of fund age, log of TNA, expense ratio, turnover ratio, post-fee FFC6 Alpha, and post-fee FFC6 Value Added) on dummies for each SPG (see Appendix D). Also shown are the *overall* averages across the full sample. We include month and fund family fixed effects. Standard errors are two-way clustered by fund and month.

	Raw Return	SPG Alpha	CAPM Alpha	FFC6 Alpha	DGTW Alpha	HKP Alpha
LargeCap	−0.0136	−0.0140	−0.0120	0.00342	−0.0133	0.000502
	(−0.90)	(−1.00)	(−0.87)	(0.30)	(−0.90)	(0.04)
Fundamental	−0.0147	−0.00242	−0.0241*	0.0144	−0.0115	−0.00181
	(−0.93)	(−0.23)	(−1.80)	(1.45)	(−0.85)	(−0.17)
ProdServ	−0.0199	0.0318	−0.00587	0.00789	−0.0184	−0.0315
	(−0.46)	(1.55)	(−0.17)	(0.43)	(−0.63)	(−1.40)
Dividends	0.00101	−0.00385	0.0191	−0.0316	0.0437	0.0155
	(0.02)	(−0.19)	(0.35)	(−1.20)	(1.11)	(0.47)
Derivatives	−0.0669**	0.0143	−0.00326	−0.00603	−0.0542***	−0.0470**
	(−2.22)	(0.82)	(−0.13)	(−0.41)	(−2.74)	(−2.45)
CompAdv	0.0161	−0.00307	0.0264	0.0264	0.0157	0.0278
	(0.44)	(−0.16)	(0.80)	(1.41)	(0.56)	(1.30)
Defensive	0.00355	0.0205	−0.0243	0.0102	−0.00183	−0.0124
	(0.12)	(0.88)	(−0.99)	(0.52)	(−0.08)	(−0.70)
Quantitative	−0.0276	−0.0310*	−0.00879	−0.0302	0.0178	0.00752
	(−0.84)	(−1.83)	(−0.30)	(−1.57)	(0.65)	(0.34)
SmallCap	0.0746	−0.0367**	−0.0112	−0.00922	0.00634	−0.0150
	(1.11)	(−2.05)	(−0.18)	(−0.52)	(0.21)	(−0.95)
LongTerm	−0.00331	−0.00649	−0.00680	−0.0104	−0.0177	0.0166
	(−0.12)	(−0.32)	(−0.26)	(−0.54)	(−0.77)	(0.83)
PERatio	0.0814**	0.0548*	0.0405	0.00354	0.0509*	0.0424*
	(2.38)	(1.86)	(1.45)	(0.19)	(1.71)	(1.80)
ForeignADR	−0.00854	−0.00168	0.00897	0.00125	−0.0225	0.00790
	(−0.44)	(−0.10)	(0.45)	(0.07)	(−1.37)	(0.52)
MidCap	0.0705**	0.0162	0.0513*	0.000426	0.0140	0.0161
	(2.23)	(1.19)	(1.67)	(0.02)	(0.61)	(1.03)
IntrValue	−0.00345	0.000642	0.0114	−0.0132	0.0221	−0.00457
	(−0.09)	(0.03)	(0.30)	(−0.58)	(0.81)	(−0.20)
FixedIncome	−0.0217	0.0145	0.00701	0.00681	−0.0223	−0.00919
	(−0.69)	(0.60)	(0.27)	(0.35)	(−0.87)	(−0.40)
Tax	−0.100***	−0.0412**	−0.0493*	0.00397	−0.0359	−0.0177
	(−3.01)	(−2.48)	(−1.80)	(0.24)	(−1.51)	(−1.00)
ForeignEM	0.0365	0.00774	0.00718	0.0169	0.0432	0.0110
	(1.12)	(0.37)	(0.22)	(0.72)	(1.35)	(0.45)
Overall	0.629***	0.000482	−0.0808***	−0.101***	−0.0397***	−0.00299**
	(239.03)	(0.22)	(−39.03)	(−47.48)	(−24.54)	(−2.48)
Obs	266,803	266,803	254,428	254,428	266,803	264,086

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix E. Pairwise analysis

To allow for more strict control variables, we compute our divergence measure, as well as differences between the first four return moments, for each *pair* of funds in the full sample, every month.

$$Divergence_{i,j,t} = \alpha + \beta_1 SameSPG_{i,j,t} + \beta_2 SameDGTW_{i,j,t} + \beta_3 SameFF3_{i,j,t} + Divergence_{i,j,t-1} + \gamma X_{i,j,t} + \eta_t + \varepsilon_{i,j,t}; \quad \text{(E.1)}$$

$$MomentDiff_{i,j,t+(1,24)} = \alpha + \beta_1 SameSPG_{i,j,t} + \beta_2 SameDGTW_{i,j,t} + \beta_3 SameFF3_{i,j,t} + MomentDiff_{i,j,t-(24,1)} + \gamma X_{i,j,t} + \eta_t + \varepsilon_{i,j,t}. \quad \text{(E.2)}$$

$Divergence_{i,j,t}$ is defined as in Eq. (2), except the average portfolio weights $\bar{w}^G_{i,t}$ are replaced with the weights of another individual fund i. $MomentDiff_{i,j,t+(1,24)}$ is the absolute difference (between fund i and fund j, in month t) in each moment of the distribution of future 24-months rolling returns, for $Moment \in [Mean, StDev, Skewness, Kurtosis]$. The variables denoted by $SameCluster_{i,j,t}$ (for $Cluster = [SPG, DGTW, FF3]$) are indicator variables that take a value of 1 if funds i and j are assigned to the same peer group, and 0 otherwise. The three peer groups are, respectively, (i) our text-based strategy peer groups ($SPGs$); (ii) Daniel et al. (1997) holdings-based peer groups, constructed from terciles of market capitalization, book-to-market ratio, and past returns ($DGTW$); and (iii) peer groups constructed using funds' exposures to the Fama–French 3-factor model ($FF3$). In both regressions, we control for differences in the same fund-level control variables as in Section 3.1.1 (represented here by $X_{i,j,t}$), as well as the *past* portfolio weight divergences and moment differences ($Divergence_{i,j,t-1}$ and $MomentDiff_{i,j,t-(24,1)}$, respectively). We also include month (η_t) fixed-effects, and cluster standard errors at the fund and month level.

The moment-similarity regressions have a predictive interpretation: a negative and significant β_1 indicates that belonging to the same SPG today correlates with lower differences (higher similarity) in *future* returns. The portfolio weight divergence regression is run contemporaneously, hence a negative and significant β_1 indicates that funds belonging to the same SPG also have more similar holdings. Since we control for alternative peer group co-membership, a positive and significant β_1 indicates that prospectuses have incremental predictive power for holdings and return similarities relative to traditional factors or characteristic portfolios.

Table E.1
Pairwise Strategy Divergence: This table reports the results of regressing pairwise portfolio weight divergence on a dummy variable for whether the two funds are grouped into the same SPG (see Appendix E). The regressions control for past differences in fund-level characteristics (log assets, log age, expense ratio, turnover ratio, net flows, net flow volatility), past portfolio weight divergence, and dummies for co-membership in alternative peer groups, based on holdings characteristics (Daniel et al. 1997) and risk factor loadings (Fama and French, 1993). All specifications include month fixed effects, and standard errors are clustered by fund and month.

	Portfolio Weight Divergence			
Same SPG	−0.0188***	−0.0172***	−0.0175***	−0.0161***
	(−12.20)	(−11.59)	(−11.79)	(−11.20)
Same DGTW		−0.174***		−0.159***
		(−22.66)		(−24.09)
Same FF3			−0.175***	−0.159***
			(−17.22)	(−17.04)
Controls	Yes	Yes	Yes	Yes
FixedEffects	Month	Month	Month	Month
Clustering	Fund+Month	Fund+Month	Fund+Month	Fund+Month
R2	0.0354	0.0739	0.0729	0.105
Observations	159681454	159681454	159681454	159681454

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table E.2
Pairwise Return Moment Distances: In this table we regress pairwise absolute return moment differences (mean, standard deviation, skewness, and kurtosis) on a dummy for whether the funds are grouped into the same SPG (see Appendix E). Moments are estimated over the subsequent 24 months. Regressions control for past moment differences (previous 24 months), fund-level characteristic differences (log assets, log age, expense ratio, turnover ratio, flows, flow volatility) and co-membership in alternative peer groups, based on holdings characteristics (Daniel et al. 1997) and risk factor loadings (Fama and French, 1993). All specifications include month fixed effects, and standard errors are clustered by fund and month.

	Ret. Mean	Ret. Std.	Ret. Skew.	Ret. Kurt.
Same SPG	−0.00731***	−0.0431***	−0.00617***	−0.00821***
	(−4.35)	(−8.39)	(−4.06)	(−3.19)
Same DGTW	−0.0481***	−0.216***	−0.0425***	−0.0692***
	(−9.84)	(−19.39)	(−6.86)	(−8.56)
Same FF3	−0.0414***	−0.197***	−0.0329***	−0.0584***
	(−8.69)	(−18.31)	(−6.23)	(−9.76)
Controls	Yes	Yes	Yes	Yes
FixedEffects	Month	Month	Month	Month
Clustering	Fund+Month	Fund+Month	Fund+Month	Fund+Month
R2	0.0870	0.0953	0.179	0.150
Observations	87 938 298	87 938 298	87 938 298	87935610

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tables E.1 and E.2 report the results. β_1 is always negative and statistically significant, even when controlling for alternative peer groups. The magnitudes of the coefficients on the $SameSPG$ indicator variable are between 6 and 10 times smaller than the coefficients on the $SameDGTW$ or $SameFF3$ indicator variables. This is not surprising. Indeed, the alternative peer groups are constructed directly from funds' holdings, which implies that they will mechanically have explanatory power for holdings similarities, and will likely predict similarities in returns. Instead, it is surprising that the text-based SPGs, which are constructed independently from funds' holdings or returns, have any incremental explanatory power at all. These results indicate the SPGs capture a novel dimension of similarity that is not subsumed by traditional classifications.

References

Abis, S., 2022. Man vs. Machine: Quantitative and discretionary equity management. Working paper.
Abis, S., Buffa, A.M., Javadekar, A., Lines, A., 2022. Learning from prospectuses. Working Paper.
Abrigo, M.R., Love, I., 2016. Estimation of panel vector autoregression in stata. Stat. J. 16 (3), 778–804.
Akey, P., Robertson, A.Z., Simutin, M., 2021. Closet active management of passive funds.
Ali, A., Chen, X., Yao, T., Yu, T., 2020. Can mutual funds profit from post earnings announcement drift? The role of competition. J. Bank. Financ. 114, 105774.
Allen, F., Bernardo, A.E., Welch, I., 2000. A theory of dividends based on tax clienteles. J. Finance 55 (6), 2499–2536.
Alvarez, J., Arellano, M., 2003. The time series and cross-section asymptotics of dynamic panel data estimators. Econometrica 71 (4), 1121–1159.
Angrist, J.D., Pischke, J.S., 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.
Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. J. Econometrics 68 (1), 29–51.
Barber, B.M., Huang, X., Odean, T., 2016. Which factors matter to investors? Evidence from mutual fund flows. Rev. Financ. Stud. 29 (10), 2600–2642.
Barber, B.M., Odean, T., Zheng, L., 2005. Out of sight, out of mind: The effects of expenses on mutual fund flows. J. Bus. 78 (6), 2095–2120.
Berk, J.B., van Binsbergen, J.H., 2015. Measuring skill in the mutual fund industry. J. Financ. Econ. 118 (1), 1–20.
Berk, J.B., Van Binsbergen, J.H., 2016. Assessing asset pricing models using revealed preference. J. Financ. Econ. 119 (1), 1–23.
Blei, D.M., Ng, A.Y., Jordan, M.I., 2003. Latent dirichlet allocation. J. Mach. Learn. Res. 3, 993–1022.
Brown, S.J., Goetzmann, W.N., 1997. Mutual fund styles. J. Financ. Econ. 43 (3), 373–399.
Chan, L.K., Chen, H.L., Lakonishok, J., 2002. On mutual fund investment styles. Rev. Financ. Stud. 15 (5), 1407–1437.
Chan, L.K., Dimmock, S.G., Lakonishok, J., 2009. Benchmarking money manager performance: Issues and evidence. Rev. Financ. Stud. 22 (11), 4553–4599.

Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. J. Political Econ. 105 (6), 1167–1200.
Christoffersen, S.E., Evans, R., Musto, D.K., 2013. What do consumers' fund flows maximize? Evidence from their brokers' incentives. J. Finance 68 (1), 201–235.
Cohen, R.B., Coval, J.D., Pástor, L., 2005. Judging fund managers by the company they keep. J. Finance 60 (3), 1057–1096.
Cooper, M.J., Gulen, H., Rau, P.R., 2005. Changing names with style: Mutual fund name changes and their effects on fund flows. J. Finance 60 (6), 2825–2858.
Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52 (3), 1035–1058.
Duffie, D., 2010. Presidential address: Asset price dynamics with slow-moving capital. J. Finance 65 (4), 1237–1267.
Elton, E.J., Gruber, M.J., Busse, J.A., 2004. Are investors rational? Choices among index funds. J. Finance 59 (1), 261–288.
Evans, R.B., 2010. Mutual fund incubation. J. Finance 65 (4), 1581–1611.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116 (1), 1–22.
Flesch, R., 1948. A new readability yardstick. J. Appl. Psychol. 32 (3), 221–233.
Gabaix, X., Koijen, R.S., 2021. In search of the origins of financial fluctuations: The inelastic markets hypothesis. National Bureau of Economic Research, Working Paper No. w28967.
Gil-Bazo, J., Ruiz-Verdú, P., 2009. The relation between price and performance in the mutual fund industry. J. Finance 64 (5), 2153–2183.
Grinblatt, M., Titman, S., 1989. Mutual fund performance: An analysis of quarterly portfolio holdings. J. Bus. 393–416.
Guercio, D.D., Reuter, J., 2014. Mutual fund performance and the incentive to generate alpha. J. Finance 69 (4), 1673–1704.
Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. Econometrica 1029–1054.
Hartzmark, S.M., Solomon, D.H., 2019. The dividend disconnect. J. Finance 74 (5), 2153–2199.
He, Z., Xiong, W., 2013. Delegated asset management, investment mandates, and capital immobility. J. Financ. Econ. 107 (2), 239–258.
Hoberg, G., Kumar, N., Prabhala, N., 2018. Mutual fund competition, managerial skill, and alpha persistence. Rev. Financ. Stud. 31 (5), 1896–1929.
Holtz-Eakin, D., Newey, W., Rosen, H.S., 1988. Estimating vector autoregressions with panel data. Econometrica 1371–1395.
Hortacsu, A., Syverson, C., 2004. Product differentiation, search costs, and competition in the mutual fund industry: A case study of SP 500 index funds. Q. J. Econ. 119 (2), 403–456.
Hunter, D., Kandel, E., Kandel, S., Wermers, R., 2014. Mutual fund performance evaluation with active peer benchmarks. J. Financ. Econ. 112 (1), 1–29.
Ivković, Z., Weisbenner, S., 2009. Individual investor mutual fund flows. J. Financ. Econ. 92 (2), 223–237.
Jain, P.C., Wu, J.S., 2000. Truth in mutual fund advertising: Evidence on future performance and fund flows. J. Finance 55 (2), 937–958.
Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved actions of mutual funds. Rev. Financ. Stud. 21 (6), 2379–2416.
Khorana, A., Servaes, H., 2012. What drives market share in the mutual fund industry? Rev. Financ. 16 (1), 81–113.
Khorana, A., Servaes, H., Tufano, P., 2009. Mutual fund fees around the world. Rev. Financ. Stud. 22 (3), 1279–1310.
Kincaid, P.J., Fishburne, R.P., Rogers, R.L.J., Chissom, B.S., 1975. Derivation of new readability formulas (automated readability index, fox count and flesch reading ease formula) for navy enlisted personel. Inst. Simul. Train. 56.
Kostovetsky, L., Warner, J.B., 2020. Measuring innovation and product differentiation: Evidence from mutual funds. J. Finance 75 (2), 779–823.
Krakow, N.J., Schäfer, T., 2020. Mutual funds and risk disclosure: Information content of fund prospectuses. Swiss Finance Institute Research Paper 20–54.
Li, S., Qiu, J., 2014. Financial product differentiation over the state space in the mutual fund industry. Manage. Sci. 60 (2), 508–520.
Loughran, T., McDonald, B., 2011. When is a liability not a liability? Textual analysis dictionaries and 10-Ks. J. Finance 66 (1), 35–65.
Loughran, T., McDonald, B., 2020. Textual analysis in finance. Annu. Rev. Finan. Econ. 12, 357–375.
Lütkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Springer Science & Business Media.
Mitchell, M., Pedersen, L.H., Pulvino, T., 2007. Slow moving capital. Amer. Econ. Rev. 97 (2), 215–220.
Reuter, J., Zitzewitz, E., 2006. Do ads influence editors? Advertising and bias in the financial media. Q. J. Econ. 121 (1), 197–227.
Roussanov, N., Ruan, H., Wei, Y., 2021. Marketing mutual funds. Rev. Financ. Stud. 34 (6), 3045–3094.
Sensoy, B.A., 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. J. Financ. Econ. 92 (1), 25–39.
Sharpe, W.F., 1988. Determining a fund's effective asset mix. Invest. Manag. Rev. 2 (6), 59–69.
Sharpe, W.F., 1992. Asset allocation: Management style and performance measurement. J. Portf. Manag. 18 (2), 7–19.
Sheng, J., Xu, N., Zheng, L., 2021. Do mutual funds walk the talk? A textual analysis of risk disclosure by mutual funds. Working Paper.
Shive, S., Yun, H., 2013. Are mutual funds sitting ducks? J. Financ. Econ. 107.1, 220–237.
Sims, C.A., 1980. Macroeconomics and reality. Econometrica 1–48.
Sirri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. J. Finance 53 (5), 1589–1622.
Stoughton, N.M., Wu, Y., Zechner, J., 2011. Intermediated investment management. J. Finance 66 (3), 947–980.
Sun, Y., 2021. Index fund entry and financial product market competition. Manage. Sci. 67 (1), 500–523.
Wahal, S., Wang, A.Y., 2011. Competition among mutual funds. J. Financ. Econ. 99 (1), 40–59.
Zhu, Q., 2020. The missing new funds. Manage. Sci.