1937

Discussion Papers

Deutsches Institut für Wirtschaftsforschung 2021

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http://www.diw.de

ISSN electronic edition 1619-4535

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Crowding of International Mutual Funds[*]

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Justus Inhoffen[¶], and Evert Wipplinger[‖]

updated
2021-07-26

Abstract

We study the relationship between crowding and performance in the active mutual fund industry. We construct a fund-specific measure of crowding using the equity holdings overlap of 17,364 global funds. Funds in the top decile of crowding underperform passive benchmark funds by 1.4% per year. The impact of crowding on performance cannot be attributed to diseconomies of scale. We explore several mechanisms: a preference for liquid stocks, externalities of peer fund flows, and a coordination problem. We find strongest support for a preference for liquid stocks. Our findings reveal that the tendency of managers to follow correlated strategies is a major concern for fund investors.

Keywords: Mutual funds, crowding, diseconomies of scale

JEL Classification: G15, G23

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[*]We would like to thank participants at the 2020 Annual Conference of the German Economic Association, the 3rd Dutch Network Economics Conference and seminar participants at EDHEC Business School, ESCP, VU Amsterdam, HU Berlin, and DIW Berlin for helpful comments and suggestions.

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1 Introduction

Globally, nearly 30 trillion USD are currently managed by active funds.[1] Among U.S. equities alone, actively managed domestic funds have increased their holdings from 2.4% in 1979 to more than 15% in the most recent decade (Pastor et al., 2015). In such a highly competitive environment (Wahal and Wang, 2011), an increasingly larger amount of capital is likely to follow similar strategies when investment opportunities are limited. This in turn leads to more overlapping equity positions, an effect that we term *crowding*. Given the prominent place of active funds in global financial markets, it is important to understand how crowding affects fund investors. Yet, the topic has so far received little attention from researchers.

We fill the gap in the literature and provide an empirical investigation of the impact of crowding on performance in the global fund industry. Perhaps not surprisingly, we first determine that crowding erodes fund performance. In a competitive equilibrium, active capital chasing the same investment opportunities is expected to eliminate predictability in stock returns and drive fund performance to zero (Berk and Green, 2004; Pastor and Stambaugh, 2012). However, we show that net alphas among the most crowded funds decrease even below the zero equilibrium. Thus, crowding of active capital is a major source of diminishing performance in the asset management industry. Second, we study economic channels that translate crowding into negative returns to investors. We find strong support for a liquidity preference channel (Pastor et al., 2020) and limited support for negative externalities of flows propagating through crowded stocks (Anton and Polk, 2014). Our results do not lend support to a coordination problem (Stein, 2009) driving the impact of crowding on performance.

The sample comprises 17,364 global actively-managed equity mutual funds. Dyck et al. (2013) show that active funds perform better in less-crowded international markets. Therefore, the international aspect of our study is important for understanding the impact of crowding on performance. In addition, the international settings allows for more powerful tests due to the higher variation in fund performance (Ferreira et al., 2013). We infer crowding by comparing the portfolio holdings of funds on a stock-by-stock basis. For each fund, we compute crowding

[1] According to data from the Global Asset Management report by the Boston Consulting Group for 2019.

as the sum of portfolio holdings overlap across all funds with which it shares common equity positions. Defined this way, crowding is increasing in the number of connected funds and the magnitude of the portfolio holdings overlap.

Our first finding is a strong, negative association between crowding and subsequent performance. In order to compute net alpha, we extend the approach of Berk and van Binsbergen (2015) and match every fund to an investment opportunity set comprising of passive domestic and international funds. We find that funds in the top decile of crowding have an alpha of -0.11% per month (t=*-4.5*). The spread in performance between funds in the least and most crowded environment is -0.22% per month (t=*-3.3*). Our findings cannot be attributed to fees and transaction costs alone, as funds in the top decile of crowding also have negative gross and holdings-based performance.

As funds grow larger, their performance is likely to deteriorate due to diseconomies of scale: they run out of ideas or suffer from an increasing price impact of their trades (Berk and Green, 2004). At the same time, funds increasing in size are likely to hold more stocks, and thus have higher portfolio holdings overlap with other funds. We analyze the nature of returns to scale and use both size and crowding to explain fund performance. Our tests employ the instrumental-variables approach developed by Pastor et al. (2015) and Zhu (2018). We find strong evidence that crowding drives fund performance, even after controlling for size. For instance, when we measure alpha using index funds, we find that a 10% increase in assets held by competitors in the same stocks is associated with a 25bp decrease in yearly fund net alpha. Our results reveal that crowding is an economically distinct phenomenon from fund-level diseconomies of scale.

When funds operate in a crowded space, they compete away positive alpha opportunities. However, even large funds may find enough stock picking opportunities when they do not face a lot of competition. A relatively large fund operating in an investment environment without many competitors can generate higher risk-adjusted returns than a smaller fund operating in a crowded space. Our results support this intuition. We double sort funds on size and crowding and examine their subsequent performance. Among all size deciles, performance is decreasing in crowding. Yet, funds in the largest decile of size exhibit a positive net alpha of 0.10% per month (t=*3.7*) in the lowest tercile of crowding, and a negative alpha of -0.07 per month (t=*-3.5*) in the top tercile.

Why is performance decreasing in crowding? In the framework of Berk and Green (2004), an increase in the amount of capital chasing limited alpha results in zero net performance. If funds run out of ideas on which stocks to trade, they can simply hold the market and avoid incurring losses relative to the market. However, the negative performance of funds in the top decile of crowding suggests that there is an additional economic channel which erodes performance.

We explore several possible explanations. In Berk and Green (2004), size lowers performance as large funds incur disproportionately larger costs. The equilibrium response of such funds is to increase holdings in liquid stocks (Pastor et al., 2020). A similar mechanism could be employed by crowded funds, even if they are not large in size. If crowded funds are concerned about the potential liquidity costs following unexpected future outflows, they will hold more liquid stocks. This leads to lower expected returns in comparison to funds operating in less crowded environments. The latter are more inclined to hold illiquid stocks and earn the associated premium. Our results offer support for this hypothesis. We study funds' trading and find that the demand for liquid stocks is monotonically increasing in crowding.[2] Moreover, the liquidity factor of Pastor and Stambaugh (2003) explains about a quarter of the spread in performance between funds in the top and bottom decile of crowding. We also observe that crowded funds overweight stocks from the more liquid U.S. market. The average weight of the U.S. equity market is 56% in the MSCI World Index versus 80% among the most crowded funds.

The second mechanism we investigate is related to fund flows. Fund flows result in scaling of positions (Coval and Stafford, 2007; Lou, 2012) which impact connected funds via the performance of their common holdings. Thus, fund flows can create externalities that can propagate shocks across connected funds. In order to quantify flow effects, we compute fund-specific $PeerFlow$ as the dollar flow of all connected funds weighted by the portfolio holdings overlap. We then use $PeerFlow$ to explain returns among funds most impacted by crowding. A challenge to this approach is the endogenous relationship between fund returns and $PeerFlow$. Fund returns impact both the contemporaneous performance and flows of connected peers. To mitigate

[2]The liquidity pattern we document is also consistent with Colla and Mele (2009). They show that when traders have correlated signals, profits decrease and the liquidity of the stocks they crowd into improves.

this problem, we regress fund returns on lagged $PeerFlow$. Specifications using gross alpha and characteristic-adjusted returns show a significant impact of $PeerFlow$ among crowded funds. The net alpha results, however, are insignificant. One possible explanation for this finding is that funds offset high liquidity costs by charging lower fees (Pastor et al., 2020), which masks the impact of $PeerFlow$ among funds with different degree of crowding. In additional tests, we follow Blocher (2016) and use lagged $PeerFlow$ as an instrument in contemporaneous regressions, but do find no statistically significant relationship. Overall, we find limited support for the fund flows channel.

The theory of Stein (2009) offers another possible mechanism for the negative returns to crowding in the form of a coordination problem. He considers sophisticated investors whose demand for a given asset is an increasing function in asset returns but who do not have an estimate of the fundamental value of the asset. Initial trading exacerbates the return signal, and investors cannot determine how much active capital is already employed by other market participants. As a result, investors can move prices away from fundamentals and thus inflict negative externalities on each other. We investigate these implications using momentum trading and find that the demand for momentum stocks is positively correlated with crowding. However, we find no relationship between momentum trading and subsequent performance, using either time-series (Lou and Polk, 2021) or cross-sectional tests (Barroso et al., 2021). Thus, our findings do not lend support to the coordination problem outlined above.

We perform various robustness tests. The impact of crowding on performance does not just stem from the passive holding of the global market portfolio by funds that run out of investment ideas. Even among funds close to the MSCI World index, we find a significant spread in performance between crowded and less crowded funds. The majority of funds in our sample are domiciled outside the U.S. Thus, another potential explanation of why crowded funds destroy value is that foreign domiciled funds suffer from an informational disadvantage. The negative returns of crowded funds could be driven by foreign funds with poor stock selection abilities among the U.S. equity overrepresented among crowded funds. Yet, the relationship between crowding and performance remains for the subset of U.S. domiciled funds. An informational gap between domestic and foreign funds is therefore unlikely to drive our findings. Our findings are further robust to alternative performance measures, they remain in Fama-Macbeth regressions, and are also not explained by differences in exposure to the net effect of common systematic factors (Song, 2020). We also compute an alternative measure of crowding, based on the eigenvalue centrality of funds in the global network of overlapping holdings. This measure captures the indirect effects of ownership from funds that are not directly connected (Gao, 2021). Results are qualitatively similar.

We contribute to the literature on capacity constraints in the active fund industry. A number of studies show that fund or industry size erode performance (e.g. Chen et al., 2004, Pastor et al., 2015, Dyakov et al., 2020). Our results show that a major concern for investors stems not from the fund's size itself, but rather from the amount of capital employed by other sophisticated investors in the same strategies. Even large funds can generate positive alpha when they exploit less crowded strategies.

Our work is also related to the literature on competition among mutual funds. Hoberg et al. (2017) study mutual funds that compete with a narrowly defined set of rivals with similar investment styles. They find that funds with fewer rivals perform better than funds with many. Our focus is different. We investigate the negative performance impact of competition among all funds holding the same equities and not just immediate rivals in investment styles. In a robustness test, we show that the impact of crowding on fund performance remains statistically significant after controlling for the two competition measures used by Hoberg et al. (2017). Our measure of crowding is closer to the measure of competition used by Wahal and Wang (2011). They study the impact of entrants on incumbent funds and find that the active fund industry is characterized with high levels of competition. We differ in that we study crowding using portfolio holdings overlap across all funds in the market, while they limit their scope to the impact of newly entering competitors.

Our findings on the impact of crowding among mutual funds stand in contrast to those of Sias et al. (2016), who find a positive relationship between crowding and subsequent performance of stocks held by hedge funds. One explanation for this difference is that crowding among mutual funds is concentrated in liquid stocks with lower levels of information asymmetries. At the same time, hedge funds are more likely to crowd into stocks that mutual funds underweight.

In addition, crowding can be related to herding. A key difference is that our measure of crowding is based on aggregate portfolio overlap, while the herding literature is primarily concerned with the correlation of portfolio changes across different funds. Early studies, such as Lakonishok et al. (1992), Grinblatt et al. (1995) and Sias (2004), find that herding among mutual funds adds value. However, more recent work by Dasgupta et al. (2011) and Jiang and Verardo (2018) find that herding leads to negative future returns. Our results are consistent with the latter.

2 Sample Construction and Risk Adjustment

2.1 Sample Construction

Our sample is based on quarterly positions of international mutual funds from Factset and stock level information from Datastream and Worldscope between 2001 and 2014. In addition, we collect data on fund net returns (in USD) and total net assets from Morningstar Direct. Factset collects the positions of more than 90,000 funds domiciled in 89 countries and covers active and passive mutual funds, insurances, pension funds, and other funds. The data covers both alive and defunct funds. Following earlier studies (e.g., Chuprinn et al., 2015), we exclude fund reports before 2001 because coverage of Factset prior to this year is limited. We also exclude funds with net assets of less than 15 million USD due to potentially biased data (see Elton et al., 2001 and Chen et al., 2004). We drop funds not classified as either open-ended or offshore. Including offshore funds in our sample ensure that we cover funds from Europe's two most prominent domiciles – Luxembourg and Ireland. We further keep only funds that hold at least 50 individual stock positions (equities and/or depository receipts) in their portfolios. This way we capture only funds with active equity components and exclude funds that hold equities for diversification purposes only. This procedure also ensures we exclude funds from countries with lax portfolio reporting regulations, such as Australia, where funds are required to report only their top 10 portfolio holdings. We match the reported fund holdings with stock specific information from Worldscope and Datastream using CUSIP, ISIN and SEDOL identifiers and match Factset to Morningstar using ISIN. Appendix A provides an overview on additional data cleaning procedures.

Descriptive statistics of our sample of funds and their portfolio weights by regions are in Table 1. In total, our sample covers 17,364 unique active equity mutual funds with average total assets under management (TNA) of 592 million USD. Similarly to Khorana et al. (2005), we find that there are more European than North-American funds, due to the large number of funds domiciled in the offshore locations of Luxembourg and Ireland. However, international funds are on average much smaller in size than North-American funds. On average, funds have a net alpha of -0.04% per month, consistent with the literature (i.e. Ferreira et al., 2013). Funds from each region exhibit a home bias and invest relatively more in their respective region's equity than funds domiciled elsewhere.

2.2 Measuring Performance

We compare the performance of each fund with a set of alternative investment opportunities as represented by low-cost passive funds (Berk and van Binsbergen, 2015). This approach has a number of advantages with respect to the traditional factor based models. First, factor portfolios, such as the Fama-French factors, do no incorporate transaction costs, trade impact, and trading restrictions (Huij and Verbeek, 2009). Hence, they are unlikely to represent the true alternative investment opportunity set. This problem is exacerbated within international markets, as investors throughout our sample do not have the opportunity to invest in e.g., momentum funds.

For each fund i, net alpha in month t is defined as the fund's return minus the return on the set of passive funds:

$$\alpha_{i,t} = R_{i,t} - \sum_{b=1}^{n(t)} \beta_i^b R_t^b, \tag{1}$$

where $R_{i,t}$ denotes the net excess return of fund i in month t, R_t^b is the excess net return earned by investors on the b-th index fund at time t, and β_i^b is the sensitivity of fund i to the b-th index fund. As reflected in the notation, the number of available benchmark funds may vary over time. When we compute gross alpha, we use gross fund and gross index fund returns, instead. We source net returns in percentages of U.S. dollars from Morningstar Direct and compute U.S. Dollars based gross returns from the last published portfolio holdings in Factset. We require at least 48 monthly observations in order to compute alphas. Finally, we employ the methodology of Berk and van Binsbergen (2015) to compute dollar value added as net alpha times total net assets.

A challenge in applying the approach outlined above lies in the selection of passive funds. To avoid a bias in selecting index funds, we follow Berk and van Binsbergen (2015) who select Vanguard index funds as benchmarks for U.S.-based funds. The selection of Vanguard index funds for investments in non-U.S. markets follows Dyakov et al. (2020), who extend Berk and van Binsbergen (2015) to international markets. We check if a fund invests on average more than 75% in one of the four broad geographical regions that we define alongside MSCI country classification: i) developed North-America (NAM), ii) developed Europe (EUR), iii) developed Asia-Pacific and Japan (APN), and iv) Emerging Markets (EM). If the condition is met, we assign the fund to that region's set of benchmark funds. If not, we refer to the fund as a global (GLO) fund. Finally, we select the set of passive Vanguard for each region as described in Appendix B and use Equation (1) to compute the fund's net alpha.

In addition, we measure performance by comparing the return of every stock k with a set of stocks with similar size, book-to-market, and momentum characteristics (also known as DGTW adjusted returns, following Daniel et al., 1997 and Wermers, 2003 who introduced this methodology to U.S. stocks). Specifically, the characteristic-adjusted return on a stock k is given by

$$\alpha_{k,t}^{DGTW} = R_{k,t} - R_{k,t}^{bench}, \tag{2}$$

where $R_{i,t}^{bench}$ denotes the return of a benchmark portfolio of stocks with similar size, book-to-market, and momentum characteristics in local currency of the individual stocks. Fund i's return is then computed as the weighted average of the α^{DGTW} across all stocks it holds in local currency of each individual stock.[3] The DGTW returns do not capture the true alternative investment opportunity set, as managers might be constrained in the stocks they could buy, due to trading costs, regulations, or other frictions. However, they offer a direct risk-adjustment

[3]See Appendix E in Dyakov et al. (2020) who provide a detailed methodology for computing benchmark-adjusted returns for international stocks belonging to broad geographical regions with different market sizes and accounting standards.

as each stocks is matched to a benchmark of stocks most similar in the size, book-to-market, and momentum space. In addition, calculated alphas are not affected by estimation error. Lastly, DGTW returns are computed in local currency and are hence not affected by swings in exchange rates. Consistent with these arguments, Dyakov et al. (2020) find that DGTW returns can better detect the impact of capacity constraints on performance among international funds.

3 Crowding

3.1 Construction of Crowding

In order to measure crowding, we establish similarities across investments. This is not a trivial task, for the following reasons. First, actual investment styles differ from the ones stated in fund prospectuses for as many as one third of all funds (Sensoy, 2009). Second, classifying funds together in the same style is arbitrary and can miss important characteristics of investment strategies. For instance, a large-cap tech fund and a large-cap precious metals fund are unlikely to hold any common positions, but both could be classified as large cap funds. Third, style classifications can vastly differ across the main data providers such as Morningstar, CRSP, and Thomson-Reuters. It is not a priori clear which classification is to be preferred.

We avoid the misclassification errors and idiosyncratic choices related to fund styles and infer crowding directly by comparing the portfolio holdings of funds on a stock-by-stock basis. For each fund, we compute crowding as the sum of portfolio holdings overlap across all funds with which it shares common equity positions. Defined this way, crowding is increasing in the number of connected funds and the magnitude of the portfolio holdings overlap. Effectively, we make inferences about crowding that stem from the resulting portfolio holdings, rather than the investment objective.

Specifically, for any two funds i and j in our sample, we compute the common portfolio holding e_{ij} as the sum of the minimum portfolio weight in a stock across all assets. The higher the overlap of portfolio holdings of two funds, the stronger the link of the two funds in our network. Let ω_i^k and ω_j^k denote the weights of fund i and fund j in stock k. The total portfolio overlap between fund i and j is then defined as

$$e_{ij} = \sum_{k \in P_i \cap P_j} \min(\omega_i^k, \omega_j^k) \tag{3}$$

where P_i is the set of stocks fund i is invested in. This measure of overlap is symmetric ($e_{ij} = e_{ji}$) and ranges from 0 to 1. If two funds hold the exact same portfolio of stocks and in the same proportion, then the overlap measure is one. If the pair of funds does not hold any asset in common, the measure equals zero. Articles that analyze networks of common asset holdings have used a number of other measures, such as common ownership (Anton and Polk, 2014), cosine similarity, and absolute differences in portfolio weights (e.g. Sias et al., 2016). We focus on common weight due to the simplicity of the measure. Our overlap measure has one drawback that it shares with the measures based on individual stock weights mentioned above. It does not recognize that stocks with similar characteristics are potential substitutes (Hoberg et al., 2017).

After having computed the portfolio overlap e_{ij} between two funds, we derive the fund-specific crowding score by summing up the pairwise overlaps with all other funds in the universe. For each fund i the crowding score is given by

$$crowd_i = \sum_{j \in Q,\ j \neq i} e_{ij} \tag{4}$$

with Q being the universe of mutual funds observed in the respective quarter of our sample. The crowding score measures how similar the portfolio holdings of a mutual fund are to the portfolio holdings of all other funds in the network. The higher the crowding score for a fund, the more it competes with other funds for the same investment opportunities. Wahal and Wang (2011) use a similar measure to study the impact of newly entering funds on incumbent funds. While they construct portfolio overlap in a similar way, they only sum across common holdings with new entrants.

3.2 Descriptive Statistics

Table 2 presents fund characteristics for fund portfolios sorted into deciles based on crowding. The average total net assets of funds in the lowest crowding decile is 302 million USD while the average TNA of funds in the top decile is nearly three times as large. Crowded funds are more diversified across firms, countries, and industries. They are also characterized by higher industry diversification measured as the inverse of the Herfindahl Index. Panel B shows average portfolio weights for stock regions. Funds with a high crowding score invest more capital into North American stocks while funds with a lower score invest more prominently in Emerging Markets, Frontier Markets, and the Asia Pacific and Japan region.

In addition, we provide stock-level characteristics in Table 3. Pastor et al. (2020) predict that larger funds hold more liquid assets and are more diversified. Their predictions extend to crowded funds, because crowding captures part of the size effect. In line with their prediction, we find that crowded funds have a preference for liquid stocks, as proxied for by Amihud illiquidity (Amihud, 2002). In addition, they hold less risky assets characterized by larger size, lower book-to-market, and lower momentum and volatility as well as stocks with lower levels of information asymmetries, as proxied for by the higher number of analysts covering them. Furthermore, funds operating in a crowded space hold more mature firms and stocks with higher dividend yield. Lastly, they diversify their portfolio holdings relatively more across foreign and geographically more distant stocks. Appendix C provides the results multivariate regressions explaining stock-level variation in crowding using stock characteristics and shows that fund crowding is persistent over time.

4 Crowding and Fund Performance

4.1 Single Sorts

At the end of each quarter, we sort funds into ten deciles based on their crowding score. Next, we track the average performance of funds in the decile portfolios over the subsequent three months after which we rebalance. Time-series averages of the returns of the decile portfolios are presented in Table 4.

We find a strong, negative relationship between crowding and subsequent performance. The pattern is consistent across different risk-adjustment methods. In addition, performance for funds in the most crowded portfolios is negative. For instance, funds in the top decile of crowding exhibit a net alpha of -0.11% per month (*t=-4.5*). The spread in net alpha between funds in the most and the least crowded environment is -0.2 per month (*t=-3.3*). Funds in the top decile of crowding feature a negative amount of dollar value added: -1.9$ million per month. Note that fees and transaction costs alone cannot explain the negative overall performance of the most crowded funds, as the return patterns are similar when we use gross instead of net returns. Appendix F shows that the results are robust to using value-weighing of funds in the decile portfolios, and that the results remain when using various traditional factor model specifications.

4.2 Crowding and Diseconomies of Scale

Previous literature (e.g., Chen et al., 2004) shows a similar monotonically decreasing pattern of fund performance when sorting on fund size. Large funds typically operate in a more crowded environment. Therefore, crowding is likely to capture at least some of the effects of fund size. In this Section, we empirically disentangle the role of crowding and fund size in explaining fund performance.

Consider a group of mutual funds, indexed $i = 1, ..., N$. The dependent variable in our analysis is $r_{i,t}$, which denotes the risk-adjusted return (alpha) of fund i in month t. The total market value of the fund at the end of the previous month is $q_{i,t-1}$. We want to estimate the effect of lagged crowding $crowd_{i,t-1}$ and lagged size $q_{i,t-1}$ on fund performance $r_{i,t}$. Following Zhu (2018), crowding and size are transformed as logarithms in the regresssion

$$r_{i,t} = a_i + b_1 \log crowd_{i,t-1} + b_2 \log q_{i,t-1} + \varepsilon_{i,t}. \quad (5)$$

In this equation, a_i represents fund fixed effects, absorbing the cross-sectional variation in managerial skills, which are assumed to be time-invariant.[4] A negative coefficient b_1 identifies the adverse effect of crowding on performance, while a negative coefficient b_2 identifies decreasing returns to scale at the fund level. A standard fixed effects estimator requires the regressors in equation (5) to be strictly exogenous. That is, regressors should be uncorrelated with the error term ε_{it} across all time periods. For equation (5), however, this is not the case as (a) fund size mechanically relates to past performance before fund flows, and (b) investor flows respond to past performance. To address this problem, we follow the methodology outlined in Pastor et al. (2015) and Zhu (2018). We forward demean all variables and use a two stage least squares approach (2SLS). In a first stage regression, we use backward-demeaned fund size and lagged fund size as instruments for forward-demeaned size. In the second stage, we regress forward demeaned alpha on the fitted values from the first stage as well as forward-demeaned crowding. Appendix D provides additional details on the 2SLS methodology.

In addition to $crowd_i$, we introduce a dollar based measure that allows us to gauge the economic impact of crowding on performance. We obtain $PeerTNA_i$ by summing the product of the total portfolio overlap between fund i and j with the size of fund j, across all funds that overlap with i:

$$PeerTNA_{i,t-1} = \sum_{j \in Q} e_{i,j,t-1} \; q_{j,t-1} \tag{6}$$

The results of the 2SLS regressions are reported in Table 5. In Panel A, we use net alpha as performance measure. Our crowding variables are significant in all specifications. After controlling for fund size, the estimated coefficient on $crowd_i$ is -0.002 (*t*=*-2.7*). This is an economically large effect, as evidenced by the estimated coefficients on $PeerTNA_i$. A 10% increase in the assets managed by competitors translates into a 25bp drop in yearly performance (*t*=*-2.4*). $crowd_i$ remains significant in specifications where we use gross alpha and DGTW returns as performance measures. In Table 13 we examine the robustness of our findings and find that crowding explains performance in Fama-Macbeth regressions where we include control variables as well as style and domicile fixed effects. Our results indicate that crowding is an economically distinct phenomenon from the previously documented diseconomies of scale

[4] In general, this term would also capture fund-specific "skill" related to, for example, operational costs at the fund or family level.

associated with fund size.

In Table 5, we find limited evidence about the role of fund size in explaining performance. These findings are consistent with Dyakov et al. (2020), who study diseconomies of scale among geographical regions of investment. They find that diseconomies of scale are weaker outside of the U.S., possibly because the active industry is below its optimal size. The lower levels of active investment indicate that capacity constraints are less binding, and thus more difficult to estimate in the data.

We offer additional insights about the role of crowding and size as determinants of performance. On the one hand, a large amount of funds chasing limited investment opportunities means that alpha quickly disappears. Even a skilled manager operating a small fund may find difficulties in beating the benchmark. On the other hand, if funds operate in a less crowded environment, mispriced stocks might be easier to identify. When there is little competition, even large funds may be able to outperform the benchmark. Thus, the effect of size on performance depends on how crowded the investment environment is. Our results support this hypothesis. We double sort funds into decile portfolios of size and then into crowding terciles, and examine their subsequent performance. Results are reported in Table 6. Among the largest funds, funds operating in the lowest tercile of crowding are able to beat the benchmark. Their average net alpha is 0.10% per month (t=*3.7*). In contrast, funds in the top tercile of crowding have an average net alpha of -0.07 per month (t=*-3.5*). Among all size deciles, funds operating in a crowded environment generate significantly lower returns.

5 Economic Channels

Our main result of decreasing performance with an increase in crowdedness is consistent with the predictions of Berk and Green (2004) where performance decreases with scale. In their model, active fund managers cannot infinitely scale their investment opportunities. Either the price impact of their trades increases, or they eventually run out of ideas. In equilibrium, investors reward individual fund managers with capital up to the point where returns going forward are zero. That is, net alpha must be zero and gross alpha equals the fund's costs. In our context, this implies that the returns of crowded funds should be nonnegative, before fees and transaction costs. While managers could invest excess capital into crowded stocks with negative performance, they should only be able to raise additional excess capital while the fund's overall performance remains positive or zero. However, we find a negative performance of the most crowded funds in Table 4. This indicates that there are additional frictions or unaccounted risk premia associated with crowding, driving aggregate performance negative. In this Section, we explore potential mechanisms.

5.1 Preference for Liquidity

Pastor et al. (2020) provide evidence of diseconomies of scale based on trade offs between funds' choices of characteristics. In equilibrium, funds endogenously choose their portfolio and fee structure in order to offset trading costs. Their arguments extend to crowded funds. First, more crowded funds will have a higher demand for liquid stocks because they need to offset trading costs associated with their more interlinked and concentrated portfolios. Second, the prediction of Berk and Green (2004) that excess capital will be allocated to passive investments also implies a preference for liquid stocks. At the margin funds will scale their passive investment with liquid stocks to meet potential future redemptions.

These arguments indicate that crowded funds should not only have a higher overall exposure to more liquid stocks as shown in Table 3 but also a higher demand for liquid stocks among their trades. Following Sias (2004), we first compute a buyer ratio BR, defined as the number of funds buying a stock k each quarter t relative to the number of funds trading the stock:

$$BR_{k,t} = \frac{\#\ of\ funds\ buying\ stock\ k}{\#\ of\ funds\ buying\ stock\ k\ +\ \#\ of\ funds\ selling\ stock\ k} \tag{7}$$

We then define the demand for funds in stock k as the standardized value of BR

$$ID_{k,t} = \frac{BR_{k,t} - \overline{BR_{k,t}}}{\sigma(BR_{k,t})} \tag{8}$$

where $\overline{BR_{k,t}}$ and $\sigma(BR_{k,t})$ stand for the cross-sectional quarterly mean and standard deviation of $BR_{k,t}$, respectively. The standardization of the variable allows us to compare funds' demand across time periods and crowding deciles.

Each quarter, we estimate a cross-sectional regression of demand on stock characteristics

$$ID_{k,t} = \alpha_t + \boldsymbol{\beta_t X_{k,t-1}} + \gamma_t ID_{k,t-1} + \epsilon_t \tag{9}$$

where $\boldsymbol{X}$ is a vector of stock characteristics, including size, value, momentum and illiquidity. Following Sias (2004), we include lagged stock demand as funds tend to herd into the same stocks over adjacent quarters. Since we study stock demand conditional on crowding, we estimate equation (9) separately for funds belonging to the ten crowding deciles.

We report the results in Table 7. The time-series average coefficient on the Amihud (2002) illiquidity score is always negative and generally decreasing in crowding. Starting with decile 4 up to the highest decile of crowding, the average coefficient is negative at significance levels of 5% and above. This pattern indicates a higher trading demand for liquid stocks among more crowded funds. Furthermore, Table 8 shows that crowded funds tilt their portfolios towards the more liquid (cf. Amihud et al., 2015) U.S. market: North-American stocks represent 55% of the MSCI World Index, but 80% among the top 5% most crowding funds. Therefore, a possible explanations for the negative returns to crowding is a liquidity premium unaccounted for in the risk-adjustment of Section 2.2.

To explore this, we compare the results of a risk adjustment using the Fama-French factors with and without an augmented liqudity factor (Pastor and Stambaugh, 2003). Results are reported in Table 9. The difference in risk-adjusted performance between the least and most crowded decile of funds amounts to -0.21% per month (*t*=*-2.8*) in the unagumented Fama-French factor model. After we include the liquidity factor the difference in performance is about a quarter smaller at -0.17% per month (*t*=*-2.3*). Moreover less crowded funds exhibit a significantly lower loading on the liquidity factor. This analysis reveals that less crowded funds are earning more liquidity premia on their portfolios.

5.2 Peer Flows

We next investigate the role of fund flows in creating externalities (Anton and Polk, 2014; Blocher, 2016) among crowded funds. It is well known that mutual fund flows can have a significant impact on subsequent fund returns (Coval and Stafford, 2007; Lou, 2012). In the context of this paper, fund flows can be considered as individual fund shocks that can propagate among connected funds via their common portfolio holdings. Suppose all funds have investors that are chasing returns. When Fund A faces poor performance, investors withdraw capital. Further suppose Fund A scales its portfolio as it sells assets to meet redemptions. Fund B holds some stocks in common with Fund A and thus exhibits a lower performance in these stocks due to the price pressure from Fund A. Since the investors of Fund B also chase returns, they will tend to withdraw capital from Fund B in the short-term as well. This process would be repeated among all connected funds and create a feedback loop. In turn, there will be additional costs or externalities as funds are forced to trade not only based on their investment strategy but also in response to flows induced by the performance of other funds.

Our focus is on the effect of flows among funds with direct connections. To this end, we construct a measure of neighboring peer flows $PeerFlow$ for each fund i and quarter t as the sum of the product of portfolio overlap $e_{i,j}$ and flows of connected funds $Flow_{j,t}$:

$$PeerFlow_{i,t} = \sum_{j \in Q} e_{i,j} \ Flow_{j,t}. \tag{10}$$

Hence, in computing peer flows for an individual fund, flows of more similar funds receive higher weights than flows of funds with lower portfolio overlap. We focus on the differential impact of

$PeerFlow$ on the returns of the most crowded funds. A contemporaneous regression faces an apparent endogenity between fund returns and $PeerFlow$. Shocks to individual fund returns influence both the contemporaneous performance and flows of connected peers.

To address this challenge, we use two approaches. First, we regress fund returns on lagged $PeerFlow$ and its interaction with an indicator variable for the 30% most crowded funds. We find some evidence for a difference in the predictive power of peer flows between crowded and non-crowded funds in Panel A of Table 10. Higher peer flows for the 30% most crowded funds have a more positive effect on future performance than compared to the rest of the funds. The effect is significant at the 5% significance level for both measures of gross performance, gross alpha (*t=2.3*) and DGTW-returns (*t=3.3*). This holds while we control for the overall level of fees of funds. However, the interaction coefficient is not significant in specifications where we predict net alpha. One possible explanation for this difference in findings between gross and net returns is that crowded funds offset high liquidity costs by charging lower fees (Pastor et al., 2020). This in turn can mask the impact of $PeerFlow$ among funds with different degree of crowding.

Our second approach to address the endogenity of $PeerFlow$ is to use lagged $PeerFlow$ as an instrument in contemporaneous regressions (Blocher, 2016). The results of the two stage least squared regressions (2SLS) are presented in Panel B of Table 10. In contrast to the predictive regressions, we are not able to find a significant impact of $PeerFlow$ on performance. As the instrumentalization of $PeerFlow$ introduces noise (see e.g., Wooldridge, 2010, chapter 5), the 2SLS regressions present a less powerful test for detecting the impact of shocks among connected funds. Alternatively, the effect of $PeerFlow$ may not be economically large enough in order to propagate to connected funds. Overall, we find weaker support for the peer flows channel than for the liquidity channel discussed above.

5.3 Coordination Externalities

Stein (2009) describes a coordination problem that arises when sophisticated investors face incomplete information. There are two important features of his model. First, demand for assets is driven solely by a return signal and is not based on a fundamental anchor. Second, investors do not ex ante observe how much capital other investors allocate towards the same strategy. In his model, initial trading exacerbates the return signal. He shows that the inability of investors to condition their trades on that of others gives rise to a coordination problem. Then, a higher number of competing investors than expected yields overreaction in prices. Thus, investors can inflict negative externalities on each other. Suppose crowding among funds results from a response to a common price signal. In the setup of Stein (2009), managers underestimating other funds' demand for the same assets would inadvertently buy too much of the asset and become crowded. This could explain their negative performance once prices revert to fundamentals.

To explore this possibility, we focus on momentum (Jegadeesh and Titman, 2002) as the most common example of a trading strategy based on price signals rather than on fundamentals. Momentum strategies are vastly popular among investors and the academic literature on momentum has failed to pinpoint a rational explanation for its success (Asness et al., 2013). We first investigate whether crowded funds are more likely to trade on momentum. The average momentum loadings in the demand regression of Equation (9) across different crowding deciles are listed in Table 7. We find that momentum trading is generally increasing with crowding. The average estimated coefficient is negative but statistically insignificant (*t=-1.4*) in the bottom decile of crowded funds but positive and highly statistically significant (*t=8.5*) in the most crowded decile.

However, a higher demand for momentum stocks among crowded funds does not necessarily imply that a coordination problem drives their negative performance. An additional prediction is that the price impact of crowding should be more pronounced when funds display a relatively stronger demand for momentum stocks. Following the work of Lou and Polk (2021) and Barroso et al. (2021), we conduct a time-series and a cross-sectional test. First, we split each crowding decile into 3 time periods, based on the estimated quarterly coefficients on momentum from Equation (9). Panel A of Table 11 shows the time-series averages of the subsequent three month returns. Funds in the top decile of crowding trade relatively more on momentum and subsequent risk-adjusted returns are negative. However, future returns are also negative, even in periods when crowded funds do not heavily trade on momentum. In our second test, we group funds each period based on momentum trading. Following Barroso et al. (2021), a fund is classified as a momentum fund if it has a positive value of the sum of return-adjusted changes in weights times lagged 12 month stock return across all stocks held by the fund. In Panel B of Table 11, we report no significant differences in the subsequent three month return between momentum funds and the rest of each crowding decile. Thus, neither the time series, nor the cross-sectional test lend support to the coordination problem driving the negative performance of crowded funds.

6 Additional Tests

6.1 Robustness

In Table 13 we show results from Fama-MacBeth regressions of performance on crowding. The implications of specifications (1) and (2) which include style and domicile fixed effects are similar to those of the portfolio sorts in Table 4. An increase in crowding is associated with a decrease in net alpha. The effect of crowding on performance cannot be explained by a mismatch between skill and scale (Song, 2020) as we control for the factor related return (FRR) in specification (3). FRR is constructed as the net return effect of the fund's exposure to size, book-to-market, and momentum factors. Appendix E provides results based on alternative measure of crowding which take indirect overlap between funds and an asymmetric relationship between crowding into account. Results are qualitatively similar. In Appendix F, we further report returns on portfolios sorted on crowding (or double sorted on size and crowding), where we use value-weighting of funds and additional performance measures, including alphas from factor models. Again, results are consistent.

6.2 Differences in Information between U.S. and non-U.S. funds

Our findings indicate that crowded funds overinvest into U.S. equity. A possible explanation is that European managers are at an informational disadvantages with respect to domestic managers in U.S. equity. However, the underperformance is not driven by an information gap between U.S. and foreign funds. When we restrict the sample to funds domiciled in the U.S. our main results hold. Specifications (4)-(6) in Table 13 show that crowding remains a statistically significant predictor of performance, after controlling for fund characteristics in the sample of U.S. domiciled funds.

6.3 Crowding and Proximity to the Market Portfolio

If crowded funds run out of investment ideas, one would expect them to remain closer to the global market portfolio (Berk and Green, 2004). Consistent with this, the descriptive statistics in Table 3 indicate that portfolio weights of stocks constituting the MSCI World Index are increasing in crowdedness. We then double sort funds on their active share (Cremers and Petajisto, 2009) with respect to the MSCI World portfolio and then crowding and tabulate their subsequent performance. Table 12 shows that crowding has explanatory power beyond deviations from the market portfolio. Specifically, the spread between high and low crowding among the five lowest deciles of active share ranges between -4 and -15 basis points, with significant t-stats. Thus, some funds are able to position their investments relatively close to the market portfolio, without having an excessive overlap with other funds that decreases their performance.

6.4 Competition and Crowding

Hoberg et al. (2017) construct fund-specific measures of competition based on similarity in style whereas we focus on portfolio overlap. For each fund, they define a set of competitors based on total distance in the space spanned by size, book-to-market, and momentum. According to their approach, stocks with similar characteristics are potential substitutes. Our measure does not identify potential substitutes and is instead derived from the observed investment decisions of all funds. In addition, our paper has a different focus. Hoberg et al. (2017) stress performance persistence among funds facing less competitive pressure whereas we study the negative impact of crowding on performance. We find that the negative relationship between crowding and subsequent performance remains after including the two measures of competition used by Hoberg et al. (2017). Closely following their work, we identify a fund-specific set of rivals based on overall similarity in the size, book-to-market, and momentum dimensions. For each fund, $TSIM$ measures total similarity across all rivals, while $NPeers$ measures the number of rivals. We restrict the analysis to U.S. domiciled funds, similar to the sample used by Hoberg et al. (2017). Specifications (7) and (8) in Table 13 present the results. In both specifications, our two crowding measures remain statistically significant.

7 Conclusion

We study the performance impact of active fund managers holding the same stocks in their portfolios. We label the resulting overlap in equity positions as crowding and show that crowding has a strong and economically significant negative effect on fund performance. Yet, crowding is an economically distinct phenomenon from the well-researched diseconomies of scale associated with fund size. Even large funds can exhibit a positive performance if they are able to trade in stocks where few competitors invest. When we explore the economic channels behind the impact of crowding on performance, our results provide strong support for the effect of crowding being at least partly driven by a preference for liquidity. We find limited support for a channel where fund flows of connected funds propagate negative externalities among crowded funds and we find no support for a coordination problem being at the core of the performance impact of crowding. Our results suggest that crowding is a key aspect of the global asset management industry and we add to the discussion on the roots of underperformance of active mutual funds. We recommend investors closely monitor crowding when allocating capital towards fund managers.

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Table 1: Descriptive Statistics

This table provides summary statistics of fund stock holdings by funds' region of domicile. We report the number of unique funds, mean total net assets under management (TNA, in million USD), mean number of stocks in portfolios, mean Net Alpha (in %) and the mean portfolio weights for each stock region (in %). We first compute cross-section and subsequently quarterly means. The region classification follows the MSCI market classification: NAM = North America, EUR = Europe, APA = Asia Pacific excluding Japan, JPN = Japan, EM = Emerging Markets, FM = Frontier Markets.

Fund region	Funds	TNA	Holdings	Net Alpha	Stock region (average weight in %)					
	#	mill USD	mean #	mean % p.m.	NAM	EUR	APA	JPN	EM	FM
North America	6,487	1,176	170	−0.05	78.2	11.0	3.2	4.0	2.9	0.7
Europe	9,958	276	140	−0.03	32.5	44.4	6.3	9.8	6.2	0.8
Asia Pacific excluding Japan	138	265	97	0.20	16.8	11.1	29.8	21.0	21.0	0.3
Japan	84	69	128	−0.60	20.4	16.4	4.7	52.7	5.3	0.5
Emerging Markets	519	93	71	−0.11	9.4	8.8	4.8	1.4	74.8	0.8
Frontier Markets	178	136	131	0.30	26.3	24.2	11.3	5.8	11.8	20.5
All domiciles	17,364	592	153	−0.04	54.3	27.5	5.0	6.8	5.6	0.9

Table 2: Summary Statistics of Fund Characteristics for Decile Portfolios Sorted on Crowding

This table provides summary statistics of decile portfolios based on crowding. We report fund characteristics in Panel A. FundSize is the total assets under management and is reported in million USD. # Firms, # Countries, # Industries and # Supersectors are the number of distinct instances of the respective classification in the fund portfolio. We identify firms by their Worldscope Permanent Identifier and industries as well as supersectors by the respective ICB classification. We report the inverse of the normalized Herfindahl Index on the ICB industry classification. In Panel B, we report average portfolio weights for regions following the MSCI market classification. Numbers in parantheses denote t-values. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Fund characteristics

Variable	Crowding											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 – 1	
Centrality	28.59	65.52	110.17	164.08	238.13	316.47	389.95	460.75	534.89	649.18	620.59***	(59.70)
FundSize	302	481	531	572	620	702	822	1.024	994	859	557.06***	(18.66)
# Firms	107	168	125	115	118	109	118	148	194	322	214.88***	(25.29)
# Countries	6	8	8	9	10	11	11	11	12	13	6.21***	(11.86)
# Industries	8	9	9	9	9	9	9	10	10	10	1.49***	(66.31)
# Supersector	15	15	15	16	15	15	16	17	17	18	3.41***	(67.90)
Inverse Normalized HHI	14.86	21.69	22.12	16.61	58.61	35.36	24.62	26.29	27.47	31.00	16.15***	(19.73)

Panel B: Weights for stock region

Stock region	Crowding											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 – 1	
North America	51.9	61.0	50.3	43.6	44.4	48.7	55.1	59.1	60.6	68.1	16.19***	(9.93)
Europe	23.2	15.4	11.7	17.2	35.3	42.1	37.0	33.5	32.8	26.3	3.12*	(1.79)
Asia Pacific excluding Japan	3.8	7.7	11.7	9.9	6.4	2.6	2.3	2.0	1.8	1.5	−2.33***	(-23.84)
Japan	6.1	4.6	13.0	16.7	7.3	4.9	4.2	4.1	3.8	3.5	−2.63***	(-15.55)
Emerging Markets	13.0	9.3	11.9	11.4	5.9	1.3	1.1	0.9	0.7	0.5	−12.46***	(-10.54)
Frontier Market	2.0	1.9	1.4	1.2	0.7	0.4	0.3	0.3	0.2	0.1	−1.89***	(-11.77)

Table 3: Summary Statistics of Stock Characteristics for Decile Portfolios Sorted on Crowding

This table provides stock summary statistics of decile portfolios based on crowding. In Panel A, we report the following variables for all stocks in each decile portfolio: Size is the natural logarithm of primary issue market capitalization in billion USD, BTM is the natural logarithm of region- and industry-adjusted book-to-market ratio; Momentum is the preceeding 3-quarter raw return; # Analysts is the number of analysts following the stock in the IBES database; Volatility is the volatility of monthly returns during the last 12 months; Price is unadjusted stock price in USD; ADR is an indicator variable taking 1 if the stock is an American Depositary Receipt and 0 otherwise; MSCI is an indicator variable taking 1 if the firm is part of the MSCI World Index and 0 otherwise; Anti-Director Index is a measure of shareholder protection based on Porta et al. (1998); Foreign Ownership is an indicator variable taking 0 if the fund's and stock issuer's domicile coincide and 1 otherwise. In Panel B, we report the following measures based on Sarkissian and Schill (2003) regarding the relation between the fund's and the stock issuer's domicile: Cultural Proximity is an indicator variable taking 1 if both countries share a common major spoken language or if they were part of the same colonial empire and 0 otherwise; Geographic Proximity is the distance between both countries' capitals in 1,000 kilometers; Economic Proximity is the percent of exports from the fund's country of domicile to the stock issuer's country of domicile. Numbers in parantheses denote t-statistics. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: All stocks

Variable	Crowding											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1	
Size	3.22	6.67	14.93	25.98	39.43	49.23	55.89	65.04	75.72	85.28	82.06***	(21.98)
BTM (industry-adjusted)	0.08	−0.07	−0.18	−0.19	−0.19	−0.22	−0.24	−0.26	−0.26	−0.26	−0.34***	(−5.84)
Momentum	0.24	0.25	0.22	0.20	0.15	0.15	0.15	0.14	0.13	0.12	−0.12***	(−4.3)
# Analysts	10.08	12.79	16.68	19.38	23.44	25.73	26.47	26.80	27.81	28.58	18.50***	(29.9)
Dividend Yield	1.54	1.47	1.68	1.86	2.15	2.05	2.16	2.16	2.15	2.16	0.62***	(5.86)
Amihud Illiquitidy	0.51	0.10	0.37	0.13	0.03	0.03	0.03	0.02	0.02	0.02	−0.49**	(−2.59)
Volatility	0.39	0.37	0.34	0.32	0.30	0.30	0.28	0.28	0.27	0.26	−0.12***	(−20.23)
Turnover	0.16	0.18	0.17	0.15	0.13	0.14	0.14	0.14	0.14	0.13	−0.03***	(−2.87)
Price	47.74	64.65	102.32	163.33	303.58	436.14	269.09	293.19	297.58	190.84	0.14***	(5.45)
ADR	0.02	0.03	0.04	0.05	0.05	0.04	0.03	0.03	0.02	0.02	0.00	(0.39)
MSCI	0.10	0.22	0.44	0.54	0.68	0.78	0.83	0.85	0.88	0.91	0.81***	(88.95)
English Legal Origin	0.79	0.82	0.76	0.73	0.74	0.76	0.79	0.82	0.83	0.86	0.07***	(4.78)
Anti-Director Index	3.41	3.31	3.44	3.55	3.53	3.42	3.32	3.27	3.22	3.19	−0.22***	(−8.09)

Panel B: Foreign stocks

Variable	Crowding											
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1	
Foreign Ownership	0.40	0.48	0.57	0.61	0.61	0.63	0.59	0.59	0.64	0.68	0.28***	(10.36)
Cultural Proximity	0.34	0.33	0.32	0.30	0.32	0.33	0.34	0.34	0.31	0.27	−0.06***	(−3.35)
Geographic Proximity	3.85	4.41	5.39	5.35	4.51	4.03	4.01	4.11	4.08	4.13	0.28**	(2.05)
Economic Proximity	9.26	8.31	9.33	10.67	11.74	11.79	10.60	10.03	9.84	8.50	−0.76	(−1.13)

Table 4: The Performance of Funds sorted on Crowding

This table provides the average monthly fund performance for portfolios conditional on crowding. At the end of each quarter, we sort funds into decile portfolios, based on their crowding score. Next, we track the equal-weighted performance of the portfolios during the next three months after which we rebalance. As fund performance measures, we use Net Alpha, Dollar Value Added, Gross Alpha, and DGTW returns. We report time-series averages on a monthly basis and in percent, with the exception of Dollar Value Added which is reported in billion USD. *t*-statistics are given in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Crowding										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
Net Alpha	0.102*	0.042	0.002	−0.034	−0.030	−0.098***	−0.100***	−0.108***	−0.116***	−0.114***	−0.215***
	(1.66)	(1.21)	(0.07)	(−0.90)	(−0.91)	(−3.43)	(−3.66)	(−4.61)	(−4.57)	(−4.54)	(−3.31)
Dollar Value Added	−0.009	0.611**	0.058	0.228	0.407	−0.921*	−0.037	−0.216	−0.687	−1.855**	−1.846*
	(−0.02)	(2.43)	(0.21)	(0.68)	(1.18)	(−1.76)	(−0.08)	(−0.44)	(−1.20)	(−2.19)	(−1.83)
Gross Alpha	0.128*	0.101*	0.094	0.005	0.015	−0.009	−0.027	−0.050*	−0.054**	−0.051**	−0.179***
	(1.77)	(1.91)	(1.40)	(0.08)	(0.29)	(−0.25)	(−0.89)	(−1.73)	(−2.09)	(−2.35)	(−2.65)
Gross DGTW	0.090	0.088	0.089	0.032	0.034	−0.018	−0.020	−0.034	−0.057*	−0.046*	−0.136**
	(1.44)	(1.21)	(1.32)	(0.55)	(0.73)	(−0.38)	(−0.55)	(−1.09)	(−1.94)	(−1.92)	(−2.49)

Table 5: Predictive Regressions of Fund Performance on Fund Size and Crowding

This table presents the results of predictive 2SLS regressions of monthly fund returns on the natural logarithm of crowding and fund size (FundSize), respectively. Crowding is measured by either crowd or PeerSize, defined in Equations (4) and (6), respectively. FundSize and PeerTNA are in 10 billions (10^{12}) adjusted to 2014 USD dollars using the value of all stocks in our sample. Instruments are defined in Section 4.2. The dependent variable is Net Alpha in Panel A, Gross Alpha in Panel B, and characteristics-adjusted return (Gross DGTW) in Panel C. We report t-statistics in parentheses using robust standard errors clustered by fund and year-month. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: $\mathrm{NetAlpha}_{t+1}$

	(1)	(2)	(3)	(4)	(5)
$\log(\mathrm{crowd}_t)$	−0.0023***			−0.0020***	
	(−3.31)			(−2.68)	
$\log(\mathrm{PeerTNA}_t)$		−0.0024***			−0.0021**
		(−2.60)			(−2.43)
$\log(\mathrm{FundSize}_t)$			−0.0010	−0.0011	−0.0009
			(−1.35)	(−1.43)	(−1.17)
Observations	450,387	450,387	450,387	450,387	450,387

Panel B: $\mathrm{GrossAlpha}_{t+1}$

	(1)	(2)	(3)	(4)	(5)
$\log(\mathrm{crowd}_t)$	−0.0025***			−0.0029***	
	(−2.85)			(−2.90)	
$\log(\mathrm{PeerTNA}_t)$		−0.0018**			−0.0023***
		(−1.96)			(−2.64)
$\log(\mathrm{FundSize}_t)$			0.0014	0.0013	0.0014
			(1.26)	(1.13)	(1.35)
Observations	454,671	454,671	454,671	454,671	454,671

Panel C: $\mathrm{GrossDGTW}_{t+1}$

	(1)	(2)	(3)	(4)	(5)
$\log(\mathrm{crowd}_t)$	−0.0022***			−0.0019**	
	(−2.94)			(−2.10)	
$\log(\mathrm{PeerTNA}_t)$		−0.0037***			−0.0034***
		(−4.35)			(−4.19)
$\log(\mathrm{FundSize}_t)$			−0.0009	−0.0010	−0.0007
			(−0.92)	(−1.05)	(−0.80)
Observations	454,671	454,671	454,671	454,671	454,671

Table 6: Performance of Funds in Sequential Sorts on Size and Crowding

This table provides the average monthly fund performance for portfolios formed based on fund size and crowding. At the end of each quarter, we sort funds into decile portfolios, based on size. Then we sort funds within each size decile into three portfolios based on crowding. We track the equal-weighted Net Alpha of the portfolios during the next three months, after which we rebalance. We report time-series averages of monthly Net Alpha in percent. t-statistics are in parentheses using Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Crowding	Fund Size										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 – 1
High	−0.194***	−0.150***	−0.147***	−0.133***	−0.131***	−0.102***	−0.100***	−0.107***	−0.073***	−0.074***	0.119***
	(−6.03)	(−6.04)	(−5.18)	(−5.07)	(−4.83)	(−4.02)	(−4.04)	(−3.93)	(−3.39)	(−3.51)	(4.72)
Medium	−0.145***	−0.062**	−0.087**	−0.074**	−0.079**	−0.062**	−0.070**	−0.062**	−0.021	−0.020	0.125***
	(−4.31)	(−2.00)	(−2.42)	(−2.21)	(−2.17)	(−2.04)	(−2.03)	(−2.19)	(−0.71)	(−0.86)	(4.41)
Low	−0.068*	0.000	0.049	0.031	0.020	0.033	0.066*	0.074*	0.063**	0.104***	0.171***
	(−1.71)	(0.00)	(1.18)	(0.70)	(0.44)	(0.68)	(1.68)	(1.89)	(2.05)	(3.72)	(4.06)
High – Low	−0.126**	−0.150***	−0.196***	−0.165***	−0.151***	−0.135**	−0.165***	−0.181***	−0.136***	−0.178***	
	(−2.56)	(−3.50)	(−4.56)	(−3.40)	(−3.04)	(−2.59)	(−3.73)	(−3.72)	(−4.06)	(−5.35)	

Table 7: Predictive Regressions of Stock Demand on Characteristics, conditional on Crowding

This table reports the results from predictive regressions of stock demand on stock characteristics, conditional on crowding. At the end of each quarter, we sort funds into decile portfolios, based on crowding. Next, using funds in each portfolio, we compute the demand for stocks they trade this quarter. For each portfolio and each quarter, we regress stock demand on lagged demand and lagged characteristics. StockSize is the natural logarithm of primary issue market capitalization in billion USD, BTM is the natural logarithm of industry-adjusted book-to-market ratio; Momentum is the 12-month return preceeding quarterly raw returns; Amihud illiquidity as in Amihud (2002), Analysts is the number of analysts following the stock in the IBES database; Volatility is the volatility of monthly returns during the last 12 months; Dividend Yield is the annual dividend yield; MSCI is an indicator variable taking 1 if the stock is part of the MSCI World Index and 0 otherwise. We report time-series averages of estimated coefficients with t-statistics in parentheses based on Newey-West standard errors. * denotes significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Dependent Variable: Demand_{t+1}									
	Crowding									
	1 (low)	2	3	4	5	6	7	8	9	10 (high)
Demand_t	0.500***	0.466***	0.439***	0.391***	0.421***	0.417***	0.361***	0.381***	0.381***	0.394***
	(18.72)	(18.05)	(21.59)	(15.79)	(21.73)	(20.98)	(11.63)	(12.19)	(11.86)	(11.87)
StockSize_t	0.007*	0.011	0.027***	0.029***	0.009	0.015*	0.031***	0.001	0.012	0.033***
	(1.95)	(1.61)	(4.04)	(4.89)	(1.51)	(1.94)	(4.43)	(0.09)	(1.10)	(4.24)
BTM_t	0.014***	0.010***	0.018***	0.007***	0.009***	0.010***	0.001	0.008**	0.009***	0.000
	(3.36)	(3.29)	(5.47)	(3.46)	(3.44)	(3.66)	(0.61)	(2.43)	(2.87)	(−0.11)
Momentum_t	−0.006	0.044***	0.045***	0.056***	0.043***	0.069***	0.099***	0.088***	0.098***	0.120***
	(−1.26)	(6.38)	(3.68)	(6.35)	(3.52)	(4.57)	(8.98)	(7.34)	(8.60)	(8.54)
Amihud Illiquidity_t	−0.207	−0.732*	−0.421	−3.789**	−2.743**	−9.628***	−9.084***	−4.671***	−8.916***	−20.666***
	(−1.36)	(−1.85)	(−0.55)	(−2.32)	(−2.58)	(−2.73)	(−3.51)	(−2.72)	(−2.69)	(−3.63)
Volatility_t	−0.064***	−0.098***	−0.093***	−0.113***	−0.204***	−0.152***	−0.112**	−0.124***	−0.088**	−0.038
	(−3.52)	(−3.14)	(−3.40)	(−3.04)	(−5.46)	(−4.72)	(−2.60)	(−3.32)	(−2.11)	(−1.07)
Analysts_t	−0.003***	−0.002***	−0.002***	−0.002***	−0.002***	−0.001***	−0.001**	−0.001***	−0.001**	−0.002***
	(−4.53)	(−3.61)	(−6.14)	(−4.22)	(−3.82)	(−5.87)	(−2.41)	(−5.03)	(−2.06)	(−4.79)
Dividend Yield_t	0.003***	−0.002**	0.002*	0.002	0.003***	0.000	−0.002*	−0.007***	−0.012***	−0.007***
	(2.69)	(−2.31)	(1.68)	(1.01)	(2.68)	(−0.14)	(−1.69)	(−3.44)	(−5.16)	(−3.93)
MSCI_t	−0.077***	−0.040***	−0.055***	−0.028**	−0.007	0.008	−0.002	0.009	0.008	0.027*
	(−5.99)	(−3.08)	(−4.68)	(−2.15)	(−0.64)	(0.79)	(−0.12)	(0.77)	(0.48)	(1.85)
Observations	408,398	352,701	319,817	276,809	253,365	219,969	203,281	230,517	246,310	234,167
R^2	0.28	0.25	0.22	0.19	0.22	0.21	0.18	0.20	0.22	0.23

Table 8: Portfolio Weights in Geographical Regions conditional on Crowding

This table compares the average stock region weights of the MSCI World Index to those of the fund universe and the bottom and top 5% crowded funds, BottomCrowd and TopCrowd respectively. In each quarter, we sort funds into ventile portfolios. We compute the average stock region weights, PWeights, and the average difference between the stock region weights between the MSCI World Index and the three fund portfolios (Δ MSCI). The stock regions follow the MSCI market classification. Numbers in parentheses are Newey-West adjusted t-statistics. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Stock region	MSCI World Index	Fund universe		BottomCrowd		TopCrowd	
	PWeights	PWeights	Δ MSCI	PWeights	Δ MSCI	PWeights	Δ MSCI
North America	55.5	69.1	13.61***	47.0	−8.54***	80.0	24.50***
			(8.93)		(−3.97)		(11.53)
Europe	30.2	18.6	−11.57***	22.9	−7.27***	15.2	−15.05***
			(−12.06)		(−11.99)		(−8.36)
Asia Pacific excluding Japan	4.4	3.5	−0.83***	4.5	0.15	1.4	−2.92***
			(−6.00)		(0.74)		(−19.58)
Japan	9.8	4.1	−5.78***	8.7	−1.18**	2.4	−7.39***
			(−42.95)		(−2.17)		(−29.94)
Emerging Markets	0.0	3.9	3.92***	15.1	15.08***	0.8	0.78***
			(9.49)		(8.12)		(5.20)
Frontier Market	0.0	0.7	0.65***	1.8	1.76***	0.1	0.08***
			(10.88)		(7.19)		(5.07)

Table 9: Crowding and Liquidity

This table reports the results from regressions of fund performance on traded factor portfolios, conditional on crowding. At the end of each quarter, we sort funds into decile portfolios, based on crowding. Next, we track the equal-weighted performance of the excess returns of portfolios during the next three months after which we rebalance. We obtain a time-series of portfolio returns. In Panel A, we use the Fama-French three factor model to estimate Alpha. In Panel B, we add the liquidity factor of Pastor and Stambaugh (2003). We report estimated Alphas and Betas with t-statistics in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: 3 factor loadings

	Crowding										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
Alpha	0.098	−0.003	0.009	0.001	−0.004	−0.074	−0.062	−0.098	−0.129**	−0.116***	−0.214***
	(1.01)	(−0.05)	(0.08)	(0.01)	(−0.03)	(−0.88)	(−0.81)	(−1.51)	(−2.50)	(−3.51)	(−2.79)
MKT beta	0.983***	1.028***	1.050***	1.068***	1.024***	1.016***	0.983***	0.972***	0.962***	0.916***	−0.067**
	(25.67)	(36.85)	(27.54)	(23.02)	(28.50)	(55.64)	(42.49)	(41.04)	(49.35)	(87.05)	(−2.22)
SMB beta	0.636***	0.583***	0.407***	0.246***	0.161***	0.032	−0.035	−0.065**	−0.090***	−0.119***	−0.756***
	(15.75)	(16.28)	(10.87)	(4.39)	(3.58)	(0.93)	(−1.01)	(−2.22)	(−3.96)	(−8.80)	(−20.60)
HML beta	0.128**	0.039	−0.005	−0.105*	−0.145**	−0.087**	−0.034	−0.013	−0.035	−0.025*	−0.154***
	(2.18)	(1.08)	(−0.10)	(−1.72)	(−2.52)	(−2.38)	(−0.97)	(−0.40)	(−1.59)	(−1.78)	(−2.91)

Panel B: Liquidity factor loadings

	Crowding										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
Alpha	0.040	−0.048	−0.057	−0.076	−0.086	−0.118	−0.101	−0.126**	−0.139***	−0.126***	−0.166**
	(0.43)	(−0.67)	(−0.59)	(−0.60)	(−0.80)	(−1.48)	(−1.40)	(−1.96)	(−2.62)	(−3.70)	(−2.27)
MKT beta	0.963***	1.012***	1.027***	1.042***	0.995***	1.000***	0.969***	0.962***	0.959***	0.913***	−0.051*
	(28.05)	(38.09)	(31.17)	(24.95)	(33.09)	(63.62)	(46.73)	(43.98)	(51.42)	(95.23)	(−1.82)
SMB beta	0.616***	0.567***	0.384***	0.219***	0.132***	0.016	−0.048	−0.075**	−0.094***	−0.123***	−0.739***
	(14.68)	(15.70)	(10.01)	(3.91)	(3.01)	(0.49)	(−1.42)	(−2.51)	(−3.95)	(−8.73)	(−19.24)
HML beta	0.166***	0.068**	0.038	−0.055	−0.093**	−0.058*	−0.009	0.006	−0.028	−0.019	−0.184***
	(3.34)	(2.09)	(1.00)	(−1.12)	(−2.06)	(−1.89)	(−0.30)	(0.20)	(−1.31)	(−1.39)	(−4.00)
Liquidity beta	0.094***	0.073***	0.106***	0.124***	0.132***	0.072***	0.063***	0.046***	0.017	0.017*	−0.077***
	(4.40)	(3.39)	(5.35)	(4.64)	(5.11)	(3.65)	(3.67)	(2.75)	(1.07)	(1.67)	(−4.86)

Table 10: Regressions of Fund Performance on PeerFlow

This table reports the results from regressions of quarterly fund performance on PeerFlow. At the end of each quarter, we compute quarterly fund performance using either Net Alpha, Gross Alpha, or DGTW returns. All performance measures are expressed on a monthly basis and in percent. In Panel A, we use lagged PeerFlow as main explanatory variable, and in Panel B we employ a 2SLS estimator with contemporaneous PeerFlow instrumented by lagged PeerFlow. In both panels, we include lagged control variables: an indicator variable TopCrowd taking the value of 1 if the fund is among the top 30% percent of crowding that quarter and 0 otherwise, the natural logarithm of *crowd*, the natural logarithm of fund size, fund flow, the most recently available fund expense ratio and turnover. Fund size and PeerFlow are inflated to millions of 2014 USD dollars using the value of all stocks in our sample and scaled by 10^6 in order to make coefficients easier to read. All specifications include fund and quarter fixed effects. We report t-statistics in parentheses based on robust standard errors clustered at the fund and quarter level. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Predictive relationship

	$NetAlpha_{t+1}$		$GrossAlpha_{t+1}$		$DGTW_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$PeerFlow_t$	17.2139	10.3426	75.0282	60.1065	−6.8134	−22.9517
	(0.39)	(0.23)	(1.41)	(1.07)	(−0.12)	(−0.39)
$PeerFlow_t \times TopCrowd_t$		45.9080		99.5920**		106.4876***
		(1.63)		(2.42)		(3.32)
$TopCrowd_t$		0.0014		0.0031**		0.0020*
		(1.65)		(2.43)		(1.97)
$Ln(Crowd^w)_t$	−0.0068***	−0.0071***	−0.0085***	−0.0094***	−0.0072***	−0.0076***
	(−3.05)	(−2.97)	(−2.79)	(−2.82)	(−3.69)	(−3.65)
$Ln(FundSize)_t$	−0.0049***	−0.0049***	−0.0033***	−0.0033***	−0.0040***	−0.0040***
	(−7.65)	(−7.64)	(−4.24)	(−4.2)	(−5.31)	(−5.22)
$Flow_t$	−0.0030*	−0.0028*	−0.0035**	−0.0031**	−0.0034**	−0.0030*
	(−1.97)	(−1.91)	(−2.48)	(−2.28)	(−2.07)	(−1.9)
$ExpRatio_t$	−0.1088	−0.1093	0.0412	0.0399	−0.0052	−0.0038
	(−1.43)	(−1.43)	(0.48)	(0.46)	(−0.12)	(−0.09)
$Turnover_t$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(−0.39)	(−0.37)	(−0.32)	(−0.26)	(−0.03)	(0.01)
Observations	94,056	94,056	94,587	94,587	104,911	104,911
R^2	0.11	0.11	0.14	0.14	0.16	0.16
Method	OLS	OLS	OLS	OLS	OLS	OLS

Panel B: Contemporaneous relationship

	$NetAlpha_{t+1}$		$GrossAlpha_{t+1}$		$DGTW_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$PeerFlow_{t+1}$	57.5902	43.0738	196.4371**	159.6994	20.2930	−16.6039
	(0.74)	(0.53)	(2.05)	(1.58)	(0.2)	(−0.15)
$PeerFlow_{t+1} \times TopCrowd_{t+1}$		77.5152		196.3949*		198.7405*
		(1.13)		(1.88)		(1.69)
$TopCrowd_t$		0.0020*		0.0049***		0.0047**
		(1.8)		(2.78)		(2.6)
$Ln(Crowd^w)_t$	−0.0057**	−0.0062**	−0.0064**	−0.0075**	−0.0065***	−0.0075***
	(−2.55)	(−2.57)	(−2.03)	(−2.2)	(−3.45)	(−3.59)
$Ln(FundSize)_t$	−0.0052***	−0.0053***	−0.0033***	−0.0034***	−0.0043***	−0.0044***
	(−7.83)	(−7.85)	(−4.23)	(−4.33)	(−5.15)	(−5.22)
$Flow_t$	−0.0024*	−0.0023	−0.0035***	−0.0031**	−0.0036**	−0.0032**
	(−1.72)	(−1.65)	(−2.73)	(−2.44)	(−2.3)	(−2.1)
$ExpRatio_t$	−0.1301*	−0.1278*	−0.0011	0.0048	−0.0038	0.0007
	(−1.83)	(−1.8)	(−0.01)	(0.06)	(−0.09)	(0.02)
$Turnover_t$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(−0.47)	(−0.37)	(−0.63)	(−0.34)	(−0.43)	(−0.15)
Observations	97,611	97,611	97,908	97,908	108,193	108,193
R^2	0.11	0.11	0.14	0.14	0.17	0.16
Method	IV	IV	IV	IV	IV	IV

Table 11: Performance of Funds in Sorts on Crowding and Momentum trading

This table provides the average monthly fund performance for portfolios conditional on crowding and momentum trading. At the end of each quarter, we sort funds into decile portfolios, based on crowding. Next, we independently group time periods into three buckets, based on the estimated coefficient on momentum in Equation (9). In Panel A, we report the equal-weighted Net Alpha of the portfolios during the next three months. In Panel B, we report the equal-weighted Net Alpha of the portfolios during the next twelve months. Net Alpha is reported on a quarterly (yearly) basis and in percent in Panel A (B). We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Time-series test

Demand for Momentum	Crowding									
	1 (low)	2	3	4	5	6	7	8	9	10 (high)
High	0.438*	0.405***	−0.163	−0.163	0.059	−0.247***	−0.181	−0.299***	−0.418**	−0.247*
	(1.91)	(3.10)	(−1.54)	(−0.80)	(0.64)	(−3.35)	(−1.59)	(−3.46)	(−2.84)	(−1.83)
Medium	0.259	0.373	0.379***	0.289*	−0.089	−0.228	−0.228**	−0.249**	−0.309***	−0.386***
	(0.90)	(1.24)	(3.05)	(1.93)	(−0.60)	(−1.54)	(−2.38)	(−2.46)	(−5.95)	(−10.39)
Low	0.474***	−0.119	0.035	−0.113	0.091	−0.167	−0.209	−0.250***	−0.151*	−0.291***
	(3.27)	(−0.72)	(0.21)	(−1.33)	(0.98)	(−1.73)	(−1.73)	(−3.10)	(−1.90)	(−3.00)

Panel B: Cross-sectional test

Momentum Fund	Crowding									
	1 (low)	2	3	4	5	6	7	8	9	10 (high)
No	0.102	0.049	0.022	−0.029	−0.052	−0.084***	−0.073***	−0.113***	−0.134***	−0.127***
	(1.52)	(1.36)	(0.56)	(−0.74)	(−1.34)	(−2.62)	(−2.84)	(−3.97)	(−4.47)	(−4.27)
Yes	0.101	0.030	−0.016	−0.064	−0.027	−0.102***	−0.128***	−0.119***	−0.118***	−0.115***
	(1.64)	(0.82)	(−0.50)	(−1.59)	(−0.82)	(−3.24)	(−3.75)	(−4.91)	(−4.34)	(−4.96)
No – Yes	0.000	0.019	0.038	0.035	−0.025	0.018	0.055*	0.006	−0.016	−0.012
	(0.01)	(0.71)	(1.44)	(1.42)	(−0.90)	(0.59)	(1.66)	(0.30)	(−0.76)	(−0.91)

Table 12: Performance of Funds in Sequential Sorts on Active Share and Crowding

This table provides the average monthly fund performance for portfolios conditional on active share and crowding. At the end of each quarter, we sort funds into decile portfolios, based on active share. Active share follows the definition of Cremers and Petajisto (2009) where we use the MSCI World Index as the benchmark. Next, we sort funds within each size decile into three portfolios based on crowding. Next, we track the equal-weighted Net Alpha of the portfolios during the next three months after which we rebalance. Net Alpha is reported on a monthly basis and in percent. We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Crowding	Active Share										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
High	−0.102***	−0.157***	−0.177***	−0.165***	−0.178***	−0.078*	0.027	−0.018	0.018	0.074	0.176***
	(−4.01)	(−5.48)	(−5.36)	(−3.83)	(−3.95)	(−1.85)	(0.57)	(−0.26)	(0.23)	(1.54)	(3.07)
Medium	−0.087***	−0.112***	−0.128***	−0.134***	−0.116***	−0.054*	−0.065**	−0.009	0.089**	0.003	0.090*
	(−3.54)	(−5.26)	(−4.76)	(−4.36)	(−3.41)	(−1.76)	(−2.19)	(−0.26)	(2.02)	(0.07)	(1.90)
Low	−0.021	−0.036	−0.059**	−0.088***	−0.070***	−0.075**	−0.055	0.056	0.119*	0.181*	0.202*
	(−0.62)	(−1.46)	(−2.50)	(−3.76)	(−2.76)	(−2.13)	(−1.56)	(1.10)	(1.69)	(1.69)	(1.89)
High − Low	−0.081***	−0.121***	−0.118***	−0.077*	−0.108**	−0.003	0.083*	−0.074	−0.101	−0.107	
	(−3.01)	(−4.52)	(−4.40)	(−1.92)	(−2.53)	(−0.08)	(1.78)	(−0.91)	(−0.93)	(−0.97)	

Table 13: Fama-MacBeth Regressions of Net Alpha on lagged Crowding

This table reports results from fixed effects regressions of quarterly fund Net Alpha on crowding, separately on the universe of funds and U.S. domiciled funds. Crowding is measured by *crowd* as defined in equation (4). Fund size and fund flow are inflated to millions of 2014 USD dollars using the value of all stocks in our sample; net expense ratio is in %; Factor related returns is defined as in (Song, 2020, equation 2) using Fama French factors over the past 48 months, and NPeers (number of fund peers) and TSIM (total similarity of fund peers) are competition measures as defined in Hoberg et al. (2017), section 3.4. Regressions use Morningstar Global Category, Morningstar style, and country of domicile fixed effects (FE). We report Newey-West corrected t-statistics in parentheses. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Dependent Variable: $\mathrm{NetAlpha}_{t+1}$							
	All Domiciles			Domicile U.S.				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crowd_t	−0.0037***	−0.0034***	−0.0021**	−0.0035***	−0.0036***	−0.0022**	−0.0023**	−0.0023**
	(−4.28)	(−3.79)	(−2.26)	(−3.47)	(−3.71)	(−2.31)	(−2.32)	(−2.32)
$\mathrm{Ln(FundSize)}_t$		−0.0001	0.0001		−0.0001	0.0001	0.0001	0.0001
		(−0.84)	(0.96)		(−1.07)	(0.48)	(0.46)	(0.46)
$\mathrm{FundFlow}_t$		0.0029	0.0003		0.0030	0.0007	0.0005	0.0005
		(1.60)	(0.31)		(1.60)	(0.53)	(0.38)	(0.38)
$\mathrm{NetAlpha}_t$		0.0506**	0.0585**		0.0673***	0.0774***	0.0771***	0.0771***
		(2.56)	(2.51)		(2.95)	(2.89)	(2.90)	(2.90)
$\mathrm{NetExpenseRatio}_t$		−0.2594***	−0.1955***		−0.2832***	−0.1998***	−0.2043***	−0.2043***
		(−5.36)	(−10.16)		(−6.53)	(−9.65)	(−10.48)	(−10.47)
$\mathrm{Turnover}_t$		−0.0006***	−0.0003*		−0.0009***	−0.0007**	−0.0007**	−0.0007**
		(−3.92)	(−2.01)		(−4.01)	(−2.46)	(−2.63)	(−2.63)
$\mathrm{FactorRelatedReturns}_t$			−0.1920			−0.4236	−0.3787	−0.3787
			(−0.93)			(−1.23)	(−1.14)	(−1.14)
NPeers_t							0.0068	
							(0.46)	
TSIM_t								0.0022
								(0.52)
MS Global Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Domicile FE	Yes	Yes	Yes	No	No	No	No	No
Observations	183,199	94,046	67,359	77,881	66,615	47,191	46,954	46,954
R^2	0.41	0.43	0.43	0.37	0.42	0.42	0.42	0.42

Appendices

Appendix A Data Screens

The data cleaning of the Factset and Datastream/Worldscope databases used in this paper closely follows Dyakov and Wipplinger (2020). In Factset, we drop fund reports in which a single security constitutes more than 25% of the total assets of the fund. Next, we exclude portfolio reports with apparent data errors where the total net asset value appears to bounce back close to its original value after a significant positive or negative spike.[5] In some cases, there exist more than one report per quarter or the report does not refer to end of-quarter positions (i.e., February rather than March). In such cases, we always choose the portfolio snapshot closest to the end of the quarter and use the reported holdings as if they were reported at the end of the quarter. Not all of the funds in our sample (about 20%) have portfolio holdings available on a quarterly basis. For those funds, we carry-on the last quarter's report to the current one in order to obtain an unbroken sequence of quarterly portfolio positions.

We next follow the data-cleaning procedures prescribed in Ince and Porter (2006), Schmidt et al. (2011), and Dyakov and Wipplinger (2020). Specifically, we exclude a) stock issues with more than 20% difference in market capitalization between Datastream and Factset, b) stocks where a single fund is reported to own more than 25% of the shares, and c) stocks with some key information missing in either Factset or Datastream. A few funds increase their holdings by a factor of e.g. 100 only to decrease their holdings by a similar factor in the next reporting period. Such changes are apparent data errors and we exclude them using the same screen for individual holdings as the one used for large reversals of total reported assets mentioned above. A detailed overview on the stock-level country selection, the merging of Factset with Datastream, the cleaning of stock information from Datastream, and the construction of characteristic-adjusted returns for international stocks is available in the Online Appendix of Dyakov et al. (2020). We report descriptive statistics for fund domiciles in our sample in Table F.1.

[5] Specifically, we drop fund portfolio reports across two periods where reported total net assets (TNA) increase/decrease by a factor of more than 9 (quarter $q-1$ vs. quarter q) and which is subsequently reversed by a factor of at least 4.5 in the opposite direction (quarter q vs. quarter $q+1$) while the increase/decrease across both periods does not exceed 4.5 in the original direction (quarter $q+1$ vs. quarter $q-1$).

Appendix B The Alternative Investment Opportunity Set

In this Appendix, we describe the choice of passive traded funds as an alternative investment opportunity set. Closely following Berk and van Binsbergen (2015), we use share classes of Vanguard funds offered to investors in the U.S. due to their popularity and their low trading costs. First, we select only equity funds and drop Morningstar Global Categories that span specific sectors of the stock market, such as technology or health care. Next, within each Global Category we select the oldest fund, offered in USD, that spans all sectors and countries in the category. We drop some country specific funds that are not offered in USD and whose coverage is already spanned by other funds. The final selection of funds results in seven domestic U.S. funds and six international funds from which we select subsets depending on fund domicile. The North-American (NAM) set of funds consists of the seven U.S. funds. For all other regions, we use the three Global Equity index funds. For the European (EUR) region, we add the European Equity index fund. For the Asia-Pacific and Japan (APN) region, we add the Asia-Pacific (including Japan) Equity fund. Similarly, for the Emerging Markets (EM) region, we add the Emerging Markets equity fund. For global (GLO) funds without a dedicated regional focus (see Section 2), we select all international funds (except for the Emerging Markets equity fund), and add the three main U.S. funds that track the S&P 500, small stocks, and value stocks.

Table F.2 presents the full list of passive funds. Our choice of selecting separate index funds for broad geographical regions is based on Fama and French (2012) and Griffin (2002), who show that global markets are not integrated and risk-premia are driven by local and global forces. We do not include funds with a distinctive momentum focus, as they are not available to investors during our sample period. For instance, Blackrock offers Europe-specific momentum ETFs only since the beginning of 2015.

The benchmark loadings in Equation (1) are estimated by regressing the fund's net excess returns on the excess net returns of the relevant benchmarks over the entire sample period that the fund is active. When we compute gross alpha, we use the gross return of the benchmarks, defined as net returns plus one twelfth of the reported net annual expense ratio. Because one of the two global funds is not available throughout the entire sample period, we estimate betas by using an augmented basis of the factors where the factor returns are orthogonalized with respect to all other variables and missing returns are replaced with the mean of the orthogonalized factor. Alphas are then computed using the estimated betas and the augmented basis where we replace missing returns with zero. See the Appendix in Berk and van Binsbergen (2015) for more details on the procedure. The augmented basis is computed separately for benchmarks in each of the geographical regions.

Appendix C Determinants of Crowding and its Persistence

Table F.3 presents the results of panel regressions detailing how characteristics influence the crowding score of funds. Crowding increases in portfolio size and in measures of diversification. The relationship between centrality and portfolio size is convex. However, for a given increase in portfolio size, the effect becomes smaller as the number of stocks increases. Increasing the share of investment in the largest markets, North America and Europe, increases the crowding score while shifting towards Asia Pacific excluding Japan decreases crowding. For robustness, we split the sample of funds into those domiciled in the USA (specification 3) and those domiciled elsewhere (specification 4) and perform the same analysis. The results are consistent but the effect on crowding of shifting into regions in which funds are not domiciled is larger than the average effect for the entire sample.

In Figure F.1, we examine the persistence of crowding. At the end of each quarter, we sort funds into deciles based on their crowding score and compute a matrix of transition rates for the following quarter. The transition matrix reveals that persistence is large with more than 69% of funds staying in the same decile across all deciles. Moreover, persistence is stronger for deciles below the median compared to those above the median. There seems to be no obvious systemic relation between crowding decile and dropping out of the sample.

Appendix D Instrumental Variables for Diseconomies of Scale

In Equation (5), we relate fund performance to lagged crowding and fund size. A standard fixed effects estimator requires the regressors to be strictly exogenous. As we argue in the main body of the paper, this is not always the case. To address this problem, we follow Pastor et al. (2015) and Zhu (2018) and first eliminate the fixed effects α_f by forward-demeaning. The forward-demeaned version of a variable x is defined as

$$\overline{x}_{it} = x_{it} - \frac{1}{T_i - t + 1} \sum_{s=t}^{T_i} x_{is}, \tag{D.1}$$

where T_i denotes the number of time periods for which fund i is observed. We then estimate the coefficients in Equation (5) using a two-stage least squares (2SLS) approach, employing instruments that are plausibly uncorrelated with the forward-demeaned error term. The literature proposes two potential instruments for forward-demeaned size. The first one, suggested by Pastor et al. (2015), is the backward-demeaned version of fund size, where the backward-demeaned version of a variable i is defined as

$$\underline{x}_{i,t-1} = x_{i,t-1} - \frac{1}{t-1} \sum_{s=1}^{t-1} x_{i,s-1}. \tag{D.2}$$

In the first stage of the 2SLS, Pastor et al. (2015) propose a reduced form for the endogenous regressor, the fitted values of which are substituted into the forward-demeaned version of (5) without an intercept. Zhu (2018), however, argues that an intercept term should be included in the reduced forms, and we follow her recommendation. She further proposes an alternative instrument for the forward-demeaned size, namely lagged fund size $q_{i,t-1}$ because it is correlated with the forward-demeaned lagged fund size and it is plausibly uncorrelated with the forward-demeaned error term. She finds it is a stronger instrument as it improves the fit of the first-stage regressions. Following Dyakov et al. (2020), we include both instruments, which should lead to more efficient inference. In order to reduce the impact of estimation error on our findings, we drop funds with less than four years of data.

Thus, in the first stage we regress forward-demeaned fund size on its backward-demeaned version as well as forward-demeaned crowding. In the second stage, we regress forward-demeaned alpha on the fitted values from the first stage regression as well as forward-demeaned crowding. Both size and crowding are expressed in logarithms, but for simplicity of notation we drop log in the equations below.

$$\overline{q}_{i,t-1} = \psi + \rho_1 \overline{crowd}^w_{it-1} + \rho_2 \underline{q}_{i,t-1} + \rho_3 q_{i,t-1} + \upsilon_{i,t}, \tag{D.3}$$

$$\overline{r}_{i,t} = \beta_1 \overline{crowd}^w_{i,t-1} + \beta_2 \overline{q}^*_{i,t-1} + \vartheta_{i,t}. \tag{D.4}$$

As results are consistent across specifications where we include either of the instruments in Equation (D.3), we only report results using both instrumental variables.

Appendix E Alternative Crowding Measures

We investigate two alternative approaches to measuring crowding. The first is based on eigenvalue centrality which includes the indirect overlap induced by funds not directly connected via common ownership of stocks. The second is derived from a directional aggregation of crowding which takes into account an asymmetric relationship of crowding in stocks between funds.

The eigenvalue centrality measure of crowding is computed using the entire active funds' network of overlapping holdings (see e.g. Gao, 2021). Each edge of the network represents the portfolio holdings overlap between two funds, as in Equation (3). The eigenvector centrality of fund i is given by

$$crowd^e_i = \frac{1}{\lambda} \sum_{j=1}^{n} A_{j,i} crowd^e_j \tag{E.1}$$

where $A_{j,i}$ is the holdings overlap between funds i and j, the constant λ is to be determined, and n is the number of funds.[6] We have dropped time subscripts for simplicity in notation. In Equation (E.1), a fund receives a higher crowding score if it is connected to other funds with a

[6]Eigenvector centrality is also often used to determine influence in social networks or relevance in search engines. For example, the PageRank algorithm from Google uses eigenvector centrality.

high crowding score. The recursive relationship (E.1) can be rewritten as an eigendecomposition:

$$\lambda \boldsymbol{c}_e^T = A^T \boldsymbol{c}_e^T \tag{E.2}$$

where $\boldsymbol{c}_e$ is the left eigenvector of adjacency matrix A^T and λ the corresponding eigenvalue. We use the largest eigenvalue for calculating $crowd_i^e$ in Equation (E.1).

Results using eigenvalue centrality are similar to our baseline findings in Table 4. In Table F.4, we sort funds in ten deciles and examine subsequent performance. Using net and gross alpha, dollar value added, and DGTW returns, we find that performance is decreasing with crowding.

For the second set of alternative measures, we relax the assumption that crowding of any two funds in a single stock has a symmetric effect on both funds. Consider a value-investing fund A that competes with fund B, which specializes in both value stocks and small stocks. Because A faces competition in its sole investment style, fund A can become be more exposed to fund B than the more diversified fund B is exposed to A. We introduce asymmetry to our benchmark portfolio overlap measure by scaling the connection from fund i to fund j by the number of overlapping stocks relative to the total number of stocks in the portfolio of fund j. Then, the weight of the edge from fund i to j, $i \to j$ becomes a directional measure of j's exposure to i. The edge is computed as

$$\tilde{e}_{ij} = \frac{|P_i \cap P_j|}{|P_j|} \sum_{k \in P_j} \min(\omega_i^k, \omega_j^k), \tag{E.3}$$

where P_i and P_j is the set of stocks held by fund i and j, respectively. Note that if $P_i = P_j$ or $P_i \cap P_j = \emptyset$, then the overlap measure is identical to the benchmark in equation (3). In all other cases, the edge is directional and an overlap among a relatively higher (lower) number of stocks receives a higher (lower) weight.

We compute both crowding scores using this alternative definition of the network edges and replicate our main analysis. Table F.5 shows that the alternative measure provide qualitatively similar results. In Panel A, funds in the top decile of crowding, calculated as weighted degree centrality, generate -0.08% (t=-*2.9*) in subsequent DGTW-adjusted monthly returns. The spread in performance between the top and bottom decile amounts to -0.17% (t=-*2.8*). Results in Panel B, based on applying eigenvalue centrality to directional overlap, are similar.

Appendix F Further Robustness of the Results

In Table 4, we find a negative relationship between crowding and subsequent performance in equal-weighted portfolio. Results for value-weighted portfolios of funds sorted on crowding are reported in Panel A of Table F.6. In Panel B. we risk-adjust returns using traditional factor regressions instead of the passive index fund approach of Berk and van Binsbergen (2015). In all sorts, we find the same repeating patterns: performance is monotonically decreasing in alpha, and performance becomes negative among funds operating in the most crowded deciles.

In Table 6, we double sort funds on size and crowding and find that within each size decile, net alpha is decreasing with crowding. We examine the robustness of this findings, and employ alternative performance measures. Results are reported in Panel A of Table F.7. We additionally sort on eigenvalue centrality instead of the baseline crowding measure in Panel B. In both panels, we tabulate the performance of the spread portfolios of the top minus bottom tercile of crowding within each decile. The estimates are predominantly negative and we determine that the findings in Table 6 are robust to alternative performance measures as well as to using the alternative measure of crowding based on eigenvalue centrality.

Table F.1: Summary Statistics by Fund Domicile

This table provides summary statistics of fund stock holdings by funds' domicile. We report the number of unique funds, mean total assets under management (in million USD), mean number of stocks in portfolios, and the mean portfolio weights for each stock region (in %). We first compute cross-section and subsequently quarterly means. Region abbreviations are as follows: NAM = North America, EUR = Europe, APA = Asia Pacific excluding Japan, JPN = Japan, EM = Emerging Markets, FM = Frontier Market. Our region classification applies to both stock issuers' and funds' country of domicile and is time invariant. In addition to the countries in which funds from our sample are domiciled, APA includes South Korea, and New Zealand, and EM includes Colombia, Mexico, Peru, Philippines, Russia, and Turkey. All other countries are classified as Frontier Markets.

Panel A: North America

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Canada	1461	319	125	72.6	14.3	4.2	5.5	2.9	0.5
United States	5026	1311	180	79.3	10.4	3.0	3.7	2.9	0.8

Panel B: Europe

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Austria	192	80	103	41.5	35.8	5.4	8.6	8.0	0.7
Belgium	285	120	149	29.8	54.4	3.5	6.3	5.4	0.5
Denmark	187	137	139	36.8	30.5	7.7	12.5	11.5	1.1
Finland	125	153	88	31.2	48.7	4.9	6.5	7.9	0.8
France	860	275	113	16.6	70.8	2.7	7.0	2.7	0.3
Germany	537	309	94	28.0	58.9	2.7	8.5	1.6	0.3
Greece	15	39	97	43.8	48.9	1.6	1.6	3.2	0.8
Ireland	842	281	186	38.6	29.4	9.5	13.3	8.2	1.0
Israel	55	33	73	14.7	80.1	1.6	0.7	2.9	0.1
Italy	286	226	113	35.2	43.5	5.7	10.0	5.0	0.6
Liechtenstein	60	115	113	36.5	32.8	7.2	19.3	3.9	0.4
Luxembourg	3666	291	151	37.3	35.5	7.4	10.8	8.0	1.0
Netherlands	182	596	120	36.7	39.7	8.3	10.1	4.5	0.7
Norway	101	306	155	31.8	52.6	4.0	8.4	2.1	1.2
Portugal	46	53	91	38.2	47.8	2.6	3.7	5.0	2.6
Spain	459	77	83	28.5	62.7	0.8	6.3	1.6	0.1
Sweden	272	325	164	29.8	51.5	4.8	7.6	5.6	0.7
Switzerland	291	198	192	32.8	44.0	6.2	12.1	4.6	0.4
United Kingdom	1497	413	122	24.9	53.8	7.0	8.5	4.9	0.8

Panel C: Asia Pacific excluding Japan

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Australia	22	494	78	33.9	15.9	31.7	4.0	14.1	0.4
Hong Kong	68	184	111	15.0	10.2	32.0	22.6	20.1	0.3
Singapore	48	71	80	18.2	11.1	26.9	20.0	23.4	0.4

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Continued Table F.1 ...

Panel D: Japan

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Japan	84	553	128	20.4	16.4	4.7	52.7	5.3	0.5

Panel E: Emerging Markets

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Brazil	5	259	56	0.0	2.0	0.0	0.0	98.0	0.0
Chile	12	64	68	44.5	0.5	1.8	0.0	52.4	0.8
China	57	1016	110	7.1	1.1	13.4	0.3	78.1	0.1
Czech Republic	9	47	74	46.1	40.0	0.8	1.5	10.4	1.2
Hungary	5	73	85	32.6	45.8	5.3	4.8	10.3	1.1
India	134	189	58	0.7	0.4	1.9	0.0	97.0	0.0
Indonesia	8	292	66	0.4	0.0	0.2	0.0	99.4	0.0
Malaysia	36	42	70	5.6	5.2	27.0	3.9	58.1	0.1
Poland	109	160	76	5.1	6.8	0.1	0.1	86.7	1.2
Taiwan	143	66	68	11.0	9.3	15.0	5.2	57.9	1.5
Thailand	1	21	126	52.1	33.6	3.7	9.8	0.0	0.8

Panel F: Frontier Markets

Fund domicile	Funds	Assets mean	Holdings	Stock region					
	#	mill USD	mean #	NAM	EUR	APA	JPN	EM	FM
Bermuda	4	549	55	6.4	9.9	20.5	4.3	58.2	0.7
British Virgin Islands	3	55	82	23.8	71.7	2.4	1.9	0.0	0.2
Cayman Islands	52	188	179	21.0	11.5	29.7	8.8	27.7	1.3
Estonia	2	42	53	5.2	10.0	0.0	0.0	80.8	4.0
Gibraltar	1	29	97	14.4	30.3	20.0	0.1	32.0	3.3
Lithuania	1	28	53	2.2	69.1	0.0	0.0	13.4	15.2
Mauritius	4	285	54	2.6	0.2	1.7	0.0	95.4	0.0
Pakistan	3	350	134	0.0	0.0	0.0	0.0	0.0	100.0
Slovakia	3	43	124	52.3	42.9	0.8	3.9	0.0	0.2
Slovenia	31	44	73	21.6	36.1	2.7	1.7	5.1	32.8
South Africa	74	93	116	25.3	27.3	1.4	4.6	0.4	41.0

Table F.2: Passive Benchmark Funds

This table shows the list of traded funds used to construct net alpha, extending the approach of Berk and van Binsbergen (2015) to international funds. CRSP indicates the Fund number in the CRSP mutual mund database. Abbreviations for regions are in Table F.1. APN includes the Asia Pacific (APA) and Japan (JPN) regions. GLO denotes the globl specification used for funds without a dedicated regional focus.

Ticker	CRSP	Fund Name	Asset Class	NAM	EUR	APN	EM	GLO
VFINX	31432	S&P 500 Index Fund	U.S. Large-Cap Blend	✓				✓
NAESX	31460	Small-Cap Index Fund	U.S. Small-Cap Blend	✓				✓
VEXMX	31433	Extended Market Index Fund	U.S. Mid and Small-Cap Blend	✓				
VIMSX	31473	Mid-Cap Index Fund	U.S. Mid-Cap Blend	✓				
VISGX	31471	Small-Cap Growth Index Fund	U.S. Small-Cap Growth	✓				
VISVX	31468	Small-Cap Value Index Fund	U.S. Small-Cap Value	✓				
VVIAX[1]	31457	Value Index Fund	U.S. Large-Cap Value	✓				✓
VFSVX	44222	All-World ex-US Small-Cap Index Fund	INT Small-Cap Blend		✓	✓	✓	✓
VGTSX	31200	Total International Stock Index Fund	INT Large-Cap Blend		✓	✓	✓	✓
VTRIX	31257	International Value Fund	INT Large-Cap Value		✓	✓	✓	✓
VEURX	31337	European Stock Index Fund	EUR Large-Cap Blend		✓			✓
VPACX	31336	Pacific Stock Index Fund	APA Large-Cap Blend			✓		✓
VEIEX	31338	Emerging Markets Stock Index Fund	EME Large-Cap Blend				✓	

[1] We use VIVAX (CRSP Fund No 031435) before VVIAX share class was introduced.

Table F.3: Explaining Variation in Crowding

This table reports regression results explaining variation in fund crowding. The following variables are included as potential determinants: Fund size is total net assets under management in million USD; # Stocks is the number of stocks in a fund portfolio; # Countries is the number of countries in which stock issuers are domiciled; # Industries is the number of ICB industries a fund invests in; Inverse Normalized HHI is the inverse of the normalized Herfindahl Index on the ICB industry classification; % North America, for example, is the portfolio weight for this stock region. We report t-statistics in paranthesis based on robust standard errors clustered at the fund and quarter level. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
Ln(FundSize)	24.248***	27.700***	26.542***	28.190***
	(9.73)	(12.71)	(10.93)	(10.62)
Ln(FundSize)^2	2.166***	2.326***	2.864***	1.983***
	(5.21)	(6.52)	(6.00)	(4.44)
# Stocks	0.055***	0.054***	0.052***	0.045***
	(6.83)	(7.02)	(6.08)	(3.04)
# Countries	1.690***	1.721***	0.888**	1.562***
	(3.96)	(7.52)	(2.39)	(5.70)
# Industries	8.645***	8.582***	7.774***	9.653***
	(10.72)	(12.98)	(7.02)	(12.01)
Inverse Normalized HHI	0.000**	0.000**	0.034	0.000*
	(−2.45)	(−2.16)	(0.33)	(−1.74)
Ln(FundSize) × # Stocks	−0.017***	−0.017***	−0.010***	−0.030***
	(−7.47)	(−7.31)	(−3.83)	(−6.43)
% North America	2.015***	1.983***	0.812**	2.427***
	(8.85)	(11.36)	(2.36)	(11.98)
% Europe	1.990***	1.686***	2.826***	1.324***
	(9.58)	(8.55)	(7.28)	(6.10)
% Japan	0.201	−0.051	−1.118**	0.074
	(0.55)	(−0.22)	(−2.21)	(0.30)
% Asia Pacific excluding Japan	−1.092***	−1.213***	−0.875**	−1.372***
	(−6.35)	(−6.31)	(−2.20)	(−6.75)
Fund Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	Yes	Yes
Fund sample	Full	Full	U.S.	ex U.S.
Funds	17,364	17,364	5,026	12,338
Observations	309,110	309,110	120,627	188,483
R^2	0.18	0.16	0.09	0.27

Table F.4: The Performance of Funds sorted on Eigenvalue Centrality

This table provides the average monthly fund performance for portfolios conditional on eigenvalue centrality. At the end of each quarter, we sort funds into decile portfolios, based on eigenvalue centrality. Next, we track the equal-weighted performance of the portfolios during the next three months after which we rebalance. As fund performance measures, we use Net Alpha, Dollar Value Added, Gross Alpha, and Gross DGTW returns. All performance measures are reported on a monthly basis and in percent, with the exception of Dollar Value Added which is reported in billion USD. We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Performance measure	Eigenvalue centrality										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
Net Alpha	0.079	0.083*	0.019	−0.068**	−0.036	−0.101***	−0.092***	−0.101***	−0.120***	−0.122***	−0.201***
	(1.50)	(1.97)	(0.49)	(−1.98)	(−1.19)	(−3.50)	(−3.30)	(−4.04)	(−4.77)	(−5.25)	(−3.44)
Dollar Value Added	0.133	0.645**	0.110	−0.142	0.339	−0.444	−0.413	0.016	−0.621	−1.876**	−2.009**
	(0.30)	(2.12)	(0.35)	(−0.42)	(0.90)	(−0.91)	(−0.92)	(0.03)	(−1.07)	(−2.18)	(−1.99)
Gross Alpha	0.104	0.131	0.078	−0.018	0.044	−0.007	−0.024	−0.043	−0.053**	−0.054***	−0.158***
	(1.64)	(1.65)	(0.89)	(−0.38)	(1.06)	(−0.17)	(−0.74)	(−1.47)	(−2.21)	(−2.75)	(−2.64)
Gross DGTW	0.097	0.088	0.089	0.017	0.023	−0.008	−0.025	−0.022	−0.049*	−0.051**	−0.148***
	(1.58)	(1.09)	(1.33)	(0.3)	(0.5)	(−0.14)	(−0.68)	(−0.74)	(−1.66)	(−2.09)	(−2.85)

Table F.5: The Performance of Funds sorted on Crowding in an Asymmetric Network

This table provides the average monthly fund performance for portfolios conditional on crowding, defined using an asymmetric network instead of portfolio holdings overlap. At the end of each quarter, we sort funds into decile portfolios, based on crowding (Panel A) or eigenvalue centrality (Panel B). Next, we track the equal-weighted Gross DGTW returns of the portfolios during the next three months after which we rebalance. The performance measure is reported on a monthly basis and in percent. We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Crowding

1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
0.095	0.072	0.101	0.049	0.034	−0.031	−0.022	−0.018	−0.044	−0.078***	−0.173***
(1.38)	(1.17)	(1.52)	(0.81)	(0.72)	(−0.67)	(−0.61)	(−0.61)	(−1.60)	(−2.84)	(−2.79)

Panel B: Eigenvector centrality

1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
0.087	0.119	0.065	0.041	0.008	−0.004	−0.024	−0.021	−0.027	−0.086***	−0.172***
(1.37)	(1.54)	(0.92)	(0.76)	(0.17)	(−0.08)	(−0.59)	(−0.66)	(−1.04)	(−2.85)	(−3.15)

Table F.6: Robustness of Aggregation and Adjustment of Fund Performance sorted on Crowding

This table provides the average monthly fund performance for portfolios conditional on crowding. At the end of each quarter, we sort funds into decile portfolios, based on crowding. In Panel A, we track the value-weighted performance of the portfolios during the next three months after which we rebalance. As fund performance measures, we use Net Alpha and Gross Alpha. In Panel B, we track the equal-weighted excess return of the portfolios during the next three months after which we rebalance. We obtain a time-series of portfolio returns. We use different factor models to adjust for risk. We report estimated Alphas. All performance measures are reported on a monthly basis and in percent, with the exception of Dollar Value Added which is reported in billion USD. We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Value-weighted portfolio returns

Performance measure	Crowding										
	1 (low)	2	3	4	5	6	7	8	9	10 (high)	10 − 1
Net Alpha	0.049	0.070**	0.001	0.024	0.034	−0.043	−0.007	−0.016	−0.054**	−0.087**	−0.136*
	(0.82)	(2.21)	(0.01)	(0.68)	(1.08)	(−1.25)	(−0.30)	(−0.64)	(−1.99)	(−2.41)	(−1.83)
Gross Alpha	0.117	0.131**	0.065	0.060	0.067	0.024	0.059*	0.015	−0.018	−0.066**	−0.183**
	(1.53)	(2.19)	(0.93)	(0.82)	(1.37)	(0.55)	(1.68)	(0.56)	(−0.55)	(−2.12)	(−2.27)

Panel B: Equal-weighted factor model alphas

Factor model	Crowding										
	1	2	3	4	5	6	7	8	9	10	10 − 1
CAPM	0.139	0.038	0.000	−0.157	−0.171**	−0.203***	−0.173***	−0.200***	−0.240***	−0.233***	−0.372**
	(1.16)	(0.37)	(0.00)	(−1.58)	(−2.57)	(−3.56)	(−3.79)	(−4.04)	(−3.88)	(−3.80)	(−2.46)
FF 3-Factor	−0.004	−0.020	−0.017	−0.150	−0.115*	−0.125***	−0.128***	−0.155***	−0.182***	−0.160***	−0.156**
	(−0.05)	(−0.22)	(−0.16)	(−1.56)	(−1.69)	(−2.94)	(−3.27)	(−4.10)	(−3.96)	(−4.01)	(−1.99)
Carhart 4-Factor	0.011	−0.013	−0.040	−0.165	−0.103	−0.113***	−0.130***	−0.163***	−0.193***	−0.161***	−0.173**
	(0.14)	(−0.14)	(−0.34)	(−1.63)	(−1.60)	(−2.75)	(−3.14)	(−4.21)	(−4.09)	(−3.92)	(−2.13)
FF 5-Factor	0.002	0.057	0.006	−0.169*	−0.092	−0.066	−0.107**	−0.152***	−0.184***	−0.143***	−0.145*
	(0.03)	(0.66)	(0.05)	(−1.68)	(−1.38)	(−1.49)	(−2.46)	(−3.63)	(−3.53)	(−3.08)	(−1.69)

Table F.7: Alternative Measures of Performance of Funds in sequential Sorts on Size and Crowding

This table provides the average monthly fund performance for portfolios conditional on size and crowding. At the end of each quarter, we sort funds into decile portfolios, based on size. Next, we sort funds within each size decile into three portfolios based on our baseline measure of crowding (Panel A) or eigenvalue centrality (Panel B). Next, we track the equal-weighted performance of the portfolios during the next three months after which we rebalance. As fund performance measures, we use Dollar Value Added, Gross Alpha, and Gross DGTW returns in Panel A and B, and additionally Net Alpha in Panel B. All performance measures are reported on a monthly basis and in percent, with the exception of Dollar Value Added which is reported in billion USD. We report time-series averages with t-statistics in parentheses based on Newey-West standard errors. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Crowding

Performance measure	Crowding									
	1(low)	2	3	4	5	6	7	8	9	10(high)
Dollar Value Added	−0.030*	−0.044**	−0.112***	−0.134**	−0.204**	−0.210	−0.454**	−1.009***	−1.108**	−7.201*
	(−1.67)	(−2.15)	(−3.38)	(−2.25)	(−2.22)	(−1.52)	(−2.49)	(−2.80)	(−2.27)	(−1.93)
Gross Alpha	−0.115**	−0.129**	−0.165***	−0.142**	−0.142**	−0.154***	−0.166***	−0.173**	−0.153***	−0.205***
	(−1.98)	(−2.57)	(−3.27)	(−2.51)	(−2.48)	(−2.94)	(−3.04)	(−2.52)	(−2.78)	(−3.27)
Gross DGTW	−0.025	−0.161***	−0.125**	−0.161***	−0.133***	−0.129***	−0.174***	−0.168***	−0.148***	−0.214***
	(−0.51)	(−3.36)	(−2.41)	(−3.31)	(−2.66)	(−2.84)	(−3.59)	(−3.56)	(−2.97)	(−3.99)

Panel B: Eigenvector centrality

Performance measure	Crowding									
	1 (low)	2	3	4	5	6	7	8	9	10 (high)
Net Alpha	−0.162***	−0.156***	−0.194***	−0.162***	−0.150***	−0.150***	−0.188***	−0.193***	−0.141***	−0.176***
	(−3.13)	(−3.71)	(−4.37)	(−3.23)	(−2.88)	(−2.83)	(−4.05)	(−3.88)	(−3.92)	(−5.64)
Dollar Value Added	−0.036**	−0.052**	−0.114***	−0.137**	−0.200**	−0.259*	−0.568***	−1.074***	−1.224**	−7.448**
	(−2.40)	(−2.56)	(−3.33)	(−2.24)	(−2.08)	(−1.82)	(−2.98)	(−3.00)	(−3.00)	(−2.04)
Gross Alpha	−0.136**	−0.124**	−0.155***	−0.126*	−0.136*	−0.147**	−0.166**	−0.169**	−0.148**	−0.181***
	(−2.06)	(−2.03)	(−2.73)	(−1.89)	(−1.96)	(−2.43)	(−2.34)	(−2.07)	(−2.21)	(−2.77)
Gross DGTW	−0.061	−0.149***	−0.127**	−0.155***	−0.137**	−0.127***	−0.168***	−0.164***	−0.139***	−0.197***
	(−1.30)	(−3.06)	(−2.49)	(−3.09)	(−2.57)	(−2.62)	(−3.44)	(−3.17)	(−2.71)	(−3.61)

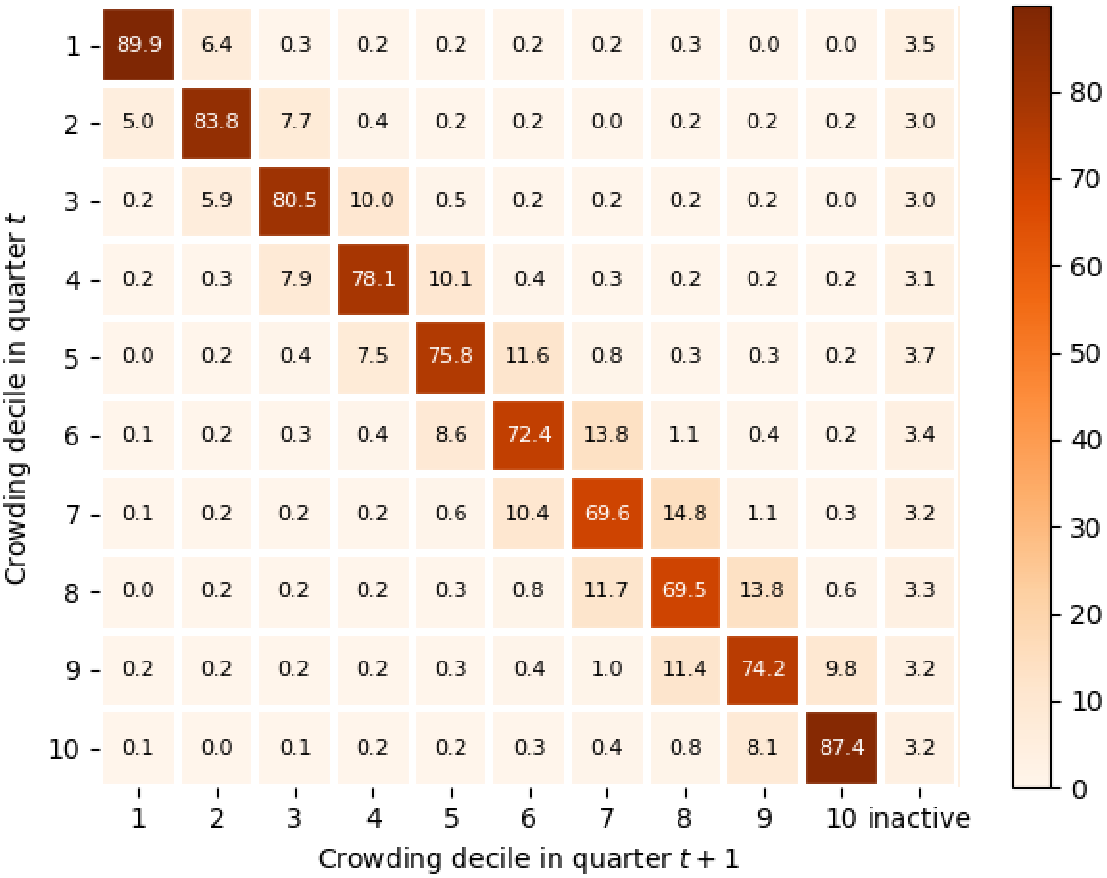

Figure F.1: Persistence of crowding

Conditional on any decile in quarter t, this figure plots the probability of transitioning to decile j or going inactive at quarter $t + 1$. The time period of analysis is between 2001 Q3 an 2014 Q1 (51 quarters).