CFR Working Paper NO. 16-07

Mutual Fund Bets on Market Power

S. Jaspersen

centre for financial research
cologne

Mutual Fund Bets on Market Power*

Stefan Jaspersen

December 21, 2020

Abstract

Taking a firm's competitive position into account benefits investors who are better at evaluating this qualitative information. I find that fund managers who overweight companies with market power outperform their peers. Placebo exercises and an exogenous shock to product market competition around the 9/11 terrorist attacks support this finding. Managers with larger bets on market power are more experienced and long-term oriented. They pursue more illiquid investment strategies, select superior innovators, and more actively avoid competition within their portfolio. My findings show how managers with a superior information production utilize hard-to-process information about industrial organization when picking stocks.

JEL classification: G11; G12; G14; G23; L11

Keywords: Mutual fund performance; Information production; Qualitative information; Product market competition

---

*Stefan Jaspersen, Department of Finance and Centre for Financial Research (CFR), University of Cologne, Albertus-Magnus-Platz, 50923 Cologne, Germany. E-mail: jaspersen@wiso.uni-koeln.de. The author would like to thank Gjergji Cici, Monika Gehde-Trapp, Alexander Hillert, Alexander Kempf, Moritz Lukas, Florian Sonnenburg, and participants at the 23rd Annual Meeting of the German Finance Association (DGF), the 2017 ACATIS Value Seminar, and the CFR Intern Seminar, University of Cologne, for helpful comments on an earlier draft of the paper.

"The key to investing is not assessing how much an industry is going to affect society, or how much it will grow, but rather determining the competitive advantage of any given company and, above all, the durability of that advantage. The products or services that have wide, sustainable moats around them are the ones that deliver rewards to investors."

- Warren Buffett, Fortune Magazine, November 22, 1999 -

1. Introduction

The emerging literature on common ownership shows the importance of a firm's product market competition for institutional investors. For example, He and Huang (2017) and Shekita (2020) find that investors coordinate among rival firms in their portfolio. Nevertheless, little is known about the way in which product market competition influences portfolio choice and performance. The common ownership literature usually relates firm outcomes and aggregate interests of the investment advisor or fund family, but does not take the individual stock selection into account that depends on fund managers' skills and incentives (e.g., Azar et al., 2018). Against this background, I develop a simple measure, the Market Power Bet (MPB), which predicts fund performance based on the portfolio tilt towards firms with market power. By adding fund managers' perpective, this study adds to our understanding on how competition and market power affect asset prices and corporate behavior. It further helps to identify superior fund managers, which is highly relevant for mutual fund investors.

The mutual fund literature shows that a portfolio tilt towards particular industries or local stocks reflects expertise and information advantages (e.g., Coval and Moskowitz, 2001; Kacperczyk et al., 2005), but this research neglects industry characteristics, such as industrial organization and industry dynamics. Intuitively, a firm's competitive position should be of interest for portfolio managers due to its qualitative nature. First, the information is usually not as readily available or quantifiable as financial statements since competitive advantages and barriers to entry matter. Second, the relation between product market competition and stock market performance is ambiguous. While market power might increase profitability, it can hamper innovation and foster managerial slack (e.g., Raith, 2003; Hou and Robinson, 2006; Bustamante and Donangelo, 2017). The relation also depends on demand and R&D intensity (e.g., Aguerrevere, 2009; Gu, 2016). If product market competition is not fully understood by market participants, some investors will make a better evaluation than others about the over- or undervaluation of market power for a company. The reason is that willingness and "costs of information interpretation" (Indjejikian, 1991, p. 278) differ across investors, which is consistent with theoretical evidence of, e.g., Kim and Verrecchia (1994) or Kandel and Pearson (1995). In a similar vein, prior research shows that low-skilled investors underweight hard-to-process information (e.g., Hirshleifer et al., 2018). Yet, the way in which investors utilize hard-to-process information about industry competition and market power to outperform peers is largely unexplored.

What are the implications of fund managers investing more or less in market power? Generally, the common ownership literature suggests that investors appreciate a firm's market power (e.g., Hansen and Lott, 1996; Azar et al., 2018).[1] After having identified more profitable firms with few competitors, investors benefit from higher cash flow stability (e.g., Hoberg and Phillips, 2014) and a lower risk of concurrently investing in close rivals. With the latter advantage, investors avoid undesired correlations and yield a better diversification across product markets (e.g., He and Huang, 2017). Fund managers who neglect such connections are at risk for within-portfolio competition.

Overweighting firms with market power also gives insights about skills and effort in information production. On the one hand, producing information about market power firms could require more skill and effort. Investors often exploit economies of scale in information production and apply their knowledge to evaluate similar firms which often results in concentrated portfolios (e.g., O'Brien and Bhushan, 1990; Kacperczyk et al., 2005; Litov et al., 2012; Foucault and Frésard, 2019). If firms with few competitors are more distinct,

[1] Industry evidence also supports the idea that professional investors strive after companies with competitive advantages to achieve stability in their portfolio (e.g., Hough, 2013; Burton, 2012; Brown, 2012).

the possibilities to exploit these economies of scale in information production and to acquire expertise are limited (e.g., Hoberg and Phillips, 2010a). In more competitive markets, it is easier to learn from and transfer information across similar firms. In a similar way, Holmstrom (1982) shows theoretically that competition offers benchmarking opportunities. As a consequence, higher bets on market power stocks can be interpreted as fund managers being more skilled or putting more effort in information production (the *sophisticated* information production channel). On the other hand, collecting information about market power firms might be attractive for low-skill and effort managers. If fewer rival firms exist and if industry dynamics are more predictable, information collection can be less costly (e.g., Gaspar and Massa, 2006; Datta et al., 2011) (the *simple* information production channel).

Due to the aforementioned reasons, whether and how differences in Market Power Bets predict fund performance is ultimately an empirical question. On the one hand, *MPB* should be positively related to fund performance if it is the result of a sophisticated information-production process. With profitable market power stocks fund managers also achieve better product market diversification and cash flow stability. On the other hand, *MPB* should negatively predict performance if the tilt towards market power reflects a simpler information production used by low-skill and low-effort managers. These managers are also more likely to pick inferior firms with market power. A third alternative is that fund performance is not predictable by *MPB*, because investments into market power firms merely reflect different preferences for particular types of stocks without any information about fund manager skill and effort.

I take the uniqueness of a firm's products based on similarity in 10-K product descriptions from Hoberg and Phillips (2016) as the source of market power. Although the data now allow quantification of a firm's competition, the interpretation of the consequences is still challenging. Firms with a more unique product range also offer less benchmarking opportunities. Using the number of rivals for a given firm, I develop a fund's Market Power Bet (*MPB*) as the value-weighted fraction of companies with the most unique products compared to their average weight in the fund's investment style.[2] First validation exercises suggest that *MPB* indeed captures differences in how fund managers react to changes in competition. Managers with higher *MPB* rely more on changes in a firm's number of rivals and they are more likely to increase the portfolio weight of a company that has taken over a close rival to reduce competition. The product market dimension, therefore, is more actively incorporated into the stock selection by funds that invest more heavily in market power.

My main investigation explores whether and how Market Power Bets predict fund performance. I find strong evidence that *MPB* positively predicts performance, consistent with the *sophisticated* information production channel and the positive values of market power for fund portfolios. Funds with above-median *MPB* in a quarter outperform below-median *MPB* funds by up to 92 basis points per year on a risk-adjusted basis. This result withstands several robustness tests including a nearest-neighbor matched sample approach or alternative definitions for a firm's market power. I further rule out several alternative explanations for the observed outperformance. The *MPB*-performance relationship cannot be explained by differences in funds' active share or industry concentration, by their bets on firm characteristics related to product market competition, or by their ability to exploit mispricing. Using placebo market power stocks and the *MPB* of index funds, I rule out a spurious or mechanical relation between *MPB* and fund performance, consistent with value added by the fund manager's active information production.

If higher *MPB* indeed reflect a more sophisticated information production and a better interpretation of whether market power is currently under- or overvalued for a given company, then high-*MPB* fund managers should select better stocks out of the subsample of market power firms. Consistently, a performance comparison of trade portfolios provides evidence that funds with larger *MPB* actually trade more successfully in market power stocks than

[2] I acknowledge that a firm's competitiveness also depends on market share, brand value, and price-setting power. However, Hoberg and Phillips (2014) and Hirshleifer et al. (2018), respectively, argue that firms with more differentiated products or novel technologies likely have a competitive advantage. Nevertheless, in Section 3.3.1, I use alternative proxies for a firm's market power including concentration measures to capture its price-setting power. Results are qualitatively the same.

managers with lower *MPB*.

To address concerns that *MPB* and fund performance are jointly determined by an omitted variable, I use two distinct approaches. First, I decompose a stock's probability to be a market power stock in a given year in an expected component predicted by its past market power status and other firm characteristics, and the unexpected component from the residual. I identify stocks with the highest unexpected component to be a market power stock in the following year and use a fund's prior-year weight in these stocks to instrument *MPB*. Since mutual funds hold onto stocks for several quarters, managers who overweighted stocks with a higher unexpected market power probability one year ago should experience a positive surprise on their current *MPB*. Indeed, first-stage results of a 2SLS instrumental variable regressions support the relevance of the instrument. Second-stage results further confirm the main result that a higher *MPB* positively predicts performance. The second identification exercise exploits the 9/11 terrorist attacks as an exogenous positive competition shock in the military goods industry. In a first step, I find that this shock reduces the *MPB* of fund managers with an increased position in affected military companies after the attacks. In a second step, I show that these fund managers exhibit a significantly lower change in fund performance around 9/11. Both identification strategies show that a plausibly exogenous variation in the *MPB* influences fund performance.

Which manager and fund characteristics are associated with *MPB*? Investment experience likely facilitates the processing of qualitative information. Moreover, information processing is a costly and time-consuming task that requires attention and effort even for skilled managers. Indeed, I find that fund managers with more experience and those who only manage one fund place larger bets on market power. Finally, fund managers with a more long-term investment horizon should value steady cash flows and lower industry dynamics offered by firms with market power more. Consistently, funds that hold stocks for a longer period of time are associated with larger *MPB*.

To address managers' motivation to invest into market power and to identify potential performance channels, I investigate the investment behavior of funds with different *MPB* levels. First, if market power provides investors with cash flow stability and less frequent industry changes, then fund managers have fewer needs to frequently rebalance the portfolio. This lower trading frequency should allow the fund manager to invest in more illiquid securities to earn an illiquidity premium (e.g., Amihud et al., 2005). The results support this notion with high-*MPB* funds having an almost six percent lower portfolio liquidity. Second, the long-term value of the firm's technologies and its innovative ability are important yet hard-to-process pieces of information when evaluating a firm's product market competition (e.g., Hirshleifer et al., 2018). Moreover, Bena and Li (2014) find that firms with more unique patent output are less likely to be involved in mergers or acquisitions, thus, causing less industry dynamics. It is also intuitive that a sustainable competitive advantage stems from more unique technologies. Consequently, I analyze whether high-*MPB* funds are able to identify better innovators as well as companies with fewer overlap in their patent output with other firms. I find that these funds hold firms with a better track record to convert R&D expenses into sales as per Cohen et al. (2013) and firms with a more unique patent output based on Li et al. (2019). Finally, high-*MPB* funds are more likely to avoid within-portfolio competition and invest less in rival firms at the same time, which is consistent with them targeting the most promising competitor for a product. In contrast, managers with lower *MPB* invest into several rivals simultaneously, suggesting that they ignore these connections or cannot decide among competitors.

This paper contributes to several strands in the literature. First, it relates to research on the role of information characteristics for the information production process. Among others, these characteristics include the aggregation level (e.g., Kacperczyk et al., 2014), softness and tangibility (e.g., Stein, 2002; Gargano et al., 2017; Chuprinin et al., 2019), complexity (e.g., Cohen and Lou, 2012), and source (e.g., Coval and Moskowitz, 2001; Cici et al., 2018; Fang et al., 2014). I contribute to this literature by showing that industrial organization is an important and hard-to-process information that matters for information production and portfolio management.

Second, my results contribute to the literature that predicts information advantages from fund portfolios. Kacperczyk et al. (2005) and Huang and Kale (2013) show that funds outperform if they are more concentrated in particular industries, while Cremers and Petajisto (2009) and Doshi et al. (2015) show that more active managers deliver a superior performance. These studies, however, do not take stock or industry characteristics, such as the market structure, into account. I add to these studies by suggesting a simple measure for a fund manager's ability and effort to incorporate difficult-to-interpret information on market power. The findings suggest that better performing investors trade off economies of scale in information production when specializing in particular industries against investments in less competitive markets. This evidence highlights the importance of industry characteristics for an investor's ability to outperform.

Finally, I broadly contribute to the vast literature regarding the impact of product market competition on asset pricing (e.g., Hou and Robinson, 2006; Bustamante and Donangelo, 2017) and corporate behavior (e.g., Giroud and Mueller, 2011; Hoberg et al., 2014; Azar et al., 2018). My findings suggest that product market competition is not fully understood by market participants, thereby offering investment opportunities for superior investors. I also show that the best investors have a preference for firms with an already strong position and actively avoid to co-invest into competitors by selecting the best-performing ones. Thereby, my focus is on the individual fund and manager rather than the aggregated advisor or fund family level usually analyzed in the common ownership literature. With investment companies owning approximately 31% of the US stock market at the end of 2017 (Investment Company Institute, 2018), differences in fund managers' abilities to take product market information into account further help to understand why competition affects stock market performance and corporate decisions.

The remainder of the paper is organized as follows. In Section 2, I describe the data and the Market Power Bet measure. Section 3 presents empirical results regarding the relation between Market Power Bets and fund performance and addresses endogeneity concerns. In Section 4, I show that *MPB* depends on the fund manager and the fund's investment horizon. Section 5 examines the relation of *MPB* to the fund's investment behavior and identifies potential channels through which the superior performance emerges, and Section 6 concludes.

2. Data and summary statistics

2.1. Data sources

For my analysis, I combine several data sources. I obtain information about fund characteristics, e.g., fund returns, total net assets under management, fund fees, fund age, fund families, and investment objectives from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database (CRSP MF). As the information is at the share-class level, I aggregate it at the fund level by value-weighting the share class information of a given fund.

I merge CRSP MF with the Thomson Reuters Mutual Fund Holdings Database (MF Holdings) using the MFLINKS tables. I focus on holdings of common stocks (share codes 10 and 11) and add information about these stocks using the CRSP/Compustat Merged Database and the IBES Database.

From the Morningstar Direct Mutual Fund Database (MS Direct), I obtain fund manager information. I merge MS Direct with the former databases using fund CUSIPs.

Finally, I use the Text-based Network Industry Classifications (TNIC) and Product Market Fluidity Data provided by Hoberg and Phillips (HP) to identify a firm's product market competition.[3] The HP dataset contains annual pairs of rival firms with a product similarity score above a certain threshold based on descriptions in 10-K annual filings. The annual

[3] The data can be accessed via `http://hobergphillips.tuck.dartmouth.edu`. An advantage of this classification is that it groups firms by the products they offer, whereas the SIC and NAICS classifications are based on input factors or production processes. The data are limited to publicly traded U.S. companies. For a detailed description, please refer to Hoberg and Phillips (2016) and Hoberg et al. (2014).

number of pairs per firm therefore identifies the number of close competitors. I additionally obtain product market fluidity, fitted HHI concentration (Hoberg and Phillips, 2010b), and text-based industry HHI concentration data from this database. Since the data are available on an annual basis, they allow to consider dynamics in a firm's product market competition.

The final sample consists of actively managed diversified U.S. domestic equity funds for the December 1999 to March 2012 period. To obtain this sample, I first eliminate all international, sector, balanced, bond, index, and money market funds. Then, I exclude all funds with less than 50 percent of their assets in common stocks and funds with less than ten stocks, on average. I categorize the remaining funds according to their dominating investment objective into six style categories using CRSP style codes (Mid Cap (EDCM), Small Cap (EDCS), Micro Cap (EDCI), Growth (EDYG), Growth & Income (EDYB), and Income (EDYI)). The final sample consists of 2,561 funds.

2.2. Variable construction and sample characteristics

I sort stocks in the HP database into quintiles based on their annual number of product rivals and define stocks in the bottom quintile as market power stocks. To obtain a fund's *MPB* each quarter, I calculate the value-weighted fraction of market power stocks within the portfolio using the market power classification in the current year.[4] To rule out that a fund invests more or less in market power stocks due to its stated investment style, I adjust the fraction of market power stocks by subtracting their average weight within the fund's investment style in a given quarter. The Market Power Bet (*MPB*) therefore represents an under- or overweighting of market power firms relative to peer funds in the same style.[5]

Panel A of Table 1 reports annual summary statistics for stock characteristics over the sample period 1999 to 2012. I present information for both the whole sample of firms and

[4] In untabulated tests, I alternatively use the number of competitors in the previous year to capture a firm's market power and find qualitatively similar results. Note that the portfolio sort is based on all firms in the HP datasets, while stock holdings of the mutual funds only contain common stocks.

[5] As shown in Table 6 in the robustness section, the main result also holds when using alternative proxies to capture a fund's propensity to invest in firms with few competitors.

for market power and non-market power firms separately. I use t-tests to test for differences in means between the subsamples.

– Insert TABLE 1 approximately here –

Panel A of Table 1 shows that market power firms indeed face fewer product market threats, as suggested by their lower average product market fluidity. These firms are significantly smaller and older and have a higher book-to-market ratio. Market power firms are also less liquid, as captured by a lower average stock turnover and a higher average Amihud (2002) illiquidity measure, both constructed using daily data within a quarter. They also exhibit a higher average idiosyncratic volatility within a quarter and are covered by fewer analysts. A possible interpretation of these differences is that the average market power firm operates in a specialized niche market that is more unknown to investors which leads to a higher information uncertainty. This interpretation is in line with Hsu et al. (2019) and Zhang (2018) who find a lower analyst coverage for firms in less competitive markets and would suggest that the information production process for firms with market power is more sophisticated. Importantly, market power stocks on average do not yield a significantly different annual return than non-market power stocks.

Panel B presents the sample distribution of the funds' portfolio weights in market power stocks and the peer-adjusted weights in market power stocks, which represents the Market Power Bet (MPB). As expected, I find a clear cross-sectional variation in the propensity to invest in market power stocks. The average fund invests almost 17% of the fund portfolio in these firms; this is unsurprising given that they represent around 20% of the stocks and that they are significantly smaller. The distribution of the MPB further shows that the 10% with the lowest MPB underweight market power stocks by more than 7.34%, while the 10% with the largest MPB overweight these stocks by more than 8.08%. Importantly, MPB exhibits high serial correlation of almost 60% even after one year.

Finally, Panel C of Table 1 reports quarterly sample characteristics at the fund level. I present information both for the whole sample of funds and for subsamples constructed by stratifying the sample funds into high-MPB (above-median) and low-MPB (below-median) funds in each quarter. Panel D shows that high-MPB funds are significantly smaller, slightly younger, and from smaller families. These funds have slightly higher expense ratios, grow at a higher rate, and hold more stocks in their portfolio. Finally, these funds have an annual turnover of only 79.20% compared to 95.02% for low-MPB funds. This result is consistent with a higher cash flow stability of market power stocks reducing the need to replace stocks frequently. Given that these fund characteristics are known to have an impact on fund performance, the performance comparisons later will control for these differences. Interestingly, the univariate comparison provides first evidence that larger Market Power Bets indicate superior performance, as shown by significantly higher raw returns, in addition to stock characteristic- and risk-adjusted fund performance. For example, high-MB funds outperform low-MPB funds by 78 basis points per year based on Carhart (1997) 4-factor alphas.

2.3. Does *MPB* actually measure a fund's response to product market competition?

Table 1 already reveals striking differences in the characteristics of market power and non-market power firms. Fund managers might overweight market power firms by chance due to preferences for other firm characteristics. To validate that the MPB measure captures differences in the reaction to product market information, I first analyze the funds' reliance on product market competition ($RPMC$). Changes in the competitive landscape should induce fund managers to update their expectations about the prospects of the firm and to trade on this new information. This sensitivity should be particularly pronounced for managers who are better at evaluating the impact of competition and market power.

I follow an approach similar to that of Chuprinin et al. (2019) when measuring a fund's reliance on product market competition. In a first step, I run fund-level regressions of annual portfolio weight changes - based on number of shares held at the end of the year - on changes in analyst recommendations and annual returns in the previous two years. The regression also includes the average portfolio weight change across all funds in the same investment style in the same year. In a second step, I calculate the R^2 from a fund-level regression of the absolute residuals from the first-stage regression on lagged absolute changes in the number of rival firms in the previous two years. To avoid a mechanical relation between *MPB* and the changes in the number of competitors, I only take non-market power stocks into account when running the fund-level regressions. I relate *RPMC* of fund i in year t to the fund's Market Power Bet (*MPB*) at the end of year t-1 and add control variables in the following pooled regression:

$$RPMC_{i,t} = \alpha + \beta_1 MPB_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

$X_{i,t-1}$ is a vector of control variables that might have an impact on a fund's reliance on product market competition. I control for the logarithm of fund's total net assets, the logarithm of the fund's age, the fund's annual turnover ratio, the fund's annual total expense ratio, quarterly fund flows measured as in Sirri and Tufano (1998), the logarithm of the number of stocks held by the fund, and the logarithm of the fund family's total net assets under management. All independent variables are valid at the beginning of the year, for which I calculate *RPMC*. To control for unobservable effects in a given period or a given style, I include time and style fixed effects in the regressions. Standard errors are clustered at the fund level.

Panel A of Table 2 reports the results of the regression in equation (1) and for a modified version in which I replace the *MPB* measure with a dummy that equals one if the *MPB* of a fund is above the median in a given period, and zero otherwise (high *MPB*).

– Insert TABLE 2 approximately here –

The results presented in Panel A of Table 2 show that funds with larger Market Power Bets react more strongly to changes in the number of firm rivals, captured by a higher *RPMC*. The effect is statistically significant at the 1% level and is also economically relevant with a *RPMC* that is approximately 0.39 percentage points larger for high-*MPB* funds. Compared to the average *RPMC* of low-*MPB* funds (3.45 percent), this effect is equal to a difference of more than 11%.[6]

If the Market Power Bet is indeed a result of fund managers utilizing a firm's market power, then managers who overweight market power stocks should have a preference for firms that actively reduce competition and increase market power, e.g. by acquiring or merging with a close rival firm (e.g., Shekita, 2020). The second validation exercise tests this assumption.

From the Thomson Reuters' Securities Data Company (SDC), I obtain a sample of mergers and acquisitions for U.S. acquirers and public U.S. targets. I use the HP data library to identify whether the acquirer and target are rivals in the year preceding the acquisition, again focusing on non-market power stocks. For all funds with a positive weight in the acquirer at any point in time from the quarter before the announcement date of the transaction to the four quarters after the transaction, I construct an indicator variable equal to one if the fund has increased the portfolio weight in the acquirer and zero otherwise. To identify changes in average portfolio weights, I calculate differences between the average portfolio weight in the post-announcement period and the portfolio weight prior to the transaction. I then use the indicator variable as the dependent variable in a linear probability model. The main independent variables are the fund's *MPB* and the high-*MPB* dummy, valid at the end of

[6] In untabulated tests, I add the fund's industry concentration as an additional control variable. The results remain qualitatively unchanged.

the quarter preceding the announcement date. I control for the same fund-level variables as in Panel A, also valid at the end of the quarter for which I measure the Market Power Bet. To rule out that funds differ in their preferences for a particular transaction type, I include stock-time fixed effects and compare funds within the same transaction event. Panel B of Table 2 reports the results.

The results in Panel B support the hypothesis that *MPB* captures differences in the importance investors assign to competition. Compared to low-*MPB* funds that trade the same company at the same point in time, high-*MPB* funds are significantly more likely to increase their portfolio weight in a firm that is taking over a rival company.

Taken together, the results from this section suggest that *MPB* indeed captures differences in processing product market information. Importantly, similar to the univariate performance comparisons in Table 1, they provide first evidence that the product market dimension matters more to funds with larger rather than smaller Market Power Bets.

3. Market Power Bets and future fund performance

In this section, I examine the empirical question whether larger or smaller Market Power Bets predict a higher fund performance. I formally test the relation in Section 3.1. In Section 3.2, I analyze differences in trade performance within the market power stock subportfolio. In Section 3.3, I investigate whether the result regarding the *MPB*-performance relation is robust to variations in the empirical setup and alternative explanations. In Section 3.4, I address endogeneity concerns for the *MPB*-performance relationship using an instrumental variable (IV) approach and by exploiting the 9/11 terrorist attack as exogenous shock to competition in the military industry.

3.1. Do Market Power Bets predict fund performance?

I employ both holdings-based performance measures and standard factor models to estimate fund performance. In particular, throughout the paper, I present results based on the stock-characteristic-adjusted performance measure of Daniel et al. (1997) (DGTW) and based on a Carhart (1997) 4-factor model. I compound the monthly DGTW-adjusted fund returns over the three months within a quarter. The quarterly alphas from the factor model are differences between the realized excess fund return and the expected excess fund return in the quarter. The expected return in a given month is calculated using factor loadings estimated over the previous 24 months and factor returns in the current month. I compound both realized and expected excess returns over the three months of a quarter before taking their difference.[7] To better capture investment abilities, I use gross-of-fee returns, i.e., the net-of-fee return plus one-twelfth of the annual total expense ratio, to calculate alphas.[8]

The univariate comparisons in Panel D of Table 1 already hint at a superior performance of high-*MPB* funds. In a more formal test, I now employ a pooled regression in which I relate fund performance in quarter t to its Market Power Bet in quarter t-1 and add control variables that are known to have an impact on fund performance:

$$Perf_{i,t} = \alpha + \beta_1 MPB_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

I measure fund performance (*Perf*) as described above. $X_{i,t-1}$ is a vector consisting of the control variables as in Table 2 except for the expense ratio. All independent variables are lagged by one quarter. As before, I run regressions with style and time fixed effects and cluster standard errors at the fund level. Table 3 reports the results of the regression in

[7] Monthly factors are obtained from Kenneth French's website. I calculate monthly alphas and factor loadings only if none of the returns in the past 24 months are missing. Therefore, younger funds are excluded from the analysis, which helps alleviate the concern of an incubation bias (Evans, 2010).

[8] For robustness, I used net returns instead of gross returns to calculate the Carhart (1997) 4-factor alpha. I also ran the analysis based on different holdings-based performance measures and different factor models. As shown in Table A.1 in the Internet Appendix, my main result does not change.

equation (2) both using the continuous *MPB* variable and the high-*MPB* dummy.

– Insert TABLE 3 approximately here –

The results presented in Table 3 support the first evidence and show a positive relation between *MPB* and fund performance, suggesting that the better evaluation of product market competition and market power results in an overweighting of stocks with market power. For both the continuous *MPB* measure and the *MPB* dummy, I find that larger Market Power Bets are positively related to fund performance. The effect is also economically relevant: After controlling for various fund characteristics, high-*MPB* funds outperform by approximately 23 basis points per quarter when using DGTW-adjusted returns or by approximately 18 basis points per quarter using Carhart (1997) 4-factor alphas. This difference corresponds to an annual outperformance of up to 92 basis points.[9]

Regarding the coefficients on the control variables, I find that fund size has a negative impact on fund performance suggesting diseconomies of scale (Berk and Green, 2004). While fund age has a positive impact on fund performance, turnover is negatively related to performance, the latter being consistent with, e.g., Carhart (1997) or Barras et al. (2010). Finally, I find a positive yet statistically insignificant impact of family size, in line with Bhojraj et al. (2012). The remaining controls have no consistent impact on performance.

In sum, the results from this section support the notion that a higher - instead of a lower - *MPB* signals fund managers' superior information, which is beneficial for their performance. This suggests that the information production for market power stocks is not easier and expected to be exploited by low-skilled fund managers. On the contrary, the results are in line with high-*MPB* managers putting more effort and skill in picking these unique firms,

[9] Table A.2 in the Internet Appendix alternatively presents results when replacing the high-*MPB* dummy with the fund's *MPB* quartile. *MPB*-quartile 2, *MPB*-quartile 3, and *MPB*-quartile 4 are indicator variables equal to one, respectively, if the fund belongs to the second, third, or fourth *MPB* quartile in a given quarter with funds in the lowest *MPB* quartile as the control group. The results become even stronger with the finer classification. For example, funds in the highest quartile outperform those in the lowest quartile by up to 1.46 percent per year when using DGTW-adjusted returns.

since they forgo economies of scale in information production.

3.2. Trading performance in market power stocks

The result from the previous section suggests that managers with higher *MPB* possess better information. This advantage potentially stems from a superior interpretation about whether market power is beneficial for a given firm or not. A manager with this superior information might therefore pick companies whose market power is currently undervalued and avoid firms with overvalued market power. As a consequence, fund managers with higher *MPB* should select better performing market power stocks than low-*MPB* managers.

To test this conjecture, I analyze the performance of trades in the market power subportfolio.[10] For each fund, I identify a buy decision if the number of shares held by the fund at the end of a quarter has increased compared to the previous quarter. I calculate the buy performance of the subportfolios as the trade size-weighted performance of all the stocks in the subportfolio in the following quarter using DGTW-adjusted returns and Carhart (1997) 4-factor alphas. The risk-adjusted quarterly stock performance is calculated analogously to fund performance. I run a similar regression as in Table 3 but replace the dependent variable with the performance of the buy subportfolios. Panel A of Table 4 reports the results.

– Insert TABLE 4 approximately here –

The results presented in Panel A of Table 4 provide clear evidence for an information advantage of high-*MPB* funds in market power stocks. For example, the market power buys of high-*MPB* funds outperform the buys of funds with lower *MPB* by almost 21 basis points per quarter when using Carhart (1997) alphas.[11]

[10] Several studies argue that trades are more appropriate than holdings to capture information advantages of fund managers (e.g., Chen et al., 2000; Pool et al., 2015).

[11] In unreported tests, I find that high-*MPB* funds also pick superior non-market power stocks, which is plausible for several reasons. For example, given that the relation between competition and corporate performance is ambiguous, fund managers with a superior interpretation of competition should also be able to identify promising firms out of a larger group of competitors. In addition, if high-*MPB* managers have a

To provide support for the conjecture that high-*MPB* funds pick the best competitors, I compare a fund's actual buy performance with the performance of hypothetical benchmark subportfolios consisting of the competing firms of the purchased stocks. To obtain the benchmark I calculate the equally weighted average quarterly performance of a stock's rivals firms using TNIC data. For each fund, I then calculate the trade-size weighted average performance of the rivals in the buy portfolios; this could be interpreted as the performance of a fund's buy portfolio if the amount used to purchase a stock had been equally distributed over its rivals. I calculate the differences between the actual buy subportfolio and the benchmark portfolios and use this difference as the dependent variable using a regression analogous to that in Panel A. Panel B of Table 4 reports the results.

The results presented in Panel B of Table 4 additionally support the notion that fund managers with larger *MPB* are more successful in identifying the most promising firms out of close rival firms as their actual buy portfolios outperform the rival firms' performance to a larger extent.

Finally, in Panel C of Table 4, I benchmark the buy performance of market power stocks with the performance of sells of market power stocks made by the fund in the same period. The dependent variable is, therefore, the next-quarter performance difference of buy- and sell-subportfolio in market power stocks. Results from Panel C are in line with the preceding panels that the trade performance in these stocks is higher for funds with larger *MPB*.[12]

Taken together, the main result of Table 3 is supported by these trade-based results. They also suggest that market power is not fully reflected in prices and understood by market participants which allows better investors to exploit this information.

---

preference for market power stocks, then stocks from more competitive industries face higher hurdles to be included in the portfolio. It is thus likely that these managers have received strong positive signals about stocks with more competition.

[12] Table A.3 of the Internet Appendix presents results from a long-short strategy as an alternative approach to show information advantages in market power stocks. In detail, the results in Table A.3 suggest that a strategy that buys market power stocks bought by high-*MPB* funds and sells the market power stocks sold by these funds delivers a significantly higher performance than a long-short strategy based on the trades of low-*MPB* funds.

3.3. Robustness and alternative explanations

In this section, I present results from a battery of robustness tests for the main result of Table 3 and address alternative explanations. In Section 3.3.1, I vary the empirical setup. Section 3.3.2 rules out that differences in the possibility to exploit mispricing and further organizational differences drive the main result. Finally, in Section 3.3.3, I run two placebo exercises.

3.3.1. Robustness tests

To show that the main result in Table 3 is not sensitive to the empirical setup, I conduct a battery of robustness tests, reported in Table 6. For brevity, I only report results based on the above-median cutoffs (high *MPB*), but the results are qualitatively the same when using continuous measures. To take into account that high-*MPB* and low-*MPB* funds differ significantly in terms of observable characteristics, Panel A of Table 6 presents average treatment effects from running the baseline regression on a nearest-neighbor matched sample with high-*MPB* funds as the treatment group. For each observation in the treatment group, the nearest neighbor is identified from the control group based on the same control variables as in Table 3. I match exactly on period and fund style.

Panel B of Table 6 reports results when I use alternative approaches to measuring a fund manager's propensity to invest in firms with fewer competitors. First, I replace the high-*MPB* dummy with an indicator variable *Overweighting market power firms* equal to one if the fund is overweighting market power stocks relative to its investment style in a quarter, and zero otherwise. Second, I calculate the *Competition bet* as the style-adjusted portfolio weight in stocks in the top quintile according to the number of competitors. I also calculate the Market Power Bet based on alternative definitions of market power. I define market power stocks respectively as stocks in the lowest quintile according to annual product market fluidity, the annual number of competition-related words in 10-K filings as in Li et al. (2013)[13], and the annual firm-to-economy technological proximity of Li et al. (2019). The latter captures the overlap in innovation output with the rest of the economy. A low proximity can, hence, be interpreted as a firm's products being more unique. I also define Fama-French-48 industries as market power industries if their annual number of firms is in the bottom quintile. Finally, to take into account that market power also depends on market concentration, pricing power, and competition from private firms, I take the fitted HHI concentration data from Hoberg and Phillips (2010b) and the text-based industry HHI concentration (e.g., Hoberg et al., 2014) when assigning firms their market power status.

Lastly, in Panels C and D, I rule out the concern that the Market Power Bet is simply a byproduct of already documented proxies of investment skills or fund managers betting on particular firm characteristics that correlate with product market competition. This is particularly relevant as Table 1 shows striking differences in several firm-level characteristics of market power and non-market power stocks. In particular, placing large bets on market power firms could be the result of fund managers taking more concentrated bets on particular industries or deviating more from the benchmark. Finally, as the average market power firm is, for instance, smaller and has a higher book-to-market ratio, larger Market Power Bets could stem from funds simply pursuing small cap or value investing strategies. To analyze whether the Market Power Bet impacts fund performance beyond these skills and strategies, I calculate an adjusted *MPB*. Panel C of Table 6 reports the results when adjusting *MPB* for a fund's investment skill. I first regress *MPB* on either the fund's current industry concentration, the Active Share of Cremers and Petajisto (2009), or both. I use the residual of these regressions instead of the unadjusted *MPB* measure in the regression presented in Table 3. Again for brevity, Panel C only presents results for an indicator variable equal to one if the fund's residual *MPB* is above the median in a given quarter and zero otherwise. Panel D of Table 6 reports the results when adjusting *MPB* for a fund's bets on other firm characteristics, in which market power and non-market power stocks differ. I construct bets similar to

[13] The data are available from 1995 to 2009 at `http://webuser.bus.umich.edu/feng/`.

the *MPB* by sorting firms each quarter into quintiles based on market capitalization, firm age, (industry-adjusted) book-to-market ratio, turnover, illiquidity, idiosyncratic volatility, and analyst coverage, all defined in Table 1. For each fund, I calculate its respective style-adjusted portfolio weight in firms of the smallest size, highest age, highest book-to-market ratio, highest illiquidity, highest idiosyncratic volatility, or lowest analyst coverage quintile. I then regress *MPB* on each firm characteristic bet individually or simultaneously and use the residual of these regressions instead of the unadjusted *MPB* measure in the baseline regression.[14]

– Insert TABLE 6 approximately here –

All tests in Table 6 support the result that funds with a stronger propensity to invest into market power firms deliver a superior performance. The result also cannot be explained by how market power of a company is defined. I also provide evidence that overweighting market power firms adds value beyond already known investment skill and style proxies. It is therefore unlikely that fund managers choose market power stocks simply for small cap or value investing. For example, Panel D shows that high-*MPB* funds outperform by about 68 basis points per year (17 basis points per quarter) after adjusting for all aforementioned firm characteristics that correlate with product market competition together. As a result, I can conclude that my main result is robust to variations in the empirical setup.

3.3.2. Differences in funds' organizational structure and the possibility to exploit mispricing

Results of Panel D of Table 6 already addresses the concern that *MPB* is just the byproduct of a fund's designated trading strategy, in particular a value-based investment approach. Moreover, since the *MPB* reflects an over- or underweighting of firms with market power relative to the fund's investment style, the results also cannot be explained by cross-sectional

[14] In unreported tests, I simply control for the firm characteristic bets an get qualitatively the same results.

differences across investment objectives.[15] Nevertheless, even within the same investment objective, cross-sectional differences in the organizational structure could exist that benefit investing in firms with market power absent any (time-varying) managerial effort and skills. For example, if firms with market power are selected to trade against mispricing, then differences in a fund's general ability to exploit mispricing may explain the outperformance of high-*MPB* funds. Since Giannetti and Kahraman (2018) show that funds with a higher flow-performance sensitivity are more constrained to trade against mispricing, I add the fund's flow-to-performance sensititity (*FPS*) as a control variable to the baseline regression. The corresponding variable *FPS* is the regression coefficient from running a fund-level regression of monthly fund flows on the prior 12-months monthly fund return (net-of-fees) over the 24 months window prior to the performance calculation. The first four columns of Panel A of Table 7 report the results when adding *FPS* as a control variable. The last two columns of Panel A further report the average treatment effect on the treated (ATET) when running the nearest-neighbor matching as in Table 6 and *FPS* as an additional matching variable.

– Insert TABLE 7 approximately here –

Results from Panel A of Table 7 rule out that the sensitivity of fund flows to performance and, therefore, the ability of funds to exploit mispricing drives the relation between *MPB* and fund performance. Irrespective of whether I control for *FPS* in the baseline regression or whether I use it as an additional matching variable, the outperformance of high-*MPB* funds is both economically and statistically similar to the main result in Table 3.

To further rule out unobservable differences in fund organization that could affect its investment in market power stocks and fund performance, in Panel B of Table 7, I also add, respectively, fund-, manager-, and fund family-fixed effects to the baseline regression of Table 3. For example, firms with market power could be geographically close to some fund

[15] Table A.4 in the Internet Appendix provides further evidence that differences between investment styles do not explain the main result, as the outperformance of high-*MPB* funds holds within each investment style.

companies so that firms have a higher *MPB* due to a profitable local bias. Moreover, the fund family could employ more analysts to facilitate the processing of qualitative information which would make *MPB* the result of analysts' (and not managers') effort and skill. Results in Panel B of Table 7, however, rule out such explanations based on the fund's organization. Irrespective of the set of fixed effects, high-*MB* funds outperform by at least 11.5 basis points per quarter or 46 basis points per year. Interestingly, the outperformance of funds with *MPB* and performance cannot be explained by differences in innate talents of fund managers, which suggests that *MPB* rather reflects time-varying managerial abilities and efforts.

3.3.3. Placebo tests

Even though the results from Panel B of 6 already rule out that the definition of market power based on product similarity explains the outperformance of high-*MPB* funds, there is still a concern that a lower number of competitors in the TNIC data is in fact positively related to a firm's performance. As a result, even absent any information advantages of fund managers a passive investment strategy that overweights firms with market power should yield a superior risk-adjusted performance. To rule out this explanation, I run a placebo test using index funds. Index fund trading is unrelated to information other than index reconstitutions. If market power firms on average outperform other firms then index funds with a larger fraction of these firms should also outperform other index funds. I therefore calculate *MPB* for a sample of index funds and repeat the regression (2) for this index fund sample.[16] Table 8 reports the results.

– Insert TABLE 8 approximately here –

The results from Table 8 mitigate the concern of a superior performance of a passive strategy that overweights companies with market power. Using the index fund sample, I find no evidence that higher *MPB* are related to a superior performance. This is in line with managers' active decisions to place higher weights on particular stocks matters for the superior performance of high-*MPB* funds.[17]

To make sure that the market power characteristic itself matters for the positive impact on fund performance, I run a second placebo exercise. I calculate a placebo *MPB* and its corresponding *MPB* dummy by randomly assigning 20 percent of the stocks in a year to the market power subportfolio. I then rerun the baseline specification of Table 3 using these new Market Power Bets. This procedure is repeated 10,000 times. The left panels of Figure 1 present the distributions of the 10,000 coefficients on the high-*MPB* dummy from this placebo exercise.

– Insert FIGURE 1 approximately here –

The coefficients of the high-*MPB* dummy using placebo market power stocks are centered around zero and often negative for both DGTW-adj. returns and Carhart (1997) 4-factor alphas. As a comparison, the right panels of Figure 1 report the distribution of coefficients on the original high-*MPB* dummy when using a bootstrap procedure that selects observations with replacement from the original sample and rerunning the baseline regression. As with

[16] To be included in the index fund sample, I require that the fund name (at any point in time) suggests that the fund is an index fund and that the fund is labeled by CRSP as a pure index fund or ETF/ETN. Additionally, I eliminate funds with less than 80% of the portfolio in common stocks on average. I do not consider enhanced index funds or index-based funds, which still have an active component.

[17] For robustness, I use a portfolio approach, in which I annually sort stocks into quintiles based on the number of competitors and calculate risk-adjusted performance in the following year. The results, presented in Table A.5 in the Internet Appendix, show that stocks in the lowest quintile in the number of competitors do not outperform companies with more competitors.

the placebo test, I repeat the procedure for 10,000 times. In contrast to the left panels, the coefficients on the original high-*MPB* dummy are always positive and centered around the coefficient values of Table 3.

This result suggests that the relation between the Market Power Bet and fund performance is unlikely to be significantly positive due to a spurious or mechanical relation.

3.4. Evidence from instrumental variables (IV) regressions and and exogenous shocks to competition

In this section, I address the concern that there is an omitted variable that jointly drives fund performance and the *MPB* measure. To do this, In Section 3.4.1, I conduct a 2SLS instrumental variable regression, and in Section 3.4.2, I provide results from a shock to the competitive environment in the military goods industry after the 9/11 terrorist attacks.

3.4.1. Holdings of surprise market power stocks as instrumental variable (IV)

As a first approach to address endogeneity, I conduct a 2SLS instrumental variable (IV) approach. I instrument the Market Power Bet and the high-*MPB* dummy with the fund's portfolio weight in stocks with the highest unexpected probability to be a market power stock in the following year (*surprise market power firms*). I decompose a stock's probability to be a market power stock in a year into an expected and an unexpected component. The expected component is predicted by a linear probability model in which I regress the market power stock indicator on its lagged values in the prior three years as well as the prior-year firm characteristics of Panel A of Table 1 that have been shown to be related to product market competition, i.e., the logarithm of average *Firm size*, the logarithm of *Firm age*, the industry-adjusted *Book-to-market ratio*, the logarithm of average *Analyst coverage*, average *Quarterly turnover*, average quarterly *Amihud illiquidity*, and average quarterly *Idiosyncratic volatility*, and year fixed effects. The unexpected component is the regression residual. I then sort stocks into quintiles based on the unexpected component and define stocks in the top quintile as stocks with the highest unexpected market power probability in the next year. As the instrument, I choose the style-adjusted weight of a fund in such stocks four quarters before the quarter for which I calculate the Market Power Bet.

I argue that the bet on such stocks satisfies both the relevance and exclusion conditions for valid instruments. First, the relevance condition is likely satisfied because managers who bet more on stocks with a higher unexpected market power probability one year ago should experience a positive surprise on their current Market Power Bet considering these stocks are likely still part of their portfolio.[18] Therefore, I expect the instrument to have a significantly positive relation to *MPB*. Second, the unexpected component of whether a stock will be a market power stock in the following year was unknown to the manager when the portfolio decision was made. Given that fund performance depends on the manager's information set, it is unlikely that the instrument directly affects fund performance one year later. The influence on fund performance should rather result indirectly from its impact on *MPB*, satisfying the exclusion restriction.

The first two columns of Table 9 present the first-stage results of the 2SLS regression, while the last two columns report results for the second stage. For brevity, I only report second-stage results for Carhart (1997) 4-factor alphas as dependent variable, but the results are similar for DGTW-adjusted returns.

– Insert TABLE 9 approximately here –

Results from the first two colums of Table 9 show the expected positive impact (significant at the 1%-level) of a fund's portfolio bet four quarters ago in stocks with the highest unexpected market power probability on the current Market Power Bet and the high-*MPB* dummy. The high values for both the Kleibergen-Paap-Wald F-statistic and the partial R-squared further support the relevance condition. The results of the second-stage regression,

[18] Both Cremers and Pareek (2015) and Lan et al. (2019) show that mutual funds hold onto stocks for several quarters.

which include the instrumented *MPB* or the instrumented high-*MPB* dummy, confirm the main result from Table 3. The coefficients are both significant at the 1%-level and have a comparable economic significance as in the baseline regression of Table 3. This comparability of regression coefficients gives additional support for the quality of my IV estimation.

3.4.2. 9/11 terrorist attacks as exogenous shock to competition

As an additional exercise to address an omitted-variable bias, I use an exogenous shock to the military goods industry due to the 9/11 terrorist attacks. A positive demand shock in the defense industry after the attacks led to increases in competition as new firms entered the industry and existing firms changed their product offerings. Hoberg and Phillips (2016) find a higher product similarity and more direct rivals for military intelligence and battlefield firms as a result of the attacks. Due to the increase in competition, fund managers who place larger Market Power Bets should reduce their average position in military goods firms after the attacks and only hold onto those military firms that benefit from the positive demand shock and are more resilient against the sudden entry of new competitors. Therefore, I first expect a negative relation between changes in the portfolio weight of military goods firms and changes in the Market Power Bet around the attacks. Second, I expect that funds with a reduction in military weights, and a resultant higher Market Power Bet, to deliver a higher performance change around the event.

To implement this idea, I identify competitors that operate in the military goods industry in the year 2000 prior to the attack using the HP data.[19] For each fund, I calculate post-minus-pre-attack average weights in these military firms using quarterly portfolio weights in 2002 to represent the post-attack period and the year before 9/11 to represent the pre-attack period. I focus on funds that have positive weights in the industry before the attack to ensure that the fund is paying attention to industry developments. I further require funds

[19] I take General Dynamics as focal firm in the military industry and identify all its close rivals. For these rival firms, I search for additional competitors that are not already identified as a rival to General Dynamics. I repeat this step once again for the additional competitors to identify a broader range of firms operating in the military goods industry.

to hold a positive weight after the attack, but the results are robust to including funds that have completely eliminated these firms after the event. Similar to the *MPB*, I use peer-group adjusted average weights before and after the attack to control for style driven differences in the exposure to military firms. For the same period, I calculate post-minus-pre-attack differences in the average quarterly Market Power Bet and average quarterly fund performance. The first two columns of Panel A of Table 10 report the results from a cross-sectional regression in which I relate the *MPB* change around the event to the military weight difference and control for the same variables as before using average values in the four quarters before the attack and style fixed effects. In the last four columns, I then present results when I use the change in average quarterly fund performance as the dependent variable. I use both the continuous difference in military weights and an indicator variable that equals one if the fund has increased the weight in military firms in 2002 compared to the pre-attack period.

– Insert TABLE 10 approximately here –

As expected, the results from Panel A in Table 10 suggest a negative relation between changes in the Market Power Bet and changes in the weight of military goods firms. A higher weight on firms that experience exogenous increases in the number of competitors therefore results in a lower weight on market power stocks. Increasing the weight on such firms additionally results in a significantly lower change in average fund performance. For instance, funds that increase their peer-adjusted weight on military goods firms after the attack show a decrease in average quarterly Carhart (1997) 4-factor alpha by more than 59 basis points compared to funds with reductions in the military weight. This is a significant effect and unlikely to stem only from trading in the military goods industry but rather from reallocations in the whole portfolio. I argue that managers who decrease their military weight do not only keep the most promising competitors in the military goods industry. These managers are overall better at incorporating product market shocks and hence adjust their total portfolio according to this new information.

Panel B of Table 10 reports results when I extend the post-attack period to also include the year 2003, since Hoberg and Phillips (2016) show that the number of competitors and product similarity strongly increase until 2003 and slightly decrease afterwards. The results are robust to including the extended period.

The results from this section provide evidence that a positive shock to competition within an industry and a subsequent increase in the industry weight first yield the expected reductions in the Market Power Bet and, second, result in a significantly lower change in fund performance. This result strengthens a causal interpretation of the relation between fund performance and a fund's investment into firms with fewer competitors.

4. Determinants of *MPB*

If *MPB* signals variation in information processing, it should be related to fund manager characteristics. Fund managers likely learn to process qualitative information during their career. In addition, their job should allow them to put sufficient effort and attention into costly information acquisition. Finally, fund managers have different investment horizons for which industry dynamics likely matter. In this section, I conjecture that the Market Power Bet depends on manager experience, the effort that she devotes to managing the fund, as well as her investment horizon. To capture manager effort, I introduce a dummy variable equal to one if the fund's managers on average manage more than one fund (*Multi-funds manager*) and zero otherwise. Agarwal et al. (2018) find that managers divert their effort when managing multiple funds. If larger Market Power Bets require more effort in information production, as suggested by the previous performance results, then managers with multiple funds are less likely to overweight market power stocks.

In addition, more experienced fund managers should be better at processing information about a firm's product market due to its qualitative nature. Therefore, I predict the manager's investment experience to be positively related to the fund's Market Power Bet. As a proxy for investment experience, I use the maximum number of years working in the fund industry over all managers of the fund (*Manager tenure*).[20]

I use the number of fund managers as an additional determinant (*# Managers*). Larger teams can produce more information at the same time when each member evaluates a subset of stocks. The resultant higher attention on each firm should facilitate the incorporation of product market information into the stock selection. However, larger groups induce managers to free-ride on the effort of others and to engage less in information production (e.g., Patel and Sarkissian, 2017). Moreover, soft information leaves more room for disagreement among team members, suggesting that larger teams prefer to focus on hard information (Stein, 2002). It is hence an empirical question whether larger teams place larger Market Power Bets.

Lastly, market power stocks may allow to pursue costly long-term investment strategies as they generate more stable cash flows (e.g., Hoberg et al., 2014). In contrast, firms with less market power adapt their strategies more often due to a dynamic competitive environment. This situation leads to a more frequent updating of investors' expectations about the firm's future cash flows (e.g., Giannetti and Yu, 2020; Irvine and Pontiff, 2009). If this is the case, investors with a more long-term focus should be more attracted to stock with market power. I use the average fund duration measure of Cremers and Pareek (2015) in the last four quarters to proxy for the fund's investment horizon. Fund duration is the quarterly value-weighted average length of time that a fund held a stock in the portfolio over the last five years.

To test these hypotheses, I run pooled regressions in which I relate *MPB* to the mentioned determinants in the previous quarter, taking into account the same control variables as in Table 2, in addition to time and style fixed effects. Standard errors are clustered at the fund

[20] Manager tenure is measured as the difference in years between the current month and the manager's first appearance as a US domestic equity fund manager in the Morningstar Direct database.

level. Table 11 presents the results of this analysis.

– Insert TABLE 11 approximately here –

Based on the results in Table 11, I find support for the notion that time-varying manager characteristics matter for the propensity to invest into market power stocks. As hypothesized, managers who can devote more effort to information production, in addition to managers with more investment experience, place larger Market Power Bets. Funds managed by larger teams invest less in market power stocks, which is consistent with free-riding in information production and a preference for hard information in larger teams. With respect to investment horizon, I find support for the notion that funds which hold stocks for a longer period of time are associated with larger *MPB*.[21]

Given that high-*MPB* managers appreciate cash flow stability and are longer-term oriented, a natural question is whether their observed outperformance is particularly high during times of downward economic movement and whether the positive performance impact holds over longer horizons. Therefore, I first investigate whether the performance impact of the Market Power Bet depends on the state of the economy by interacting *MPB* with a recession indicator based on the three months moving average of the Chicago Fed National Activity Index (CFNAI). Consistent with the hypothesis, Panel A of Table A.6 of the Internet Appendix shows that the outperformance of high-*MPB* funds is significantly stronger in recession than in expansion periods, thereby supporting the stability argument. Panel B of Table A.6 further analyzes the performance over the next 12, 24, or 36 months. For brevity, I only report coefficients on the high-*MPB* dummy but the results also hold for the continuous variable. Results of Panel B show that the information advantage of of high-*MPB* funds indeed materializes over longer horizons.

[21] This result admittedly raises the concern that the Market Power Bet is just an alternative proxy for the fund's investment horizon. Since Lan et al. (2019) show that long-horizon funds outperform, the previously established outperformance of high-*MPB* funds could just stem from their long-term investment approach. However, in unreported tests, I add the fund's average duration as a control variable in the regression of Table 3 and still find a significant and positive impact of *MPB* on fund performance.

With respect to the remaining fund control variables, only the fund's turnover ratio and family size have a consistent relation with the *MPB*, also in combination with the results of Panel C of Table 1. The negative impact of the turnover ratio is in line with the cash flow stability and fewer industry dynamics of market power stocks resulting in less rebalancing needs. Interestingly, funds from smaller families are more likely to invest into firms with market power. A possible interpretation of this relation is that smaller fund families will find it more difficult to engage in corporate governance and coordinative actions when investing in same-industry and competing firms and, therefore, might have a preference for firms with less competitors (e.g., Boller and Scott Morton, 2020).

Taken together, results from this section provide evidence that differences in information-processing and long-term orientation explain cross-sectional differences in Market Power Bets. The results are also consistent with the equilibrium model of Grossman and Stiglitz (1980), in which investors who invest more effort in costly information production are rewarded with higher returns.

5. *MPB* and investment behavior

To better understand why fund managers invest more into market power firms when incorporating product market information and to identify potential channels for the observed outperformance, I analyze whether and how Market Power Bets are associated with illiquid investing, better information about innovation abilities and technological uniqueness, and within-portfolio competition.

First, the cash flow stability and resultant lower trading frequency should allow the fund manager to invest more expensively, i.e., in more illiquid assets to earn an illiquidity premium (e.g., Amihud et al., 2005). I test this hypothesis by calculating the fund's portfolio liquidity following Massa and Phalippou (2005) as the value-weighted average stock liquidity measure (*Portfolio liquidity*). I estimate pooled regressions in which the dependent variable is the fund's *Portfolio liquidity* in quarter t. The key independent variable is *MPB* or the *MPB* dummy in quarter t-1. I control for the same control variables as in Table 2 and include time and style fixed effects, while standard errors are clustered at the fund level. The regression results are summarized in the first two columns in Panel A of Table 12.

– Insert TABLE 12 approximately here –

As expected, funds with larger *MPB* have a significantly lower portfolio liquidity. The difference is almost 0.42 between high- and low-*MPB* funds which represents about 5.8 percent of the *Portfolio liquidity* of low-*MPB* funds (7.19). However, the more illiquid investment strategy does not fully explain the superior performance of funds with larger *MPB*, as indicated by results of Panel D of Table 6 and a significantly positive coefficient for the Pástor and Stambaugh (2003) 5-factor alpha in Table A.1 in the Internet Appendix.

Second, both Hirshleifer et al. (2018) and Cohen et al. (2013) argue that the innovative activities of a company are difficult to assess. Yet, innovation is a costly effort for firms to obtain a long-term competitive advantage (e.g., Porter, 1985). If high-*MPB* funds are better to assess competition, and specifically to assess how sustainable a competitive advantage is, then this information advantage might stem from a better evaluation of a firm's ability to innovate and a superior understanding of how unique its technologies are. I take this idea to the data by first calculating a firm's innovative ability as in Cohen et al. (2013). For each firm and year, I take the average of five regression coefficients from rolling regressions over the past eight years, in which I relate sales growth to R&D expenses (scaled by sales) in each of the previous five years respectively. A higher value of this measure captures a higher ability to translate R&D activities into sales. I then take the value-weighted average of the firms' ability measures in a fund portfolio to calculate the *Innovative ability*. Second, I calculate a firm's technological proximity to the rest of the economy following Li et al. (2019), which is the cosine similarity between a firm's patent output (number of patents across technology classes) with the patent output of other publicly-listed firms. As with

Innovative ability, I calculate the value-weighted technological proximity of the firms in the fund portfolio (*Technological proximity*). I run a similar regression to the first four columns of Panel A but with *Innovative ability* or *Technological proximity* as dependent variable. The last four columns of Panel A in Table 12 report the results.

I find clear evidence for the hypothesis that funds with larger Market Power Bets pick firms with a better track record to turn R&D expenses into sales as well as firms with a more unique patent output. The average ability measure in a high-*MPB* fund portfolio is higher by approximately 0.35, which is approximately 16% of the average ability in a low-*MPB* fund portfolio (2.23). The average technological proximity of high-*MPB* funds is lower by approximately 0.0129 which is more than 8% of the average proximity in portfolios of low-*MPB* funds. In unreported tests, I replace the dependent variable with the value-weighted R&D expenses of the firms in the portfolio. Interestingly, I find that funds with higher *MPB* invest in firms with less R&D. This result suggests that high-*MPB* fund managers do not believe that all R&D is value-renhancing and focus on the quality of innovation rather than on its level.

Finally, fund managers likely invest in market power stocks to avoid within-portfolio competition. If this were the case, we would expect managers with larger Market Power Bets to hold fewer rival firms at the same time. Consequently, even in more competitive markets, the manager should only choose a few out of multiple rival firms. To test this hypothesis, I calculate for each fund and stock the number of direct competitors currently held by the fund in the quarter. To avoid a mechanical relation, I limit the analysis to stocks in the non-market power subportfolio. I aggregate the number of concurrently held competitors at the fund level by value-weighting over all stocks in the subportfolio. Similar to the calculation of the Market Power Bet, I use a style-adjusted version of this measure. I regress the value-weighted number of competitors held on the *MPB* measure or the *MPB* dummy and the same control variables as in Panel A of Table 12, in addition to style and time fixed effects. Standard errors are clustered at the fund level. The results are summarized in the first two columns of Panel B of Table 12. In the last two columns of Panel B, I repeat the analysis but use the trade size-weighted number of direct competitors that are bought at the same time by the fund as dependent variable.

The results presented in Panel B of Table 12 show that funds with larger Market Power Bets hold and buy a significantly lower number of direct competitors at the same time. The effect is statistically significant at the 1% level and is also economically meaningful. Low-*MPB* funds have an average peer-adjusted number of rivals concurrently held of 0.14 and thus on average hold more in close rivals than peer funds. In contrast, the peer-adjusted number of close rivals concurrently held is approximately 0.40 lower for high-*MPB* funds, as shown in the second column of Panel B. Hence, these funds on average hold less in close rival firms than peer funds.

In sum, the results from this section suggest that fund managers exploit the market power of companies for their investment strategies, which should contribute to the outperformance of high-*MPB* funds. In particular, a higher fraction of market power stocks signals profitable trading behavior, such as investments in illiquid stocks. The results also provide evidence for a potential source of the superior interpretation of competition in that funds with higher *MPB* are able to identify the quality and potential sustainability of innovations. Finally, market power stocks are heavily used by funds that prefer to invest in single competitors rather than in several rivals at the same time, which corroborates the idea that they are better able to identify the most promising competitor and to diversify more across product markets.

6. Summary and conclusion

Processing qualitative information is challenging and costly, thereby making it particularly valuable for investors with superior skills and the willingness to put more effort in information production. A firm's product market competition is an important example for this type of information because it is neither easy to observe nor easy to interpret. The emerging common ownership highlights the importance of product market competition for asset pricing and corporate behavior, but remains relatively silent on the incentives and abilities of the individual fund manager to take competition into account when selecting stocks.

To analyze how and why fund managers incorporate industrial organization into their stock selection, I develop the Market Power Bet. *MPB* is a simple measure to differentiate managers by their ability and effort to process information about a firm's market power. Mutual fund managers with larger *MPB* exhibit a superior performance. Several exercises show that this result cannot be explained by fund managers' preferences for other firm characteristics related to the competitive position, by a general outperformance of firms with market power, or by different opportunities to exploit mispricing. Furthermore, my tests based on instrumental variable regressions and an exogenous shock to competition in the military goods industry suggest a causal interpretation of the link between a fund's propensity to overweight market power firms and its performance.

Consistent with differences in information-processing, I further provide evidence that the tendency to invest in market power firms is likely a time-varying manager attribute and strongly depends on their investment experience and effort. Fund managers with a longer investment horizon also invest more into market power stocks.

As expected, managers with larger *MPB* avoid concurrent investment in close rivals and exploit the market power property of the firms for illiquid investment strategies that have been shown to affect performance in a positive way. Finally, they are able to identify companies that are more successful in translating R&D into sales and companies with a more unique patent strategy.

Taken altogether, it appears that market power is not fully taken into account by all market participants. Professional investors with a superior information production can extract valuable information from a firm's competitive position and utilize this hard-to-process information to gain an advantage over their peers.

References

Agarwal, V., Ma, L., Mullally, K., 2018. Managerial multitasking in the mutual fund industry. Unpublished working paper. Georgia State University, Peking University HSBC Business School, and University of Central Florida.

Aguerrevere, F. L., 2009. Real options, product market competition, and asset returns. Journal of Finance 64, 957–983.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amihud, Y., Mendelson, H., Pedersen, L. H., 2005. Liquidity and asset pricing. Foundations and Trends in Finance 1, 269–364.

Azar, J., Schmalz, M. C., Tecu, I., 2018. Anticompetitive effects of common ownership. Journal of Finance 73, 1513–1565.

Barras, L., Scaillet, O., Wermers, R., 2010. False discoveries in mutual fund performance: Measuring luck in estimate alphas. Journal of Finance 65, 179–216.

Bena, J., Li, K., 2014. Corporate innovations and mergers and acquisitions. Journal of Finance 69, 1923–1960.

Berk, J. B., Green, R. C., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269–1295.

Bhojraj, S., Cho, Y. J., Yehuda, N., 2012. Mutual fund family size and mutual fund performance: The role of regulatory changes. Journal of Accounting Research 50, 647–684.

Boller, L., Scott Morton, F., 2020. Testing the theory of common stock ownership. Unpublished working paper. Duke University and Yale University.

Brown, A., 2012. Berkshire follower? Try these 5 Buffett wannabe mutual funds. Forbes, May 16th .

Burton, J., 2012. Follow the buffett strategy. The Wall Street Journal, August 2nd .

Bustamante, M. C., Donangelo, A., 2017. Product market competition and industry returns. Review of Financial Studies 30, 4216–4266.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chen, H.-L., Jegadeesh, N., Wermers, R., 2000. The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. Journal of Financial and Quantitative Analysis 25, 343–368.

Chuprinin, O., Gaspar, S., Massa, M., 2019. Adjusting to the information environment: News tangibility and mutual fund performance. Management Science 65, 1430–1453.

Cici, G., Gehde-Trapp, M., Göricke, M.-A., Kempf, A., 2018. The investment value of fund managers' experience outside the financial sector. Review of Financial Studies 31, 3821–3853.

Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. Review of Financial Studies 26, 635–666.

Cohen, L., Lou, D., 2012. Complicated firms. Journal of Financial Economics 104, 383–400.

Cohen, R. B., Coval, J. D., Pástor, L., 2005. Judging fund managers by the company they keep. Journal of Finance 60, 1057–1096.

Coval, J. D., Moskowitz, T. J., 2001. The geography of investment: Informed trading and asset prices. Journal of Political Economy 109, 811–841.

Cremers, M., Pareek, A., 2015. Short-term trading and stock return anomalies: Momentum, reversal, and share issuance. Review of Finance 19, 1649–1701.

Cremers, M., Petajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. Review of Financial Studies 22, 3329–3365.

Cremers, M., Petajisto, A., Zitzewitz, E., 2012. Should benchmark indices have alpha? Revisiting performance evaluation. Critical Finance Review 2, 1–48.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035–1058.

Datta, S., Iskandar-Datta, M., Sharma, V., 2011. Product market pricing power, industry concentration and analysts' earnings forecasts. Journal of Banking and Finance 35, 1352–1366.

Doshi, H., Elkamhi, R., Simutin, M., 2015. Managerial activeness and mutual fund performance. Review of Asset Pricing Studies 5, 156–184.

Evans, R. B., 2010. Mutual fund incubation. Journal of Finance 65, 1581–1611.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fang, L. H., Peress, J., Zheng, L., 2014. Does media coverage of stocks affect mutual funds' trading and performance? Review of Financial Studies 27, 3441–3466.

Foucault, T., Frésard, L., 2019. Corporate strategy, conformism, and the stock market. Review of Financial Studies 32, 905–950.

Gargano, A., Rossi, A. G., Wermers, R., 2017. The freedom of information act and the race toward information acquisition. Review of Financial Studies, 30, 2179–2228.

Gaspar, J.-M., Massa, M., 2006. Idiosyncratic volatility and product market competition. Journal of Business 79, 3125–3152.

Giannetti, M., Kahraman, B., 2018. Open-end organizational structures and limits to arbitrage. Review of Financial Studies 31, 773–810.

Giannetti, M., Yu, X., 2020. Adapting to radical change: The benefits of short-horizon investors. Management Science forthcoming.

Giroud, X., Mueller, H. M., 2011. Corporate governance, product market competition, and equity prices. Journal of Finance 66, 563–600.

Grossman, S. J., Stiglitz, J. E., 1980. On the impossibility of informationally efficient markets. Americian Economic Review 70, 393–408.

Gu, L., 2016. Product market competition, R&D investment, and stock returns. Journal of Financial Economics 119, 441–455.

Hansen, R. G., Lott, J. R., 1996. Externalities and corporate objectives in a world with diversified shareholder/consumers. Journal of Financial and Quantitative Analysis 31, 43–68.

He, J. J., Huang, J., 2017. Product market competition in a world of cross-ownership: Evidence from institutional blockholdings. Review of Financial Studies 30, 2674–2718.

Hirshleifer, D., Hsu, P.-H., Li, D., 2018. Innovative originality, profitability, and stock returns. Review of Financial Studies 31, 2553–2605.

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

Hoberg, G., Phillips, G., 2010b. Real and financial industry booms and busts. Journal of Finance 65, 45–86.

Hoberg, G., Phillips, G., 2014. Product market uniqueness, organizational form and stock market valuations. Unpublished working paper. University of Southern California and Dartmouth College.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. Journal of Political Economy 124, 1423–1465.

Hoberg, G., Phillips, G., Prabhala, N., 2014. Product market threats, payouts, and financial flexibility. Journal of Finance 69, 293–324.

Holmstrom, B., 1982. Moral hazard in teams. Bell Journal of Economics 13, 324–340.

Hou, K., Robinson, D. T., 2006. Industry concentration and average stock returns. Journal of Finance 61, 1927–1956.

Hough, J., 2013. Top-rated ”wide-moat” stocks. Barron’s, January 17th .

Hsu, C., Li, X., Ma, Z., Phillips, G., 2019. Product market competition and analyst coverage decisions. Unpublished working paper. HKUST, University of Arkansas, Peking University, and Dartmouth College.

Huang, L., Kale, J. R., 2013. Product market linkages, manager quality, and mutual fund performance. Review of Finance 17, 1895–1946.

Indjejikian, R. J., 1991. The impact of costly information interpretation on firm disclosure decisions. Journal of Accounting Research 29, 277–301.

Investment Company Institute, 2018. Investment company fact book 2018. Investment Company Institute Research Series .

Irvine, P. J., Pontiff, J., 2009. Idiosyncratic return volatility, cash flows, and product market competition. Review of Financial Studies 22, 1149–1177.

Jensen, M. C., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389–416.

Kacperczyk, M., Sialm, C., Zheng, L., 2005. On the industry concentration of actively managed equity mutual funds. Journal of Finance 60, 1983–2011.

Kacperczyk, M., Van Nieuwerburgh, S., Veldkamp, L., 2014. Time-varying fund manager skill. Journal of Finance 69, 1455–1484.

Kandel, E., Pearson, N. D., 1995. Differential interpretation of public signals and trade in speculative markets. Journal of Political Economy 103, 831–872.

Kim, O., Verrecchia, R. E., 1994. Market liquidity and volume around earnings announcements. Journal of Accounting and Economics 17, 41–67.

Lan, C., Moneta, F., Wermers, R., 2019. Holding horizon: A new measure of active investment management. Unpublished working paper. UNSW Business School, Queen's University, and University of Maryland.

Li, F., Lundholm, R., Minnis, M., 2013. A measure of competition based on 10-K filings. Journal of Accounting Research 51, 399–436.

Li, K., Qiu, J., Wang, J., 2019. Technology conglomeration, strategic alliances, and corporate innovation. Management Science 65, 5065–5090.

Litov, L. P., Moreton, P., Zenger, T. R., 2012. Corporate strategy, analyst coverage, and the uniqueness paradox. Management Science 58, 1797–1815.

Massa, M., Phalippou, L., 2005. Mutual funds and the market for liquidity. Unpublished working paper. University of Oxford and INSEAD.

O'Brien, P. C., Bhushan, R., 1990. Analyst following and institutional ownership. Journal of Accounting Research 28, 55–76.

Pástor, L., Stambaugh, R. F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642–685.

Patel, S., Sarkissian, S., 2017. To group or not to group? Evidence from mutual fund databases. Journal of Financial and Quantitative Analysis 52, 1989–2021.

Pool, V. K., Stoffman, N., Yonker, S. E., 2015. The people in your neighborhood: Social interactions and mutual fund portfolios. Journal of Finance 70, 2679–2732.

Porter, M. E., 1985. Technology and competitive advantage. Journal of Business Strategy 5, 60–78.

Raith, M., 2003. Competition, risk, and managerial incentives. American Economic Review 93, 1425–1436.

Shekita, N., 2020. Interventions by common owners. Unpublished working paper. Yale School of Management.

Sirri, E. R., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589–1622.

Stein, J. C., 2002. Information production and capital allocation: Decentralized versus hierarchical firms. Journal of Finance 57, 1891–1921.

Zhang, R., 2018. Product market competition, competitive strategy, and analyst coverage. Review of Quantitative Finance and Accounting 50, 239–260.

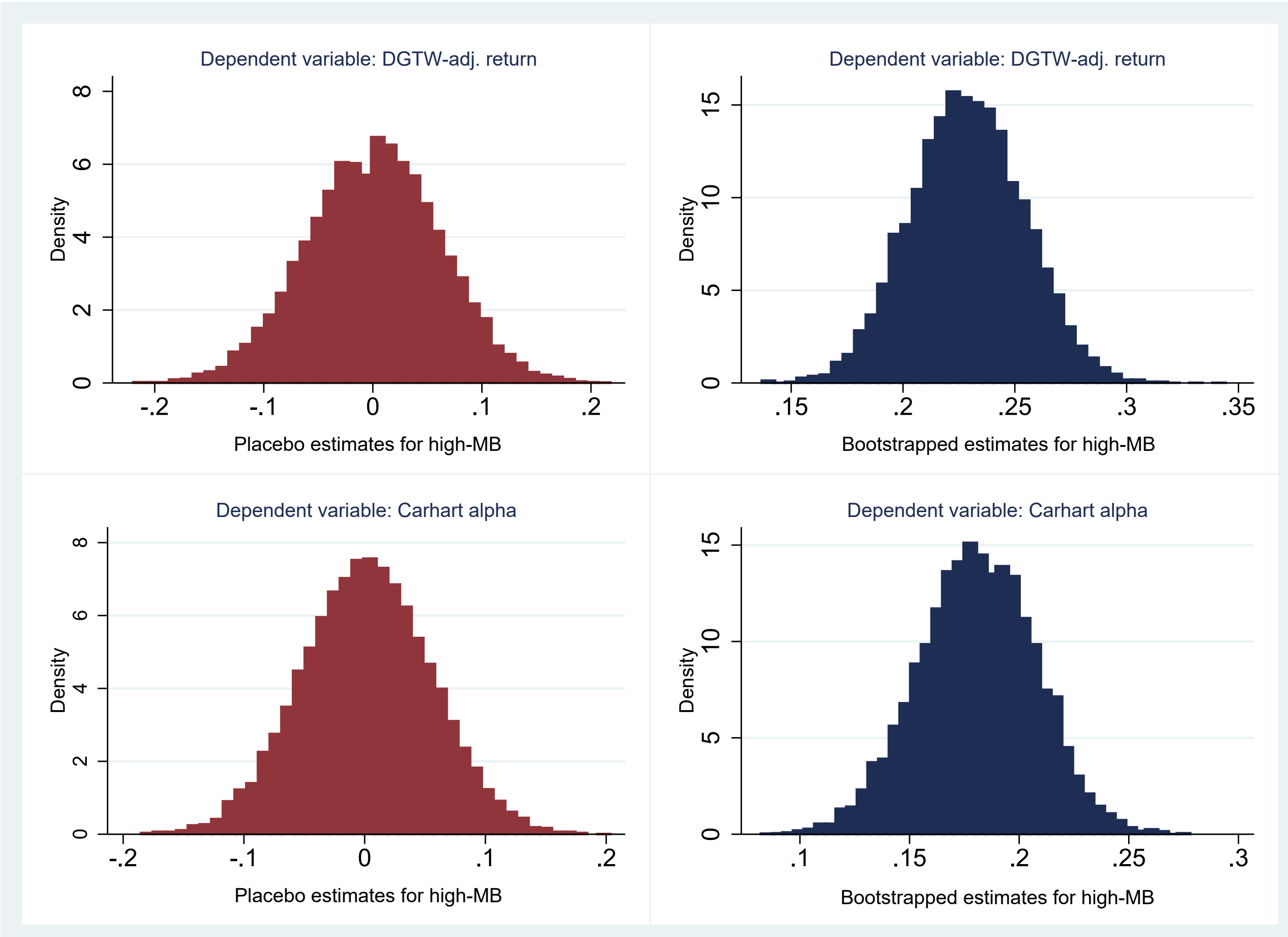

Figure 1.
Placebo assignment of market power status.
This figure presents histograms of the 10,000 estimated coefficients for the high-*MPB* dummy using the specifications of Table 3. The left panels (in red) present the distributions of the coefficients when randomly assigning the market power status. In each round, I randomly select 20 percent of the stocks in a given year as market power stocks and calculate the Market Power Bet as before using these random market power stocks. I then re-run the baseline regression of Table 3 with the new measure. This procedure is repeated 10,000 times. The right panels (in blue) present the distribution of 10,000 coefficients from a bootstrap procedure in which I resample the original sample (i.e. with the original *MPB* and *MPB* dummy) with replacement and re-run the baseline regression.

Table 1. Sample characteristics

Panel A: Stock characteristics

	All (N=9,212)	Market power	Non-market power	Diff.	
Number of competitors	132.74	5.62	165.58	-159.95	***
Product market fluidity	7.56	5.02	8.21	-3.19	***
Firm size	2,880	2,175	3,061	-887	***
Firm age	15.18	17.41	14.61	2.80	***
Book-to-market ratio	0.82	0.88	0.80	0.08	***
Quarterly turnover (*100)	0.77	0.65	0.80	-0.15	***
Amihud illiquidity	8.92	13.38	7.77	5.61	***
Idiosyncratic volatility	0.22	0.23	0.22	0.01	***
Analyst coverage	5.04	3.89	5.29	-1.40	***
Annual return (%)	12.09	11.86	12.15	-0.29	

Panel B: Portfolio weights in market power stocks

	Mean	SD	p10	p50	p90	Serial correlation (1 year)
Market Power Weight (%)	16.66	7.68	7.85	15.99	26.22	0.64
Market Power Bet (*MPB*, %)	0.01	6.78	-7.34	-0.70	8.08	0.59

Panel C: Fund characteristics

	All (N=2,561)	High-*MPB*	Low-*MPB*	Difference	
Fund size	1,353	1,180	1,526	-346	***
Fund age	14.81	14.68	14.95	-0.27	***
Turnover ratio (%)	87.09	79.20	95.02	-15.82	***
Expense ratio (%)	1.30	1.31	1.29	0.02	**
Fund flows (%)	2.24	2.71	1.76	0.95	***
Number of stocks	111.68	114.17	109.18	4.99	***
Family size	23,961	21,775	26,166	-4,391	***
Raw return (%)	3.72	4.47	2.98	1.49	***
DGTW-adjusted return (%)	0.19	0.64	-0.27	0.91	***
Carhart alpha (%), gross	0.23	0.62	-0.16	0.78	***

This table reports summary statistics. Panel A reports annual characteristics for the total stock sample as well as separately for market power and non-market power stocks between 1999 and 2012. market power stocks are stocks in the bottom quintile based on the annual number of competitors. The last column reports differences in mean stock characteristics for market power and non-market power stocks. *Number of competitors* is the number of direct rival firms (based on pairwise similarity scores of 10-K product descriptions) according to the Text-based Network Industry Classification (TNIC) in Hoberg and Phillips (2016). *Product market fluidity* measures competitive threats (Hoberg et al., 2014). *Firm size* is the average monthly market capitalization of the firm in a year in millions of dollars. *Firm age* is the difference in years between the current year and the first CRSP listing date. *Book-to-market ratio* is the ratio of book value of shareholder equity and market capitalization of equity. *Quarterly stock turnover* is the average quarterly turnover ratio of a stock in a year with turnover defined as the daily number of shares traded divided by total shares outstanding. *Amihud illiquidity* is the average quarterly stock illiquidity based on a daily Amihud (2002) illiquidity measure. *Idiosyncratic volatility* is the stock's unsystematic risk in a year. It is the average quarterly standard deviation of the residuals from a Carhart (1997) 4-factor model estimated using daily stock returns within a quarter. *Analyst coverage* is the average number of analysts in a year who issue a forecast for the firm's quarterly earnings. *Annual return* is the annual stock return. Returns are winsorized at the 1st and 99th percentiles. Panel B reports the sample distribution for the value-weighted fraction of market power stocks in the fund portfolios (*Market Power Weight*) and for the main variable of interest, the *Market Power Bet* (*MPB*), which is the peer group-adjusted *Market Power Weight*. The last column presents the correlation of the two measures with the fund's respective values one year before. Panel C presents quarterly summary statistics at the fund level for the total sample as well as for high- and low-*MPB* funds with high-*MPB* funds defined as funds with an *MPB* above the median in the respective quarter. The last column reports differences in fund characteristics between high- and low-*MB* funds. *Fund size* is total net assets under management in millions of dollars. *Fund age* is shown in years. *Family size* is total net assets under management of the fund family in millions of dollars. *Turnover ratio* is fund turnover, defined as the minimum of security purchases and sales divided by the average total net assets under management during the calendar year. *Expense ratio* is annual fees charged for total services. *Fund flows* are estimated as the fund's percentage growth rate over a quarter adjusted for the internal growth of the fund as in Sirri and Tufano (1998). *Number of stocks* is the number of distinct stocks held by the fund. *Raw return* is the (annualized) quarterly gross-of-fee fund return. *DGTW-adjusted return* is the (annualized) value-weighted characteristic adjusted quarterly return as in Daniel et al. (1997). *Carhart alpha* is the (annualized) quarterly Carhart (1997) 4-factor alpha based on gross-of-fee returns. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 2. *MPB* and a fund's reaction to product market dynamics

Panel A: Reliance on changes in product market competition

Dependent variable:	RPMC			
Market Power Bet (MPB)	0.0478	***		
	(0.0000)			
High *MPB*			0.0039	***
			(0.0000)	
Fund size	0.0006	**	0.0006	*
	(0.0500)		(0.0561)	
Fund age	-0.0009		-0.0009	
	(0.1790)		(0.1659)	
Turnover ratio	-0.0040	***	-0.0042	***
	(0.0000)		(0.0000)	
Expense ratio	0.0057		0.0106	
	(0.8246)		(0.6621)	
Fund flows	0.0027		0.0026	
	(0.1161)		(0.1260)	
Number of stocks	-0.0243	***	-0.0244	***
	(0.0000)		(0.0000)	
Family size	-0.0005	***	-0.0005	***
	(0.0017)		(0.0010)	
Time- and style fixed effects	Yes		Yes	
Number of Observations	13,055		13,055	
Adj. R-Squared	0.1360		0.1347	

Panel B: Reaction to rival mergers and acquisitions

Dependent variable:	Portfolio weight increase			
Market Power Bet (MPB)	0.1195	***		
	(0.0084)			
High *MPB*			0.0105	**
			(0.0299)	
Fund size	-0.0001		-0.0001	
	(0.9169)		(0.9213)	
Fund age	-0.0253	***	-0.0253	***
	(0.0000)		(0.0000)	
Turnover ratio	0.0307	***	0.0304	***
	(0.0000)		(0.0000)	
Expense ratio	-1.5045	***	-1.4981	***
	(0.0011)		(0.0011)	
Fund flows	0.0547	***	0.0546	***
	(0.0000)		(0.0000)	
Number of stocks	-0.0223	***	-0.0225	***
	(0.0000)		(0.0000)	
Family size	0.0019	***	0.0018	**
	(0.0095)		(0.0130)	
Stock-time fixed effects	Yes		Yes	
Style fixed effects	Yes		Yes	
Number of Observations	61,563		61,563	
Adj. R-Squared	0.1425		0.1424	

This table presents results from pooled OLS regressions on the relation between the Market Power Bet and the reaction to changes in competition. In Panel A, the dependent variable is *RPMC*, the R^2 from the regression of absolute residual holdings changes of a fund in a given (non-market power) stock on abolute changes in the number of competitors of the stock in the previous two years. To obtain residual changes, the annual holdings changes are first regressed on analyst recommendations and annual returns in the previous two years and the average holdings change within the investment style in the current year. The main independent variables are the fund's Market Power Bet (*MPB*) and the high-*MPB* dummy, defined as in Table 1. Additional independent controls include fund size, fund age, turnover ratio, expense ratio, fund flows, number of stocks, and family size. *Fund size* is the logarithm of total net assets under management in millions of dollars and *Fund age* is the logarithm of a fund's age in years. *Turnover ratio* is fund turnover, defined as the minimum of security purchases and sales divided by the average total net assets under management during the calendar year. *Expense ratio* is funds' annual fees charged for total services. *Fund flows* are estimated as the fund's percentage growth rate over a quarter adjusted for the internal growth of the fund as in Sirri and Tufano (1998). *Number of stocks* is the logarithm of the number of distinct stocks held by the fund. *Family size* is the logarithm of total net assets under management of the fund family in millions of dollars. All independent variables are valid at the beginning of the year, for which I calculate *RPMC*. Regressions are run with time and style fixed effects. In Panel B, the dependent variable is an indicator variable equal to one if the fund has increased the average portfolio weight in the acquiring firm's stock around the announcement of a rival takeover. Rivals are identified using TNIC data in the year preceding the announcement. To identify changes in portfolio weights, I compare the average weight in the four quarters after the announcement date with the portfolio weight in the acquiring firm in the quarter preceding the announcement. Only acquirers that do belong to the non-market power stock group before the event are considered. Independent variables are the same as in Panel A, but now valid as of the end of the quarter preceding the announcement date. Regressions are run with stock-time and style fixed effects. p-values in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 3. Market Power Bet and fund performance

	Fund performance							
Dependent variable:	DGTW-adj. return				Carhart alpha			
Market Power Bet (MPB)	1.7509	***			1.0574	***		
	(0.0000)				(0.0004)			
High *MPB*			0.2286	***			0.1807	***
			(0.0000)				(0.0000)	
Fund size	-0.0513	***	-0.0506	***	-0.0217	*	-0.0209	*
	(0.0000)		(0.0000)		(0.0519)		(0.0608)	
Fund age	0.0902	***	0.0894	***	0.0452	*	0.0449	*
	(0.0002)		(0.0002)		(0.0646)		(0.0659)	
Turnover ratio	-0.1081	***	-0.1120	***	-0.1052	***	-0.1043	***
	(0.0000)		(0.0000)		(0.0005)		(0.0005)	
Fund flows	0.0773		0.0798		-0.1238	*	-0.1234	*
	(0.3072)		(0.2935)		(0.0793)		(0.0799)	
Number of stocks	0.0031		-0.0068		0.0070		0.0005	
	(0.8765)		(0.7345)		(0.7447)		(0.9822)	
Family size	0.0051		0.0034		0.0086		0.0081	
	(0.3040)		(0.4799)		(0.1166)		(0.1351)	
Time fixed effects	Yes		Yes		Yes		Yes	
Style fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	65,465		65,465		63,950		63,950	
Adj. R-Squared	0.1322		0.1322		0.0767		0.0769	

This table presents results from pooled OLS regressions on the relation of quarterly mutual fund performance and the lagged fund Market Power Bet *(MPB)* using either DGTW-adjusted returns or Carhart (1997) 4-factor alphas. The performance measures are based on gross-of-fee returns and are presented in percent. The main independent variable is the fund's Market Power Bet (*MPB*). I run separate regressions for the continuous variable as well as the *MPB* dummy, which is equal to one if the fund's *MPB* is above the median in a given quarter and zero otherwise. Additional independent controls include *Fund size, Fund age, Turnover ratio, Fund flows, Number of stocks,* and *Family size*, all defined as in Table 2. All independent variables are valid as of the end of the quarter preceding the fund performance calculation. Regressions are run with time and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 4. Trade performance in market power stocks

Panel A: Performance of market power buys

Dependent variable:	Buy performance: DGTW-adj. return				Buy performance: Carhart alpha			
Market Power Bet (MPB)	2.3871	***			1.5400	*		
	(0.0020)				(0.0796)			
High *MPB*			0.3016	***			0.2078	**
			(0.0005)				(0.0337)	
Fund size	-0.0249		-0.0234		0.0132		0.0143	
	(0.4136)		(0.4434)		(0.7084)		(0.6851)	
Fund age	-0.0099		-0.0121		-0.0208		-0.0223	
	(0.8862)		(0.8612)		(0.7893)		(0.7753)	
Turnover ratio	-0.0947		-0.0998		-0.2105	***	-0.2127	***
	(0.1672)		(0.1433)		(0.0050)		(0.0047)	
Fund flows	0.2175	*	0.2195	*	0.0152		0.0166	
	(0.0610)		(0.0589)		(0.9036)		(0.8946)	
Number of stocks	-0.0387		-0.0577		-0.1573	**	-0.1694	***
	(0.5025)		(0.3125)		(0.0162)		(0.0095)	
Family size	-0.0050		-0.0076		0.0037		0.0022	
	(0.7570)		(0.6396)		(0.8459)		(0.9073)	
Time and style fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	58,331		58,331		58,192		58,192	
Adj. R-Squared	0.0252		0.0252		0.0272		0.0272	

Panel B: Performance relative to a firm's rivals

Dependent variable:	Buy performance difference: Diff. DGTW-adj. Return				Buy performance difference: Diff. Carhart alpha			
Market Power Bet (MPB)	1.8964	**			1.3969			
	(0.0214)				(0.1333)			
High *MPB*			0.2602	***			0.2007	*
			(0.0055)				(0.0627)	
Controls	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	
Style fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	58,270		58,270		58,025		58,025	
Adj. R-Squared	0.0204		0.0204		0.0340		0.0340	

Panel C: Performance relative to market power sells

	Trade (buy minus sell) performance					
Dependent variable:	Diff. DGTW-adj. return			Diff. Carhart alpha		
Market Power Bet (MPB)	1.6530			3.1697	**		
	(0.1415)			(0.0126)		
High *MPB*		0.2569	**		0.3497	**
		(0.0389)			(0.0132)	
Controls	Yes	Yes		Yes	Yes	
Time fixed effects	Yes	Yes		Yes	Yes	
Style fixed effects	Yes	Yes		Yes	Yes	
Number of Observations	53,095	53,095		52,917	52,917	
Adj. R-Squared	0.0204	0.0016		0.0033	0.0033	

This table presents results from pooled OLS regressions on the relation of quarterly performance of buy subportfolios in market power stocks and the lagged Market Power Bet (*MPB*). market power stocks are defined as stocks in the bottom quintile according to the annual number of competitors. In Panel A, the dependent variable is the next-quarter performance of a subportfolio consisting of a fund's stock purchases in a given quarter. I define a purchase as an increase in the number of shares held by a fund in a stock between two consecutive reporting dates. Subportfolio performance is measured using DGTW-adjusted returns and Carhart (1997) 4-factor alphas of the stocks. The performance is presented in percent. I value-weight the performance of stocks making up each subportfolio by the dollar value of the trade (stock price times the number of shares bought or sold of a given stock). In Panel B, the dependent variable is the performance difference between the buy subportfolio of Panel A and a hypothetical portfolio in which the dollar value spent for the actual purchase is equally split over the stock's rival firms as identified in the TNIC data. In Panel C, the dependent variable is the performance difference between the buy subportfolio of Panel A and the sell subportfolio of the fund in the same quarter, i.e. the next-quarter performance of the fund's sells in a given quarter, defined as decreases in the number of shares held. The main independent variable in all three panels is the fund's Market Power Bet (*MPB*). I run separate regressions for the continuous variable as well as the *MPB* dummy, which is equal to one if the fund's *MPB* is above the median in a given quarter and zero otherwise. Additional independent controls are as in Table 3 and suppressed in Panels B and C of the table. The independent variables are valid at the end of the quarter preceding the subportfolio performance calculation. Regressions are run with time and style fixed effects and standard errors are clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 6. Robustness and alternative explanations

Panel A: Matched sample

	DGTW-adj. return				Carhart alpha			
	ATE		ATET		ATE		ATET	
High *MPB*	0.2022	***	0.2265	***	0.1477	***	0.1247	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	

Panel B: Alternative proxies

	DGTW-adj. return		Carhart alpha	
Overweighting market power firms	0.2306	***	0.1801	***
	(0.0000)		(0.0000)	
High competition bet	-0.3479	***	-0.2721	***
	(0.0000)		(0.0000)	
High *MPB* - fluidity	0.3462	***	0.1328	***
	(0.0000)		(0.0000)	
High *MPB* - Fitted SIC-based HHI	0.3099	***	0.1331	***
	(0.0000)		(0.0020)	
High *MPB* - TNIC HHI	0.1234	***	0.1473	***
	(0.0000)		(0.0000)	
High *MPB* - 10-K	0.3682	***	0.0921	***
	(0.0000)		(0.0000)	
High *MPB* - technological proximity	0.0666	**	0.1168	***
	(0.0257)		(0.0002)	
High *MPB* - FFI48	0.2527	***	0.1126	***
	(0.0000)		(0.0000)	

Panel C: Residual *MPB* adjusted for skill measures

	DGTW-adj. return		Carhart alpha	
Skill measure				
ICI	0.2187	***	0.1701	***
	(0.0000)		(0.0000)	
Active Share	0.2555	***	0.1383	***
	(0.0000)		(0.0001)	
ICI + Active Share	0.1885	***	0.0930	***
	(0.0000)		(0.0088)	

Panel D: Residual *MPB* adjusted for bets on other firm characteristics

	DGTW-adj. return		Carhart alpha	
Firm characteristic (quintile)				
Lowest size	0.2453	***	0.1878	***
	(0.0000)		(0.0000)	
Highest age	0.2290	***	0.1824	***
	(0.0000)		(0.0000)	
Highest book-to-market ratio	0.2403	***	0.1851	***
	(0.0000)		(0.0000)	
Lowest turnover	0.2262	***	0.1603	***
	(0.0000)		(0.0000)	
Highest illiquidity	0.2361	***	0.1845	***
	(0.0000)		(0.0000)	
Highest idiosyncratic volatility	0.2381	***	0.1847	***
	(0.0000)		(0.0000)	
Lowest analyst coverage	0.2278	***	0.1893	***
	(0.0000)		(0.0000)	
All firm characteristic bets	0.1786	***	0.1710	***
	(0.0000)		(0.0000)	

This table presents robustness checks for the baseline regression of Table 3. For brevity, I only report coefficients for the above-median cutoffs and suppress control variables. Fund performance is measured using DGTW-adjusted returns or Carhart (1997) 4-factor alphas. If not indicated otherwise, the main independent variable is the *MPB* dummy. Panel A reports the average treatment effect (ATE) as well as the average treatment effect on the treated (ATET) of a nearest-neighbor matched sample with high-*MPB* as the treatment group. For each observation in the treatment group, the nearest neighbor from the control group is identified based on the same control variables as in Table 3. I match exactly on period and fund style. p-values are based on robust standard errors. In Panel B, I construct alternative measures to capture a fund's tendency to invest in stocks with few competitors. *Overweighting market power firms* is a dummy variable equal to one if the fund overweights market power stocks relative to the investment style in a given quarter, and zero otherwise. *Competition bet* is the style-adjusted weight of the fund portfolio in stocks in the top quintile according to the number of competitors. In the remaining columns of Panel B, I calculate the Market Power Bet using a different market power definition. Market power stocks are, respectively, defined as stocks in the bottom quintile according to annual product market fluidity, in the top quintile industries according to annual fitted HHI (Hoberg and Phillips, 2010b), in the top quintile of TNIC-3 industry concentration, in the bottom quintile in the annual fraction of competition-related words in 10-K filings (Li et al., 2013), or in the bottom quintile of firm-to-economy technological proximity (Li et al., 2019). Lastly, I define Fama-French-48 industries (FFI48) in a year as market power industries if they are in the bottom quintile in the number of firms. For each market power definition, I calculate the fund's style-adjusted weight in these firms in a quarter. In Panel C, I adjust *MPB* for investment skills. I first regress a fund's *MPB* measure on either the fund's industry concentration *ICI*, measured as the Herfindahl index of portfolio weights in the ten industries of (Kacperczyk et al., 2005), the Active Share (Cremers and Petajisto, 2009), or both. I replace the unadjusted *MPB* with the respective regression residual. The panel reports coefficients for a dummy variable which is equal to one if the respective residual is above the median of all funds in a given quarter. In Panel D, I adjust *MPB* for a fund's bets on other firm characteristics. In each quarter, I sort stocks into quintiles based on market capitalization, firm age, (industry-adj.) book-to-market ratio, turnover, illiquidity, idiosyncratic volatility, and analyst coverage, all defined in Table 1. For each fund, I calculate its respective style-adjusted weight in firms of the smallest size, highest age, highest book-to-market ratio, highest illiquidity, highest idiosyncratic volatility, or lowest analyst coverage quintile. I then regress a fund's *MPB* on each of these firm characteristic bets individually or simultaneously. I replace the unadjusted *MPB* measure with the respective regression residuals. The panel reports coefficients for a dummy variable which is equal to one if the respective residual is above the median of all funds in a given quarter. If not indicated otherwise, the regressions include style and time fixed effects. In Panels B to D, p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 7. Controlling for mutual fund's organizational structure

Panel A: Control for flow-performance sensitivity

	Standard control				Nearest-neighbor matching	
Dependent variable:	DGTW-adj. return		Carhart alpha		DGTW-adj. return	Carhart alpha
Market Power Bet (MPB)	1.5127 ***		1.0554 ***			
	(0.0000)		(0.0004)			
High *MPB*		0.2085 ***		0.1806 ***	0.2226 ***	0.1276 ***
		(0.0000)		(0.0000)	(0.0000)	(0.0000)
FPS	0.0051	-0.0024	-0.0030	-0.0028		
	(0.1251)	(0.6591)	(0.6043)	(0.6291)		
Controls	Yes	Yes	Yes	Yes		
Time fixed effects	Yes	Yes	Yes	Yes		
Style fixed effects	Yes	Yes	Yes	Yes		
Number of Obs.	63,082	63,082	63,924	63,924	63,082	63,924
Adj. R-Squared	0.1348	0.1349	0.0767	0.0770		

Panel B: Organizational fixed effects

	Fund fixed effects		Manager fixed effects		Family fixed effects		All fixed effects	
Dependent variable:	DGTW	Carhart	DGTW	Carhart	DGTW	Carhart	DGTW	Carhart
High *MPB*	0.1760 ***	0.1419 ***	0.1749 ***	0.1294 ***	0.1889 ***	0.1623 ***	0.1567 ***	0.1153 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	(0.0032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style f.e.	No	No	Yes	Yes	Yes	Yes	No	No
Fund f.e.	Yes	Yes	No	No	No	No	Yes	Yes
Manager f.e.	No	No	Yes	Yes	No	No	Yes	Yes
Family f.e.	No	No	No	No	Yes	Yes	Yes	Yes
Obs.	65,465	65,465	62,022	60,578	65,465	63,950	61,023	59,610
Adj. R-Sq.	0.1461	0.1462	0.1597	0.0984	0.1482	0.0921	0.1466	0.0768

This table presents the robustness of the baseline regression of Table 3 when taking differences in a fund's organizational structure into account. Fund performance is measured as in Table 3. In Panel A, I additionally control for the fund's flow-performance sensitivity (*FPS*) in the two years prior to the measurement of fund performance. *FPS* is the regression coefficient from running a fund-level regression of monthly fund flows on the average (over the past 12 months) monthly fund return (net-of-fees) over a 24 months window. Panel A also reports the average treatment effect on the treated (ATET) when running the nearest-neighbor matching of Panel A in Table 6 and *FPS* as an additional matching variable. In Panel B, I add fund-, manager-, and fund family-fixed effects to the baseline regression. Additional independent variables are the same as in Table 3 and suppressed for brevity in all panels. If not indicated otherwise, the regressions include style and time fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. In the nearest-neighbor matching, p-values are based on robust standard errors. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 8. Market Power Bet and index fund performance

	Index fund performance							
Dependent variable:	DGTW-adj. return				Carhart alpha			
Market Power Bet (MPB)	2.6483				-1.5001			
	(0.1935)				(0.2540)			
High *MPB*			0.0674	*			-0.0423	
			(0.0901)				(0.3468)	
Fund size	-0.0635	***	-0.0526	***	-0.0498	**	-0.0557	***
	(0.0008)		(0.0079)		(0.0107)		(0.0090)	
Fund age	0.1211	*	0.1032		0.0064		0.0153	
	(0.0808)		(0.1409)		(0.9250)		(0.8312)	
Turnover ratio	-0.0113		-0.0058		0.0099		0.0067	
	(0.6040)		(0.7908)		(0.6977)		(0.8005)	
Fund flows	-0.0026		0.0002		-0.0688		-0.0704	
	(0.9457)		(0.9954)		(0.3390)		(0.3264)	
Number of stocks	-0.0804		-0.0742		-0.0407		-0.0428	
	(0.1307)		(0.1934)		(0.3329)		(0.3338)	
Family size	0.0102		0.0057		0.0100		0.0121	
	(0.4766)		(0.7111)		(0.5252)		(0.4586)	
Time fixed effects	Yes		Yes		Yes		Yes	
Style fixed effects	Yes		Yes		Yes		Yes	
Number of Observations	3,775		3,775		3,662		3,662	
Adj. R-Squared	0.3374		0.3363		0.1085		0.1081	

This table presents results when running the baseline regression of Table 3 on a sample of index funds. To identify index funds, I require that the fund name (at any point in time) suggests that the fund is an index fund and that the fund is labeled by CRSP as a pure index fund or ETF/ETN. Enhanced index funds and index-based funds are ignored. I further require funds to hold at least 80% of the portfolio in common stocks on average. Fund performance is measured as in Table 3. I run separate regressions for the continuous variable as well as the *MPB* dummy, which is equal to one if the fund's *MPB* is above the median in a given quarter and zero otherwise. Additional independent controls are as in Table 3. All independent variables are valid as of the end of the quarter preceding the fund performance calculation. Regressions are run with time and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 9. Instrumental variable (IV) regressions

	First stage				Second stage			
Dependent variable:	*MPB*		High *MPB*		Carhart alpha			
Bet on high surprise market power stocks	0.5263	***	2.8567	***				
	(0.0000)		(0.0000)					
MPB (IV)					1.5011	***		
					(0.0013)			
High *MPB* (IV)							0.2765	***
							(0.0012)	
Fund size	-0.0009	*	-0.0091	***	-0.0187	*	-0.0174	
	(0.0548)		(0.0019)		(0.0860)		(0.1089)	
Fund age	-0.0006		-0.0013		0.0519	**	0.0513	**
	(0.5420)		(0.8573)		(0.0383)		(0.0403)	
Turnover ratio	-0.0086	***	-0.0566	***	-0.0690	**	-0.0663	**
	(0.0000)		(0.0000)		(0.0281)		(0.0350)	
Fund flows	-0.0004		-0.0011		-0.0854		-0.0857	
	(0.8071)		(0.9024)		(0.2076)		(0.2054)	
Number of stocks	-0.0022	**	0.0180	***	0.0098		0.0016	
	(0.0284)		(0.0096)		(0.6553)		(0.9416)	
Family size	-0.0017	***	-0.0073	***	0.0094	*	0.0089	
	(0.0000)		(0.0000)		(0.0987)		(0.1162)	
Time- and style fixed effects	Yes		Yes		Yes		Yes	
Kleibergen-Paap rk Wald F-stat	2,072.60		2,613.36					
Partial R-squared	0.3008		0.1550					
Number of Observations	55,485		55,485		55,485		55,485	
Adj. R-Squared					0.0781		0.0781	

This table presents results from 2SLS instrumental variable (IV) regressions. The first two columns present first-stage results, while the last two columns report results for the second stage. For brevity, I only report second-stage results for Carhart (1997) 4-factor alphas as dependent variable. The instrument is *Bet on high surprise market power stocks* in t - 4, which is the style-adjusted portfolio weight in the stocks with the highest unexpected market power probability in the next year. I decompose a stock's probability to be a market power stock in a year into an expected and an unexpected component. The expected component is predicted by a linear probability model in which I regress the market power stock indicator on its lagged values in the prior three years as well as the logarithm of avg. *Firm size*, the logarithm of *Firm age*, the industry-adj. *Book-to-market ratio*, the logarithm of avg. *Analyst coverage*, avg. *Quarterly turnover*, avg. quarterly *Amihud illiquidity*, avg. quarterly *Idiosyncratic volatility*, all defined in Table 1 and lagged by one year, and year fixed effects. The unexpected component is the regression residual. I sort stocks into quintiles based on the residual and define stocks in the top quintile as high surprise market power stocks. The main independent variable in the second stage is the instrumented *MPB* or the instrumented high-*MPB* dummy. Additional independent control variables are the same as in Table 3. The regressions include time and style fixed effects. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 10. Performance effect around the 9/11 terrorist attacks

Panel A: One year after the attack (2002)

			Change in fund performance			
Dependent variable:	Δ *Avg. MB*		Δ DGTW		Δ Carhart	
Δ *Military weight*	-0.1295 ***		-7.3905 ***		-3.4809 *	
	(0.0000)		(0.0000)		(0.0931)	
Military increase		-0.0142 ***		-0.9540 ***		-0.5915 *
		(0.0003)		(0.0000)		(0.0508)
Avg. fund size	-0.0001	0.0002	-0.1073	-0.0984	-0.5265 ***	-0.5298 ***
	(0.9710)	(0.9005)	(0.2038)	(0.2445)	(0.0000)	(0.0000)
Fund age	0.0070 **	0.0067 **	-0.3060 *	-0.3121 *	0.8321 ***	0.8335 ***
	(0.0128)	(0.0172)	(0.0623)	(0.0580)	(0.0004)	(0.0004)
Avg. turnover ratio	0.0058 **	0.0063 **	-0.0481	-0.0385	-0.7385 ***	-0.7510 ***
	(0.0272)	(0.0174)	(0.7539)	(0.8024)	(0.0004)	(0.0003)
Avg. fund flows	0.0051	0.0068	-0.5124 *	-0.4186	-0.5452	-0.5019
	(0.3313)	(0.1950)	(0.0964)	(0.1735)	(0.1922)	(0.2270)
Avg. number of stocks	-0.0037	-0.0034	0.1177	0.1381	0.2142	0.2279
	(0.2265)	(0.2704)	(0.5089)	(0.4399)	(0.3758)	(0.3457)
Avg. family size	0.0003	0.0001	0.0703 *	0.0574	0.1205 **	0.1152 **
	(0.6855)	(0.9200)	(0.0987)	(0.1787)	(0.0363)	(0.0448)
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	845	845	832	832	749	749
Adj. R-Squared	0.0387	0.0274	0.0656	0.0605	0.0441	0.0454

Panel B: Two years after the attack (2002-2003)

			Change in fund performance			
Dependent variable:	Δ *Avg. MB*		Δ DGTW		Δ Carhart	
Δ *Military weight*	-0.1627 ***		-12.0318 ***		-4.4526 **	
	(0.0000)		(0.0000)		(0.0128)	
Military increase		-0.0171 ***		-1.2915 ***		-0.3093
		(0.0000)		(0.0000)		(0.2405)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	846	846	837	837	750	750
Adj. R-Squared	0.0755	0.0509	0.1363	0.1060	0.0213	0.0148

This table presents results from a cross-sectional OLS regression of changes in the Market Power Bet and fund performance around the 9/11 terrorist attacks in Q3/2001. In the first two columns of Panel A, the dependent variable is the change in *Avg. MB*, measured as the difference in average quarterly *MPB* in the year 2002 after the attacks and the average quarterly *MPB* in the year before the attacks. In the last four columns, the dependent variable is the change in fund performance measured as the difference between average quarterly performance in 2002 after the attacks and the average quarterly performance in the year before the attacks. I use both DGTW-adjusted returns and Carhart (1997) 4-factor alphas to measure fund performance, based on gross-of-fee returns and presented in percent. The main independent variable is Δ *Military weight*, defined as the change in the peer-adjusted average weight in military goods firms (defined using TNIC data in 2000 before the attack) in the same quarters for which I measure the Market Power Bet and fund performance. I use both the continuous variable as well as a *Military increase* dummy equal to one if the fund has increased the peer-adjusted weight in military goods firms around the attacks and zero otherwise. The analysis is limited to funds that invest into the military goods firms both before and after the event. Additional independent control variables are *Fund size, Turnover ratio, Fund flows, Number of stocks*, and *Family size*, all defined as in Table 2 but averaged over the last four quarters before the event quarter, as well as *Fund age* at the event quarter. The regressions include style fixed effects. In Panel B, I repeat the analysis, but also include 2003 to calculate post-attack values for the variables of interest. Additional independent control variables are suppressed for brevity. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 11. Determinants of *MPB*

Dep. variable:	*MPB*									
Multi-funds	-0.0049	**							-0.0056	**
	(0.0260)								(0.0141)	
Manager tenure			0.0004	**					0.0005	***
			(0.0218)						(0.0025)	
# Managers					-0.0006	**			-0.0008	**
					(0.0312)				(0.0178)	
Fund duration							0.0021	***	0.0021	***
							(0.0000)		(0.0001)	
Fund size	-0.0008		-0.0010		-0.0006		-0.0003		-0.0006	
	(0.2930)		(0.1930)		(0.3979)		(0.6637)		(0.4232)	
Fund age	-0.0005		-0.0007		-0.0006		-0.0018		-0.0030	*
	(0.7414)		(0.6460)		(0.6996)		(0.2726)		(0.0646)	
Turnover ratio	-0.0124	***	-0.0121	***	-0.0124	***	-0.0092	***	-0.0086	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Expense ratio	0.1094		0.1037		0.1152		0.0896		0.0824	
	(0.1762)		(0.2019)		(0.1518)		(0.2658)		(0.3132)	
Fund flows	0.0006		0.0006		0.0006		0.0018		0.0019	
	(0.6960)		(0.7325)		(0.7325)		(0.3220)		(0.3262)	
# stocks	-0.0046	***	-0.0045	***	-0.0042	***	-0.0052	***	-0.0043	***
	(0.0024)		(0.0029)		(0.0066)		(0.0007)		(0.0086)	
Family size	-0.0022	***	-0.0024	***	-0.0025	***	-0.0024	***	-0.0020	***
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	
Time f.e.	Yes		Yes		Yes		Yes		Yes	
Style f.e.	Yes		Yes		Yes		Yes		Yes	
Obs.	52,009		52,009		52,710		50,805		48,366	
Adj. R2	0.0426		0.0429		0.0417		0.0472		0.0494	

This table presents results on the influence of fund and manager characteristics on a fund's Market Power Bet (*MPB*). The dependent variable is the Market Power Bet for the fund in a given quarter. The main independent variables are Multi-funds, Manager tenure, # Managers, and Fund duration. *Multi-funds* is an indicator variable equal to one if the fund's managers on average manage more than one fund and zero otherwise. *Manager tenure* is the maximum manager tenure in the fund industry over all managers of the fund. *# Managers* is the number of managers of the fund. *Fund duration* is the fund's average duration in the past four quarters, measured as in Cremers and Pareek (2015). *Fund duration* is the value-weighted average length of time that a fund held a stock in the portfolio over the last five years. Additional independent control variables are the same as in Table 2. All independent variables are lagged by one quarter. Regressions are run with time and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table 12. Investment behavior

Panel A: Portfolio characteristics

	Characteristic					
Dependent variable:	Portfolio liquidity		Innovative ability		Technological proximity	
Market Power Bet (MPB)	-4.7907 ***		3.6239 ***		-0.1533 ***	
	(0.0000)		(0.0000)		(0.0000)	
High *MPB*		-0.4156 ***		0.3464 ***		-0.0129 ***
		(0.0000)		(0.0000)		(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	54,755	54,755	54,717	54,717	44,211	44,211
Adj. R-Squared	0.5585	0.5471	0.1682	0.1673	0.3529	0.3337

Panel B: Within-portfolio competition

Dependent variable:	(Peer-adjusted) Average number of competitors Held		Bought	
Market Power Bet (MPB)	-2.9878 ***		-1.2959 ***	
	(0.0000)		(0.0000)	
High *MPB*		-0.4044 ***		-0.2132 ***
		(0.0000)		(0.0000)
Controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Number of Observations	54,517	54,517	53,956	53,956
Adj. R-Squared	0.5206	0.5206	0.3877	0.3884

This table presents results from pooled OLS regressions that analyze the impact of the lagged Market Power Bet on a fund's investment behavior. For brevity, I only report coefficients of interest and suppress control variables. In Panel A, I report results of pooled OLS regressions in which the dependent variable is either *Portfolio liquidity*, *Innovative ability*, or *Technological proximity*. *Portfolio liquidity* is the value-weighted stock-level Amihud (2002) illiquidity measure within a quarter. As in Massa and Phalippou (2005), I take the natural logarithm of the fund-level illiquidity measure and multiply it by -1 to obtain a liquidity measure. *Innovative ability* represents the value-weighted innovative ability of the firms in the portfolio. Each firm's innovative ability is calculated as the average of five regression coefficients from a firm-level regression on sales growth on lagged R&D expenses as in Cohen et al. (2013). *Technological proximity* is the value-weighted firm-to-economy technological proximity of the firms in the portfolio. Each firm's technological proximity is calculated following Li et al. (2019) as the cosine similarity between its patent output, i.e., the number of patents across technology classes, and the patent output of all other publicly-listed firms in the economy. The main independent variables are the Market Power Bet (*MPB*) or the *MPB* dummy, defined as in Table 2. Additional independent control variables are as in Table 2. All independent variables are valid at the beginning of the quarter, for which I calculate *Portfolio liquidity, Innovative ability*, and *Technological proximity*. In the first two columns of Panel B, the dependent variable is the value-weighted number of direct competitors of the stock concurrently held by the fund in the non-market power stock portfolio in a given quarter. In the last two columns of Panel B, the dependent variable is the trade-size-weighted number of direct competitors concurrently bought in the non-market power stock portfolio. Both dependent variables are peer-adjusted by deducting the mean value per investment style and period. The independent variables are the same as in Panel A. Regressions are run with time and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Internet appendix

This Internet Appendix presents additional results to accompany the paper "Mutual Fund Bets on Market Power". The contents of the Appendix are as follows.

Table A.1 reports robustness of the main result in Table 3 when using net performance and alternative performance measures.

Table A.2 reports robustness of the main result in Table 3 when replacing the high-*MPB* indicator with *MPB* quartiles.

Table A.3 reports performance and performance differences of buy and sell subportfolios of high- and low-*MPB* funds in market power stocks.

Table A.4 reports results when estimating the main result in Table 3 for each investment objective separately.

Table A.5 reports results from a portfolio sort of stocks by number of competitors and subsequent risk-adjusted portfolio performance.

Table A.6 reports results when including a recession indicator and its interaction with the Market Power Bet in the regression of Table 3 as well as results on long-run performance consequences.

Table A.1. Robustness using alternative performance measures

	MPB		high *MPB*	
Carhart alpha (net)	0.9627	***	01779	***
	(0.0028)		(0.0000)	
Jensen alpha	2.2015	***	0.2714	***
	(0.0000)		(0.0000)	
Fama-French alpha	0.8726	***	0.1413	***
	(0.0041)		(0.0000)	
Pástor-Stambaugh alpha	0.8688	***	0.1506	***
	(0.0037)		(0.0000)	
CPZ-4-factor alpha	1.4967	***	0.2283	***
	(0.0000)		(0.0000)	
CPZ-7-factor alpha	1.1681	***	0.1650	***
	(0.0001)		(0.0000)	
CCP-4-factor alpha	0.0621	***	0.0073	***
	(0.0019)		(0.0000)	

This table presents robustness checks for the baseline regression of Table 3 when using net performance or alternative performance measures as dependent variable. For brevity, I only report coefficients of interest and suppress control variables. The main independent variables are the Market Power Bet (*MPB*) or the *MPB* dummy, defined as in Table 2. The first row presents results when calculating the Carhart (1997) 4-factor alpha based on net returns instead of gross returns. In the remaining rows, I use (gross-of-fees) Jensen (1968) 1-factor, the Fama and French (1993) 3-factor, the Pástor and Stambaugh (2003) 5-factor, as well as the Cremers et al. (2012) 4-and 7-factor models to estimate fund performance in a similar way as the Carhart (1997) 4-factor alpha. I also calculate a fund's Cohen et al. (2005) alpha, which is the value-weighted average stock quality measure based on the average gross-of-fees Carhart (1997) 4-factor alpha of all funds holding a particular stock. The control variables are as in Table 3. The regressions include style and time fixed effects and p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.2. Robustness using *MPB* quartiles

	Fund performance			
Dependent variable:	DGTW-adj. return		Carhart alpha	
MPB-quartile 2	0.1396	***	0.1328	***
	(0.0002)		(0.0005)	
MPB-quartile 3	0.2455	***	0.2387	***
	(0.0000)		(0.0000)	
MPB-quartile 4	0.3665	***	0.2516	***
	(0.0000)		(0.0000)	
Controls	Yes		Yes	
Time fixed effects	Yes		Yes	
Style fixed effects	Yes		Yes	
Number of Observations	65,465		63,950	
Adj. R-Squared	0.1326		0.0770	

This table presents robustness checks for the baseline regression of Table 3 when replacing the high-*MPB* dummy with the fund's *MPB* quartile. In each period, funds are sorted into quartiles based on their *MPB*. *MPB*-quartile 2, *MPB*-quartile 3, and *MPB*-quartile 4 are indicator variables equal to one, respectively, if the fund belongs to the second, third, or fourth *MPB* quartile. The control group, therefore, are funds in the lowest *MPB* quartile. Performance is measured as in Table 3. Additional control variables are the same as in Table 3 and suppressed for brevity. All independent variables are valid as of the end of the quarter preceding the fund performance calculation. The regressions include style and time fixed effects and p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.3. Performance of buys and sells in market power stocks

Panel A: Performance of subportfolios over 3 months

	DGTW-adj. return						Carhart alpha					
	high *MPB*		Low *MPB*	High-Low			high *MPB*		Low *MPB*	High-Low	
Buy	0.2735	***	-0.0572	0.3308	***	Buy	0.2245	***	-0.0707	0.2952	***
	(0.0000)		(0.3376)	(0.0001)			(0.0003)		(0.2918)	(0.0016)	
Sell	0.0649		-0.0121	0.0771		Sell	-0.0717		0.0817	-0.1534	
	(0.2677)		(0.8406)	(0.3600)			(0.2749)		(0.2252)	(0.1028)	
Buy-Sell	0.2086	***	-0.0451	0.2537	**	Buy-Sell	0.2962	***	-0.1525	0.4487	***
	(0.0079)		(0.5887)	(0.0292)			(0.0008)		(0.1008)	(0.0005)	

Panel B: Difference-in-differences of buy and sell subportfolios

Dependent variable:	DGTW-adj. return		Carhart alpha	
high *MPB*	0.2474	**	0.4445	***
	(0.0325)		(0.0008)	
Time fixed effects	Yes		Yes	
Number of observations	58,798		58,818	
Adj. R-Squared	0.0013		0.0024	

This table presents results on the subsequent quarterly performance of trades in market power stocks for high- and low-*MPB* funds in the period of the trade. market power stocks are defined as stocks in the bottom quintile according to the number of competitors. I define a buy as an increase and a sell as a decrease in the number of shares held by a fund in a stock between two consecutive reporting dates. Subportfolio performance is measured using DGTW-adjusted returns and Carhart (1997) 4-factor alphas of the stocks in the quarter following the trade. The performance is reported in percent. I value-weight the performance of stocks making up each subportfolio by the dollar value of the trade (stock price times the number of shares bought or sold of a given stock) at the beginning of portfolio formation. Panel A presents the average subportfolio performance of buys and sells in market power stocks across the two *MPB* groups. The third and sixth column report differences in performance of buy (sell) subportfolios between high- and low-*MPB* funds. The third row reports differences in the performance of buys and sells separately for high- and low-*MPB* funds. The last entry in each subtable of Panel A reports differences-in-differences of buy and sell performance between high- and low-*MPB* funds. In Panel B, I present results from a pooled OLS regression in which the dependent variable is a fund's performance difference in buy and sell subportfolio in a given quarter. I only report differences in subportfolios if none of the two is missing. The main independent variable is the high-*MPB* dummy, defined as in Table 2 and valid at the end of the quarter preceding the subportfolio performance calculation. Regressions are run with time fixed effects and standard errors are clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.4. Results per investment style

	Growth		Growth & Income		Income		Mid cap		Small & Micro cap	
Dependent variable:	Carhart alpha									
High *MPB*	0.1101	**	0.0963	**	0.3365	***	0.3109	***	0.2383	***
	(0.0110)		(0.0362)		(0.0019)		(0.0000)		(0.0002)	
Controls	Yes		Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes		Yes	
Number of Observations	26,934		11,739		2,336		8,171		14,770	
Adj. R-Squared	0.0864		0.0964		0.2161		0.2299		0.1424	

This table presents the robustness of the baseline regression of Table 3 separately for each investment style. Fund performance is measured as in Table 3. For brevity, only the results for Carhart alpha as dependent variable and the high-*MPB* dummy are reported. Additonal control variables are the same as in Table 3 and suppressed for brevity. The regressions include time fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.5. Portfolio sorts and stocks' risk-adjusted performance

Quintile portfolio (# of competitors)	Stock performance (%)		
	DGTW-adj. return	Carhart alpha	
1 (Low)	-0.0194	0.0982	
	(0.8536)	(0.5410)	
2	0.0969	0.1855	
	(0.2025)	(0.1656)	
3	0.0501	0.1887	
	(0.4696)	(0.1375)	
4	0.1293	0.2808	*
	(0.2733)	(0.0960)	
5 (High)	-0.2639	-0.1561	
	(0.1299)	(0.3761)	
5 (High) - 1 (Low)	-0.2445	-0.2543	
	(0.2236)	(0.2549)	
3 - 1	0.0695	0.0905	
	(0.4833)	(0.3733)	

This table reports results from a portfolio sort of stocks based on the number of competitors and the subsequent risk-adjusted performance of each portfolio. At the end of each year, I sort stocks into quintiles by number of competitors. For each portfolio, I calculate equally-weighted monthly stock returns adjusted for stock characteristics (DGTW-adj. returns). I also estimate the Carhart (1997) 4-factor model from the monthly time series of quintile returns. The last two rows report differences in risk-adjusted returns between stocks in the highest and lowest quintile portfolio as well as for the medium and lowest quintile portfolio. p-values are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Table A.6. Recession and long-run performance

Panel A: Recession performance

	Fund performance			
Dependent variable:	DGTW-adj. Return		Carhart alpha	
Market Power Bet (MPB)	1.3030 ***		0.5245	
	(0.0001)		(0.1133)	
Market Power Bet (MPB) * Recession	1.7713 **		2.1690 ***	
	(0.0140)		(0.0008)	
High *MPB*		0.1522 ***		0.1384 ***
		(0.0000)		(0.0000)
High *MPB* * Recession		0.3150 ***		0.1763 **
		(0.0000)		(0.0142)
Recession	-3.2634 ***	-3.4179 ***	1.4619 ***	1.3728 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	65,465	65,465	63,950	63,950
Adj. R-Squared	0.1324	0.1325	0.0770	0.0770

Panel B: Long-run fund performance

	Next 12 months		Next 24 months		Next 36 months	
Dependent var.:	DGTW-adj.	Carhart	DGTW-adj.	Carhart	DGTW-adj.	Carhart
High *MPB*	0.9079 ***	0.9143 ***	1.3883 ***	1.5965 ***	1.5399 ***	1.9371 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	62,021	62,229	58,345	58,514	54,954	55,057
Adj. R-Squared	0.1653	0.0867	0.1042	0.1130	0.0824	0.1232

This table presents results from pooled OLS regressions that analyze the impact of the lagged Market Power Bet on fund performance in recessions and on the long-run fund performance. Panel A reports results on the relation of quarterly mutual fund performance and the lagged fund Market Power Bet *(MPB)* interacted with a recession indicator. Performance is measured using either DGTW-adjusted returns or Carhart (1997) 4-factor alphas. The performance measures are based on gross-of-fee returns and are presented in percent. The main independent variables are the fund's Market Power Bet (*MPB*) or the high-*MPB* dummy, respectively, as well as *Recession*. *Recession* is an indicator variable equal to one if at least one month of the quarter, for which I calculate the Market Power Bet, is a recession month according to the three-months moving average of the Chicago Fed National Activity Index (CFNAI). In Panel B, the dependent variable is fund performance measured over the next 12, 24, or 36 months following the calculation of the Market Power Bet. For brevity, I only report results for the high-*MPB* dummy. Fund performance is measured as either the compounded monthly DGTW-adj. fund return or the fund's Carhart (1997) 4-factor alpha from a fund-level regression using monthly returns over the next 12, 24, or 36 months, respectively. Additional control variables are the same as in Table 3 and suppressed for brevity. All independent variables are valid as of the end of the quarter preceding the fund performance calculation. Regressions are run with time and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

centre for financial research cologne

cfr working papers are available for download from www.cfr-cologne.de.

2021

No.	Author(s)	Title
21-01	T. Bali, F. Weigert	Hedge Funds and the Positive Idiosyncratic Volatility Effect

2020

No.	Author(s)	Title
20-14	V. Agarwal, Y. Lu, S. Ray	Are hedge funds' charitable donations strategic?
20-13	M. Jagannathan, W. Jiao, R. Wermers	International Characteristic-Based Asset Pricing
20-12	E. Theissen, L. Zimmermann	Do Contented Customers Make Shareholders Wealthy? - Implications of Intangibles for Security Pricing
20-11	M. Hendriock	Implied Cost of Capital and Mutual Fund Performance
20-10	J. Fink, Stefan Palan, E. Theissen	Earnings Autocorrelation and the Post-Earnings-Announcement Drift – Experimental Evidence
20-09	E. Theissen, C. Yilanci	Momentum? What Momentum?
20-08	V. Agarwal, L. Jiang, Q. Wen	Why Do Mutual Funds Hold Lottery Stocks?
20-07	V. Agarwal, S. Ruenzi, F. Weigert	Unobserved Performance of Hedge Funds
20-06	M. Ammann, S. Fischer, F. Weigert	Factor Exposure Variation and Mutual Fund Performance
20-05	P. Limbach, P. R. Rau, H. Schürmann	The Death of Trust Across the Finance Industry
20-04	A. Y. Chen, T. Zimmermann	Open Source Cross-Sectional Asset Pricing
20-03	L. Ahnert, P. Vogt, V. Vonhoff, F. Weigert	Regulatory Stress Testing and Bank Performance
20-02	P. Schuster, E. Theissen, M. Uhrig-Homburg	Finanzwirtschaftliche Anwendungen der Blockchain-Technologie
20-01	S. Ruenzi, M. Ungeheuer, F. Weigert	Joint Extreme Events in Equity Returns and Liquidity and their Cross-Sectional Pricing Implications

2019

No.	Author(s)	Title
19-06	S. Greppmair, E. Theissen	Small Is Beautiful? How the Introduction of Mini Futures Contracts Affects the Regular Contract
19-05	G. Cici, M. Hendriock, A. Kempf	Finding your calling: Skill matching in the mutual fund industry
19-04	O. Korn, P. M. Möller, Ch. Schwehm	Drawdown Measures: Are They All the Same?
19-03	G. Cici, M. Hendriock, S. Jaspersen, A. Kempf	#MeToo Meets the Mutual Fund Industry: Productivity Effects of Sexual Harassment
19-02	T. Johann, S. Scharnowski, E. Theissen, C. Westheide, L. Zimmermann	Liquidity in the German Stock Market
19-01	A. Betzer, P. Limbach, P. Raghavendra Rau, Henrik Schürmann	Till death (or divorce) do us part: Early-life family disruption and investment behavior

2018

No.	Author(s)	Title
18-06	M. Goergen, P. Limbach, M. Scholz-Daneshgari	On the Choice of CEO Duality: Evidence from a Mandatory Disclosure Rule
18-05	F. Brochet, P. Limbach, D. Bazhutov, A. Betzer, M. Doumet	Where Does Investor Relations Matter the Most?
18-04	G. Cici, A. Kempf, C. Peitzmeier	Knowledge Spillovers in the Mutual Fund Industry through Labor Mobility
18-03	T. Rischen, E. Theissen	Underpricing in the Euro Area Corporate Bond Market: New Evidence from Post-Crisis Regulation and Quantitative Easing
18-02	S. Lesmeister, P. Limbach, M. Goergen	Trust and Shareholder Voting
18-01	G. Cici, M. Hendriock, A. Kempf	The Impact of Labor Mobility Restrictions on Managerial Actions: Evidence from the Mutual Fund Industry

2017

No.	Author(s)	Title
17-04	G. Cici, P.B. Shane, Y. S. Yang	Do Connections with Buy-Side Analysts Inform Sell-Side Analyst Research?
17-03	G. Cici, S. Gibson, R. Moussawi	Explaining and Benchmarking Corporate Bond Returns
17-02	S. Jaspersen, P. Limbach	Screening Discrimination in Financial Markets: Evidence from CEO-Fund Manager Dyads
17-01	J. Grammig, E.-M. Küchlin	A two-step indirect inference approach to estimate the long-run risk asset pricing model

This document only covers the most recent CFR working papers. A full list can be found at www.cfr-cologne.de.

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de