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ABSTRACT

I provide evidence that fund managers who overweight firms with the most differentiated products ('*monopolies'*) exhibit a superior risk-adjusted performance. This is consistent with information advantages due to a better understanding of qualitative information on a firm's competitive environment. I find that funds with above median *monopoly bets* outperform by up to 92 basis points annually and trade more successfully in both their monopoly and non-monopoly sub-portfolios. My identification strategy includes exogenous shocks to information quality using the Sarbanes-Oxley Act and to a firm's product market environment using the 9/11 terrorist attacks. I document that managers who place larger *monopoly bets* are less likely to invest into rival firms at the same time, have a longer investment horizon, and hold more illiquid and high quality stocks.

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

Keywords: Mutual fund performance; Information production; Fund manager skill; Investment behavior; Product market competition

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“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 -

Investors can choose which type of information they acquire and process in their stock selection. Clearly, information from financial statements is usually easier to collect and evaluate than softer and qualitative information, such as the firm’s business model, its brand value, or its competitors. Empirical evidence even suggests that low skill investors underweight information that is hard to process (e.g., Engelberg, Reed, and Ringgenberg (2012), Hirshleifer, Hsu, and Li (2013)). However, in the case of venture capitalists, Gompers et al. (2016) document that qualitative factors are more important for investment decisions than the project’s valuation. In a similar spirit, Cici et al. (2016) and Gargano, Rossi, and Wermers (2016) argue that more experienced and sophisticated investors interpret softer information to gain an information advantage over their peers. Processing qualitative information that leaves more room for interpretation, hence, seems to offer more valuable trading opportunities for skilled investors than processing quantitative information. For fund investors, identifying fund managers with the ability to process qualitative information is highly relevant, as only few actively managed funds have been shown to outperform (e.g., Barras, Scaillet, and Wermers (2010), Fama and French (2010)).

In this paper, I use the information on a firm’s competitive environment to differentiate fund managers by their ability to process qualitative information. Product market competition is ideal for this purpose. First, it is not obvious for an investor to what extent a firm is threatened by rivals and how substitutable its product range is. Second, it is not clear whether more or less competition is desirable for a given firm. Though less competition might increase a firm’s profitability due to higher price-setting power, it can have a negative impact on corporate decisions by increasing managerial slack or reducing innovation incentives (e.g., Raith (2003), Hou and Robinson (2006), and Bustamante (2015)). Accordingly, the literature is still inconclusive on the impact of product market competition on stock market performance. For example, Aguerrevere (2009) and Gu (2016) find that the relation between competition and stock returns strongly depends on product market demand and R&D intensity, respectively. This ambiguity makes the interpretation of a firm's competitive environment a challenging but important aspect in investment decisions. Yet, little is known on whether professional investors exploit this type of information to gain an advantage over their peers.

Anecdotal evidence suggests that a firm's competition matters for fund managers. Many seem to follow the Warren Buffett approach and look for firms with a competitive advantage and few rivals.[1] The challenge for these managers is to find firms for which market power results in a positive stock market outcome. If a fund manager knows about her ability to judge the consequences of market power for a given firm, she should capitalize on this advantage and process more product market information when picking stocks. This is in line with theoretical predictions of Kim and Verrecchia (1994) that some market participants make superior judgements than others of the same information. In addition, Jiang and Sun (2014) argue that better information-processing makes informed managers receive a positive signal about a stock that is unobserved by the remaining investors. As a result, the former place larger bets on the stock relative to latter. Consequently, larger investments in firms with competitive advantages signal high attention to and a better understanding of the product market.

Based on this reasoning, I differentiate fund managers by their investment in firms with competitive advantages and analyze whether this predicts differences in investment skills. Concretely, I choose the uniqueness of a firm's products as the source of a competitive

[1] E.g., Burton (2012): "Follow the Buffett Strategy" in *The Wall Street Journal* (August 2, 2012) or Brown (2012) "Berkshire Follower? Try These 5 Buffett Wannabe Mutual Funds" in *Forbes* (May 16, 2012). Both articles point out that managers invest in companies with few competitors to achieve stability in the portfolio with one fund manager calling these businesses an "ultimate 'sleep well' kind of investment" (Burton (2012)).

advantage.[2] Using mutual fund holdings and the number of rivals for a given firm based on similarity in 10-K product descriptions (Hoberg and Phillips (2015)), I develop a fund's *monopoly bet* (*MB*) as the value-weighted fraction of firms with the most differentiated products, henceforth *monopolies*, compared to the average portfolio weight of these firms in the fund's investment style.

Despite the ambiguous impact on stock returns, investing in monopoly firms is desirable for several reasons. First, having differentiated products results in more stable cash flows as the barriers to entry are higher (e.g., Peress (2010), Hoberg, Phillips, and Prabhala (2014)). Monopoly firms thereby stabilize the portfolio and reduce the manager's need to frequently monitor industry dynamics. Holding a larger fraction of monopolies also lowers the risk to invest into close rivals concurrently, which counteracts undesired correlations and yields a better diversification over different products. Consistent with this view, recent evidence by Azar, Schmalz, and Tecu (2016) and Antón et al. (2016) suggests that rival firms are pushed towards monopolistic behavior if they are concurrently held by the same institutional investor. On the contrary, fund managers neglecting such connections are therefore at risk for within-portfolio competition.

Managers might still abstain from investing in monopoly firms. As noted above, determining the extent of product differentiation and the number of competitors require information-processing skills. Identifying firms with market power is therefore challenging and costly, in particular for low-skilled investors. Second, investors try to learn about a company from similar and related firms (e.g., Foucault and Frésard (2016)). For instance, Alldredge and Puckett (2016) show that institutional investors exploit economies of scale in information acquisition and invest in both supplier and customer firms at the same time. The uniqueness of monopolies, however, hinder information spillovers and learning opportunities. That is why

[2] I acknowledge that a firm's competitiveness not only depends on its product differentiation, but also on market share, brand value, and price-setting power. Yet, Hoberg and Phillips (2014) argue that firms with more differentiated products are likely to have a stronger competitive position.

fund managers might prefer to invest more aggregately in several close rivals to fully exploit their research effort.[3] Given costs and benefits, it is likely to find cross-sectional differences in the monopoly bets of fund managers.

My main investigation explores whether larger monopoly bets predict a superior fund performance. Assuming investors capitalize on their higher information-processing skills of qualitative information, an overweighting of monopoly firms should indicate a better understanding of the product market. These managers forgo economies of scale in information production, but are able to exploit the benefits of monopoly firms. Indeed, two validation exercises provide first evidence that managers with higher *MB* put more weight on information on product market competition. First, they react more strongly to changes in a firm's number of rivals. Second, they are more likely to avoid within-portfolio competition. This is consistent with them targeting the most promising competitor for a product and neglecting rivals firms. In contrast, managers who ignore these connections or cannot decide among competitors more likely invest into multiple rivals simultaneously.

Using a broad sample of actively-managed US domestic equity funds in the period from 1999 to 2012, I then find strong support for the main hypothesis that a larger *MB* positively predicts performance. Funds with above median *MB* in a quarter outperform below median *MB* funds by up to 92 basis points per year. This result withstands several robustness checks including different sets of fixed effects or alternative proxies for the propensity to invest in unique products.

If higher monopoly bets indicate a better understanding of the product market and, ultimately, higher information-processing skills, then fund managers with these skills should profit from this information irrespective of the competitive environment of the firm. I therefore

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[3] In a similar spirit, Hsu et al. (2015) find that analysts exploit the similarity of competing firms and are more likely to cover a stock if it is a close rival to an already covered firm. Due to lower information production costs, Engelberg, Ozoguz, and Wang (2013) further show that institutional investors are more likely to hold firms from the same industry if they are geographically close to each other.

examine whether fund managers with larger monopoly bets only select better monopoly stocks or whether they are also more successful in picking stocks with more competitors. A performance comparison of buy portfolios indeed provides evidence that funds with larger monopoly bets trade more successfully in both monopoly- and non-monopoly stocks. This result also holds when comparing the buy performance with hypothetical buy portfolios consisting of a firm's rivals.

To support a causal interpretation for the relationship between the monopoly bet and fund performance, I exploit two exogenous shocks. First, I use a positive shock to the investors' information environment with the passage of the Sarbanes-Oxley Act in 2002 (SOX). The improvement in the quality of public information reduces the advantage of informed investors. If high-*MB* funds actually gain information advantages, they should experience a stronger deterioration in fund performance around the passage of SOX than low-*MB* funds. My results from a cross-sectional regression provide support for this assumption with a quarterly performance decline that is about 1.18 percentage points stronger for funds with above median *MB* before SOX. Second, I exploit the 9/11 terrorist attacks as a positive shock to demand and the number of competitors in the military goods industry. As would be expected from funds with larger monopoly bets, managers who decrease their position in military good firms around 9/11 exhibit a significantly higher change in fund performance.

In line with differences in information-processing, I provide evidence that the monopoly bet strongly depends on the manager of the fund, especially on her experience and the effort she can devote to information acquisition. First, I exploit manager switches of a fund and document that *MB* increases around the switch if the new manager has a higher pre-switch propensity to invest into monopoly stocks than the former manager. Second, I investigate fund and manager attributes as determinants of the monopoly bet. I hypothesize that *MB* should be higher if the manager is more experienced and puts more effort in collecting and processing information. For one, investment experience should facilitate the processing of qualitative information. Moreover, information-processing is a costly and time-consuming task that requires effort. Consistently, I find that funds managed by more experienced managers, funds whose managers do not manage multiple funds concurrently as well as funds managed by smaller teams with fewer free-riding incentives place larger bets on monopoly firms.

Finally, to further understand why managers with a better understanding of the product market might choose to overweight monopoly firms and to identify potential channels for the documented outperformance, I investigate the investment strategies of funds with different *MB* levels. Consistent with monopoly stocks providing stability with secure cash flows and less product market threats, funds with a higher *MB* have a lower portfolio turnover and hold stocks over a longer period. Moreover, the lower trading frequency should allow the fund manager to invest into more illiquid securities to earn a liquidity premium (e.g., Amihud, Mendelson, and Pedersen (2005)), which is also supported by the results. Finally, their potential profitability makes monopoly firms suitable instruments to pursue quality investing. In line with this, I show that funds with higher *MB* trade more heavily on the Quality-Minus-Junk (QMJ) factor (Asness, Frazzini, and Pedersen (2014)).

My paper contributes to several strands in the literature. First, the paper relates to the literature on the information production of investors. Among other things, this literature classifies the type of information that investors use, e.g., by aggregation level (e.g., Kacperczyk, Nieuwerburgh, and Veldkamp (2014)), softness and complexity (e.g., Stein (2002), Gargano, Rossi, and Wermers (2016)), or source (e.g., Coval and Moskowitz (2001), Kacperczyk and Seru (2007), Fang, Peress, and Zheng (2014)). I contribute to this literature by identifying product market linkages as hard-to-process information that offers valuable trading opportunities for investors.

Second, my results contribute to the literature that predicts investment skills from fund portfolios. Kacperczyk, Sialm, and Zheng (2005), Huang and Kale (2013), and Alldredge and Puckett (2016) document that funds outperform if they are more concentrated in particular industries or related industries, while Cremers and Petajisto (2009) and Doshi, Elkamhi, and Simutin (2015) show that more active managers deliver a superior performance. I add to these studies by differentiating funds by their information-processing skill. Different from the studies on simultaneous investments in customer and supplier firms, my findings suggest that skilled investors avoid rival firms from the same industry and rather hold a larger fraction of stocks from less competitive markets.

Finally, I also contribute to the vast literature on common ownership and the impact of product market competition on asset pricing (e.g., Hou and Robinson (2006), Hoberg and Phillips (2010) and Peress (2010)) and corporate behavior (e.g., Giroud and Mueller (2011), Hoberg, Phillips, and Prabhala (2014), and Azar, Schmalz, and Tecu (2016)). With investment companies owning around 30% of the US stock market (Investment Company Institute (2015)), differences in the fund managers' ability to take product market information into account help to understand why competition affects stock market performance as well as corporate decisions.

The remainder of the paper is organized as follows. In Section 1, I describe the data and the monopoly bet measure. Section 2 presents empirical results on the relation of the monopoly bet fund as well as trade performance and addresses endogeneity concerns. In Section 3, I show that *MB* depends on the fund manager. Section 4 examines the relation of *MB* to the fund's investment behavior and identifies potential channels through which the superior performance emerges, and Section 5 concludes.

1 Data and summary statistics

1.1 Data sources

For my analysis, I combine several data sources. I obtain information on 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 all 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.

From the Morningstar Direct Mutual Fund Database (MS Direct) I obtain fund manager information and come up with a unique identifier for each fund manager. 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.[4] 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 number of pairs per firm therefore identifies the number of close competitors with a higher number indicating a more competitive product market. I additionally obtain similarity scores and product market fluidity data from this database. As the pairwise similarity is calculated on an annual basis, the data allow me 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 as well as 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

4 The data sets can be accessed via http://cwis.usc.edu/projects/industrydata/. An advantage of this classification is that firms are grouped by the products they offer whereas more traditional classifications (SIC or NAICS) are based on input factors or production processes. Yet, the data is limited to publicly traded U.S. firms so competition from private or foreign firms is not taken into account. A detailed description of the data is given, for example, in Hoberg and Phillips (2015) and Hoberg, Phillips, and Prabhala (2014).

(EDCS), Micro Cap (EDCI), Growth (EDYG), Growth & Income (EDYB), and Income (EDYI)).[5] The final sample consists of 2,561 funds managed by 5,002 distinct managers.

1.2 Variable construction and sample characteristics

I sort all stocks in the HP database into quintiles based on the number of product rivals in a given year. Stocks in the bottom quintile are labeled as monopoly stocks. To obtain a fund's monopoly bet each quarter, I calculate the value-weighted fraction of monopoly stocks within the portfolio using the monopoly information in the current year.[6] To rule out that a fund is placing larger or smaller weights on monopoly stocks due to its stated investment style, I adjust the fraction of monopoly stocks by subtracting the average monopoly weight within the same investment style in a given quarter. The monopoly bet (*MB*), therefore, can be interpreted as an under- or overweighting of monopoly firms relative to all funds within the same style.[7]

Panel A of Table 1 reports annual summary statistics for stock characteristics over the sample period 1999 to 2012. I present information for the whole sample of firms as well as for monopoly and non-monopoly firms, separately. Panel B of Table 1 reports sample characteristics for key variables at the fund level. I present information both for the whole sample of funds as well as for subsamples constructed by stratifying the sample funds into high- (above median) and low- (below median) *MB* funds in each period. I use t-tests to test for differences in means between the subsamples.

– Insert TABLE 1 approximately here –

5 In the rare cases that a share class does not have CRSP Style Code information, I use the old classification according to Lipper, Strategic Insight, and Wiesenberger to identify a fund's dominating objective.

6 Note that the portfolio sort is based on all firms in the Hoberg and Phillips data sets while stock holdings of the mutual funds only contain common stocks.

7 As documented in the robustness section, the main result also holds when using alternative proxies to capture a fund's propensity to invest in firms with more unique products.

Panel A of Table 1 shows that monopoly firms indeed face fewer product market threats, as suggested by their lower average product market fluidity. They are significantly smaller and older than the remaining firms, and have a higher book-to-market ratio. Monopoly firms are also less liquid, captured by a lower average stock turnover and a higher average Amihud (2002) illiquidity measure, both constructed using daily data within a quarter. A possible interpretation of these differences is that the average monopoly firm operates in a specialized niche market which is more unknown to investors. This is also in line with Hsu et al. (2015) who document a lower analyst coverage and accuracy for firms in less competitive markets. While monopoly stocks on average do not have a higher annual return, they are held by more skilled investment funds, as indicated by their higher Cohen, Coval, and Pástor (2005) stock quality measure using a fund's Carhart (1997) 4-factor alpha.[8] This is consistent with the view that more skilled fund managers are better able to identify profitable investment opportunities within the group of monopoly firms to exploit their benefits.

In terms of fund characteristics, above and below median *MB* funds differ significantly. Funds with a higher propensity to overweight monopoly firms are significantly smaller and slightly younger and come from smaller fund families. They 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 percent compared to 95.02 percent for below median *MB* funds. This is consistent with a higher stability provided by monopoly stocks which reduces the need to frequently replace stocks. Given that these fund characteristics are known to have an impact on fund performance, the later performance comparisons will control for these differences. Yet, even in a univariate comparison larger monopoly bets indicate superior manager abilities as shown by their significantly higher raw returns, as well as stock characteristic- and risk-adjusted fund performance. For example, the average quarterly Carhart (1997) 4-factor alpha based on

[8] A portfolio approach (not reported), in which I annually sort stocks into quintiles based on the number of competitors and calculate risk-adjusted performance in the following year, yields a similar picture. A monopoly stock portfolio does not outperform portfolios of companies with more competitors.

gross-of-fee returns in the whole sample amounts to only 23 basis points on an annual basis and is therefore comparable to other studies. Nevertheless, high-*MB* outperform low-*MB* funds by 78 basis points per year.

1.3 Does *MB* really capture a fund's response to product market competition?

Table 1 already reveals striking differences in the characteristics of monopoly and non-monopoly firms. Fund managers might therefore overweight monopolies by chance due to preferences for other firm characteristics. To validate that the *MB* measure indeed captures differences in the reaction to product market information, I analyze the behavior of funds according to two dimensions: their sensitivity to product market dynamics and their propensity to invest into rival firms at the same time. Changes in a firm's competition should induce fund managers to update their expectations on the future prospects of the firm and to trade on this new information. This sensitivity should be particularly pronounced for managers with a better understanding of the product market, as captured by *MB*.

To measure a fund's sensitivity, I calculate the R^2 from a fund-level regression of changes in the number of shares held in a stock on lagged changes in the number of rival firms, which is conceptually similar to the procedure in Kacperczyk and Seru (2007). As the set of rival firms for a given firm is updated on an annual basis, I calculate annual holdings changes using year-end reports for each fund and use changes in the number of competitors for all stocks in the previous two years. I relate *Sensitivity* of fund *i* in year *t* to the fund's monopoly bet (*MB*) at the end of year *t*-1 and add control variables in the following pooled regression:

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

$X_{i,t-1}$ is a vector of control variables, which might have an impact on a fund's sensitivity to product market dynamics. 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 *Sensitivity*. To control for unobservable effects in a given period or for a given style, the regressions include time and style fixed effects. Standard errors are clustered at the fund level.

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

– Insert TABLE 2 approximately here –

The results from Panel A of Table 2 support the view that funds with larger monopoly bets react more strongly to changes in the number of firm rivals. Irrespective of whether I include additional control variables and fixed effects or not, funds with a higher *MB* are related to a higher *Sensitivity*. The effect is statistically significant at the 1%-level and also economically relevant with a *Sensitivity* that is about 0.17 percentage points larger for high-*MB* funds after taking fund-level controls and fixed effects into account. Compared to the average *Sensitivity* of low-*MB* funds (2.66 percent) this is equal to a difference of more than 6%.

The second validation exercise is based on the assumption that fund managers overweight monopoly stocks to avoid within-portfolio competition. If this is the case, we would expect managers with larger monopoly bets to hold less rival firms at the same time. Consequently, even in more competitive markets, the manager should only choose a few out of multiple rival firms.[9]

[9] Alternatively, a manager could hold a long position in one firm while shorting a close competitor (e.g., Akbas, Boehmer, and Genc (2015)). Due to a lack of data on short-positions in mutual funds, I only present results based on concurrent long-positions in direct competitors.

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 between *MB* and the number of competitors held, I limit the analysis to stocks in the non-monopoly sub-portfolio. I aggregate the number of concurrently held competitors at the fund level by value-weighting over all stocks in the sub-portfolio. As for the monopoly bet, I use a style-adjusted version of this measure. I regress the value-weighted number of competitors held on the *MB* measure or the *MB* dummy and the same control variables as in Panel A in the previous quarter as well as 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 2. In the last two columns of Panel B, I repeat the analysis but use the value-weighted number of direct competitors that are concurrently bought by the fund as dependent variable.[10]

The results from Panel B of Table 2 show that funds with larger monopoly bets hold and trade a significantly lower number of direct competitors at the same time, even in their non-monopoly sub-portfolios. The effect is statistically significant at the 1%-level and also economically meaningful. Low-*MB* 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. On the contrary, the peer-adjusted number of close rivals concurrently held is about 0.40 lower for above median *MB* funds, as documented in the second column of Panel B. Hence, these funds on average hold less in close rival firms than peer funds.[11]

Taken together, the results from this section provide strong evidence that the product market dimension matters more to funds with larger monopoly bets. This suggests that *MB* indeed captures differences in processing this type of information.

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[10] To obtain the value-weighted number of direct rivals concurrently bought, I calculate for each stock bought by the fund in a given quarter the number of close rivals that are simultaneously bought. To obtain a fund-level measure, I aggregate the number of rivals using the trade size as a weight.

[11] In Table A.1 in the Internet Appendix, I provide further evidence that high-*MB* funds more actively avoid within-portfolio competition by documenting that they are more likely to replace rival firms, i.e., they have a stronger tendency to sell a stock with a higher similarity to the stocks that newly enter the portfolio during the quarter.

2 Monopoly bets and future fund performance

In this section I examine the hypothesis that funds with a better understanding of the product market place larger monopoly bets and gain an information advantage leading to a higher fund performance. I formally test this hypothesis in Section 2.1. In Section 2.2, I analyze differences in buy performance in monopoly and non-monopoly stocks. Then, in Section 2.3, I investigate whether the result on the *MB*-performance relation is robust to variations in the empirical setup. In Section 2.4, I address endogeneity concerns for the *MB*-performance relationship by exploiting exogenous shocks to the information environment and to a firm's product market competition.

2.1 Do monopoly bets predict fund performance?

To examine the relation between a fund's performance and its monopoly bet, I employ both holdings-based performance measures as well as 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.[12] I compound the monthly DGTW-adjusted fund returns over the three months within a quarter. Quarterly alphas from the factor model are constructed as the difference of 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.[13] To better capture the investment skill of the fund manager, 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.

[12] For robustness, I ran the analysis also based on different holdings-based performance measures as well as different factor models. As shown in the robustness section, my main result does not change when using these alternative performance measures.

[13] Monthly factors are obtained from Kenneth French's website. Monthly alphas and factor loadings are only calculated, 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)).

The univariate comparisons in Panel B of Table 1 already hint at a superior performance of funds with above median *MB*. In a more formal test, I now employ a pooled regression in which I relate fund performance in quarter *t* to its monopoly bet, *MB,* in quarter *t*-1 and add control variables that are known to have an impact on fund performance:

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

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 for regression (2) both using the continuous *MB* variable as well as the high-*MB* dummy.

– Insert TABLE 3 approximately here –

The results in Table 3 support the hypothesis for a positive relation between *MB* and fund performance. For both, the continuous *MB* measure and the *MB* dummy, I find that larger monopoly bets are positively related to fund performance. The effect is also economically relevant: After controlling for various fund characteristics, funds with above median *MB* outperform funds with below median *MB* by around 23 basis points per quarter when using DGTW-adjusted returns or by around 18 basis points per quarter using Carhart (1997) 4-factor alphas. This corresponds to an annual outperformance of up to 92 basis points.

Regarding the coefficients on the control variables, I find that fund size has a negative impact on fund performance suggesting diseconomies of scale in the mutual fund industry (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 Carhart (1997) or Barras, Scaillet, and Wermers (2010)). Finally, I find a positive impact of family size on fund performance, in line with Chen et al. (2004) and Pollet and Wilson (2008). However, the relation is statistically insignificant which is consistent with more recent evidence by Bhojraj, Cho, and Yehuda (2012). The remaining controls have no consistent impact on performance.

In sum, the results from this section support the notion that funds with a better understanding of the product market, as captured by a higher *MB*, obtain an information advantage which is beneficial for their performance.

2.2 Evidence from trades in monopoly and non-monopoly stocks

If monopoly bets signal an information-processing skill, then this skill should be reflected irrespective of a firm's competitive environment. In this section, I therefore explore whether the better comprehension of product market competition of managers with higher monopoly bets also allows them to outperform in more competitive markets. For one, Peress (2010) shows that more competitive markets are less informationally efficient. Skilled fund managers should exploit the inefficiencies in these segments to generate a higher performance than their unskilled peers.[14] Second, a higher fraction of monopoly stocks reduces the need to constantly monitor industry dynamics, so fund managers can devote more attention to firms with stronger competition. I therefore explore the performance of trades in monopoly and non-monopoly sub-portfolios.[15] 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 sub-portfolios as the trade size-weighted performance of all the stocks in the sub-portfolio in the following quarter using DGTW-adjusted returns and Carhart (1997) 4-factor alphas. Risk-adjusted quarterly stock performance is calculated analogously to fund

[14] A similar argument is made by Fang, Kempf, and Trapp (2014) who document that a manager's skill is rewarded more in the less efficient high yield bond market segment.

[15] Several studies argue that trades are more appropriate than holdings to capture information advantages, and, hence, skill of fund managers (e.g., Chen, Jegadeesh, and Wermers (2000), Pool, Stoffman, and Yonker (2015)).

performance. I run a similar regression as in Table 3, but replace the dependent variable with the performance of the buy sub-portfolios. Panel A of Table 4 reports the results.

– Insert TABLE 4 approximately here –

Table 4 results provide clear evidence for an information advantage of high-*MB* funds irrespective of the competitive environment. For both monopoly- and non-monopoly stocks, the buy portfolios of funds with higher *MB* outperform the buys of funds with lower *MB*. For example, the monopoly buys of high-*MB* funds outperform by almost 21 basis points per quarter when using Carhart (1997) alphas.

To provide further support for the higher stock-picking skills of funds with larger monopoly bets, I compare their actual buy performance with the performance of hypothetical benchmark sub-portfolios consisting of the competing firms of the purchased stocks. To obtain the benchmark, for each stock, I calculate the equally-weighted average quarterly performance of its 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 can be interpreted as the performance of a fund's buy portfolio if the amount that was actually used to purchase a stock had been equally distributed over the stock's rival firms. I calculate the differences between the actual buy sub-portfolio and the benchmark portfolios and use this difference as dependent variable in an analogous regression as in Panel A. Panel B of Table 4 reports the results.

The results from Panel B of Table 4 additionally support the notion that fund managers with larger *MB* 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.

In Table A.2 of the Internet Appendix, I also present evidence from a long-short strategy as an alternative approach to document information advantages in monopoly and non-monopoly sub-portfolios. In detail, the results in Panel A of Table A.2 suggest that buying stocks bought by high-*MB* funds and selling the stocks sold by these funds delivers a significantly higher performance than a long-short strategy based on the trades of low-*MB* funds. This result is robust to the inclusion of time fixed effects as well as standard errors clustered at the fund level, as summarized in Panel B of Table A.2.

Taken together, the main result of Table 3 is supported by these trade-based results. More importantly, the outperformance of high-*MB* funds does not stem from a specialization in monopoly firms, but also from their trading in more competitive product markets. This is consistent with the idea that funds with a better comprehension of the product market are able to exploit investment opportunities irrespective of a firm's competitive position.

2.3 Robustness and alternative specifications

In this section, I present results from a battery of robustness tests for the main result of Table 3. Panel A of Table 5 reports results when using different performance measures, both based on factor models as well as holdings-based measures, as dependent variable. For brevity, here and in the rest of the Table 5, I suppress control variables. As alternative factor models, I estimate quarterly fund performance using a Jensen (1968) 1-factor, a Fama and French (1993) 3-factor, a Pástor and Stambaugh (2003) 5-factor as well as Cremers, Petajisto, and Zitzewitz (2012) 4-factor and 7-factor models. Finally, I calculate a fund's value-weighted average Cohen, Coval, and Pástor (2005) stock quality measure which is the Carhart (1997) 4-factor alpha, estimated over the last 24 months, of all funds holding a stock in a particular period.

In Panel B of Table 5, I vary the estimation method. In particular, I estimate the regression (2) using fund fixed effects, manager fixed effects, family-time fixed effects or style-time fixed effects to control for any unobservable effects at the fund or manager level or within a given family or investment style in a quarter.[16] Next, I perform a permutation test in which I assign a

[16] The fund family, for example, could employ more analysts to facilitate the processing of qualitative information. Alternatively, monopoly firms could be geographically close to certain fund families that overweight these stocks due to a (profitable) local bias (Coval and Moskowitz (2001)).

fund a random *MB* (high-*MB* dummy) and rerun my baseline regression of Table 3. This is repeated for 10,000 random draws. The p-value of this exercise indicates the number of draws that result in a regression coefficient as large as or larger than the reported coefficient of Table 3. To take into account that high-*MB* and low-*MB* funds differ significantly on observable characteristics, I finally run the baseline regression on a weighted sample where weights are based on a propensity score matching. To estimate propensity scores, I estimate a logistic regression of the high-*MB* dummy on all control variables of regression (2) as well as time and style fixed effects. This approach overweights observations from low-*MB* funds that are more similar to the high-*MB* group based on observable fund characteristics.

As a last set of robustness tests, Panel C of Table 5 reports results when I use alternative approaches to measure a fund manager's propensity to invest in firms with fewer competitors as a signal for understanding product market competition. These include the equally-weighted instead of the value-weighted fraction of monopoly stocks, the value-weighted number of close rivals over all stocks in the fund portfolio, the definition of monopoly firms based on low product market fluidity as well as the value-weighted product market fluidity of all firms in the fund portfolio.[17]

– Insert TABLE 5 approximately here –

All tests in Table 5 support the result that funds with a stronger propensity to invest into monopolies deliver a superior performance. In particular, the result is statistically significant in all specifications and economically similar to the one in Table 3. I can therefore conclude that my main result is robust to variations in the empirical setup.

[17] Note that in the last approach, a higher product market fluidity indicates stronger product market threats. Therefore a higher value indicates a lower tendency to invest into monopoly stocks. In unreported tests, I also used the value-weighted number of rivals concurrently held or traded, as in Panel B of Table 2, to proxy a better understanding of the product market. As expected, the results show that these measures have a significantly negative impact on fund performance.

2.4 Exogenous shocks to information quality and competitive environment

In this section, I exploit two quasi-natural experiments to support a causal interpretation of the previously established performance result. In Section 2.4.1, I use the Sarbanes-Oxley Act in 2002 as an exogenous shock to the overall quality of publicly-available information and in Section 2.4.2, I provide results from an exogenous shock to the competitive environment in the military goods industry after the 9/11 terrorist attacks.

2.4.1 Evidence from a shock to information quality around the Sarbanes-Oxley Act

If fund managers with larger monopoly bets obtain an information advantage by incorporating hard-to-process information, then this advantage should be diminished, once the overall reporting quality of firm information improves. With the passage of the Sarbanes-Oxley Act (SOX) in 2002 firms face enhanced requirements in their financial reporting which generally improves the information set of investors. This makes it less likely for informed investors to fully reap the profits from their privately obtained information (e.g., Bernile, Kumar, and Sulaeman (2015)). I therefore expect a stronger deterioration in fund performance around SOX for funds with larger monopoly bets before the event. To test this hypothesis, I run a cross-sectional regression similar to Agarwal et al. (2015) of the change in fund performance, measured as the difference between average quarterly performance in the four quarters after the event and the four quarters before the event on the average quarterly *MB* in the four quarters before SOX and the same control variables as in equation (2), all averaged over the same quarters as *MB* except for fund age, which is measured at the event quarter. The regression also includes style fixed effects. Table 6 reports the results from this exercise using both the continuous average *MB* measure as well as a dummy variable equal to one, if the fund has an average *MB* above the median, and zero otherwise.

– Insert TABLE 6 approximately here –

The results in Table 6 provide support for the hypothesis that funds with larger monopoly bets experience a stronger decline in fund performance around the passage of SOX. For example, funds with above median average *MB* before the event quarter experience a decline in quarterly performance of 1.18 percentage points in terms of DGTW-adjusted returns relative to below median average *MB* funds.[18]

These results suggest that the improvement in the quality of publicly available information induced by the passage of the Sarbanes-Oxley Act in 2002 hurts the more informed investors to a larger extent. This is consistent with the notion that high-*MB* funds indeed have an information advantage over low-*MB* funds.

2.4.2 Evidence from a large shock to competition around the 9/11 terrorist attacks

As an additional identification strategy I use an exogenous shock to the military goods industry due to the 9/11 terrorist attacks. The positive demand shock in the defense industry after the attacks led to increases in competition as new firms entered the industry or existing firms changed their product offerings towards the higher demand. This resulted in higher product similarity and more direct rivals for military good firms (Hoberg and Phillips (2015)). Consequently, fund managers who place larger monopoly bets should reduce their position in military good firms after the sudden increase in competition. Therefore, I expect funds with decreases in the portfolio weight of military goods firms to exhibit a higher performance change around the event.

[18] To rule out the concern of a potential mean reversion in fund performance, I repeat the analysis using Q4/2005 as a placebo period without a similar regulatory shock. The results, reported in Panel A of Table A.3 in the Internet Appendix, suggest that, in the absence of an information shock, funds with higher *MB* do not experience a significant decline in fund performance. The comparison of the coefficients for the SOX quarter and the placebo period, summarized in Panel B of Table A.3, shows that the decline in performance around SOX is significantly larger than in the placebo period.

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 with a positive weight in the military industry before the attack I calculate post-minus-pre-attack average weights in these military firms using quarterly values in the four quarters before the terrorist attacks, i.e., from September 2000 to June 2001, and after the attacks in the period March to December 2002. I skip the quarter directly after the terrorist attacks as the industry change is likely to develop over a couple of months. Similar to the *MB* measure, I use peer-group adjusted average weights before and after the attack to control for style driven differences in the exposure to military firms.[20] For the same period, I calculate post-minus-pre-attack differences in average quarterly fund performance. Table 7 reports results from a cross-sectional regression in which I relate the performance difference to the military weight difference and control for the same variables as before using average values in the four quarters before the attack as well as style fixed effects. I present results both for the continuous difference in military weights as well as for a modified version in which I replace the difference with a dummy that equals one, if the fund's change in its military weight is above the median of all funds.

– Insert TABLE 7 approximately here –

As expected, the results from Table 7 suggest a negative relation between performance changes and changes in the weight of military goods firms. For instance, funds with above median changes in their peer-adjusted weight in military good firms after the attack show a decrease in average quarterly Carhart (1997) 4-factor alpha by almost 47 basis points compared to funds with below median changes. This is a significant effect and unlikely to stem solely from trading in the military goods industry but from trading in the whole portfolio. I argue that

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[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.

[20] The results (unreported) remain qualitatively unchanged when using unadjusted weights in military good firms.

managers who decrease their military weight are generally better in incorporating product market shocks and therefore adjust their total portfolio according to this new information.

These results provide evidence that a positive shock to the product market competition within an industry and a subsequent reduction in the industry weight, as would be expected for funds with higher monopoly bets, bring about changes in fund performance. This strengthens a causal interpretation of the relation between fund performance and a fund's investment into more differentiated products.

3 Is *MB* capturing a manager-related characteristic?

In this section, I provide evidence that the monopoly bet results from differences in information-processing by showing that it is related to the fund manager and her characteristics. If *MB* depends on the fund manager, we should see changes in a fund's monopoly bet when the manager is replaced. I therefore identify cases when a single-managed fund is taken over by another single manager and calculate changes in average quarterly monopoly bets in the year before and after the switch quarter.[21] I compare the new manager's propensity to invest into monopoly stocks, measured as the average monopoly bet of the new manager in the year before the switch over all of her (team- and single-managed) funds, with the average monopoly bet of the old manager in the respective fund (Δ *MB propensity*). If the new manager tends to place larger monopoly bets than the old manager, then the fund's monopoly bet should increase around the switch.

Panel A of Table 8 provides results of a pooled regression in which I regress the fund's change in *MB* around the manager switch on the difference in fund managers' monopoly bet propensities. I control for the same variables as in Table 2, measured at the end of the switch

[21] Jin and Scherbina (2011) provide evidence that newly appointed managers only need two quarters to implement their own investment strategy in the fund portfolio.

quarter, as well as style and time fixed effects. Standard errors are, as before, clustered at the fund level.

– Insert TABLE 8 approximately here –

The results in Panel A of Table 8 support the hypothesis that a new manager with a stronger propensity to invest into monopoly firms than the old manager increases the fund's *MB*.[22]

After having documented a general influence of the fund manager on the propensity to invest into monopoly firms, an obvious question that arises is if different manager attributes predict differences in *MB*. The robustness tests in Panel B of Table 5 already rule out that the relation between *MB* and performance is driven by time-invariant skill differences between management teams. It is, thus, unlikely that the ability to process qualitative information stems only from the manager's innate talent. However, it is possible that fund managers learn to process qualitative information and to better understand the product market. Moreover, their job should allow them to put sufficient effort in costly information acquisition.

I conjecture that the monopoly bet depends on manager experience as well as the effort she devotes to manage the fund. To capture manager effort, I introduce a dummy variable equal to one if the fund's managers on average manage more than one fund (*Multiple funds per manager*), and zero otherwise. Agarwal, Ma, and Mullally (2016) find that managers divert their effort when managing multiple funds. If larger monopoly bets require more effort in information production, then managers with multiple funds are less likely to overweight monopoly stocks.

In addition, more experienced fund managers should be better in processing information on 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 monopoly bet. As a proxy for

[22] This results also holds when controlling for fund performance, measured as the Carhart (1997) 4-factor alpha over the past 24 months.

investment experience, I use the maximum number of years working in the fund industry over all managers of the fund (*Manager tenure*).[23]

Lastly, I use the number of fund managers as additional determinant (*# Managers*). Larger teams can produce more information at the same time when each member is allocated a subset of stocks to evaluate. 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 (2015)). 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 therefore an empirical question whether larger fund manager teams place larger monopoly bets.

To test these hypotheses, I run pooled OLS regressions in which I relate *MB* to the mentioned manager attributes in the previous quarter also taking into account the same control variables as in Panel A, as well as time and style fixed effects. Again, standard errors are clustered at the fund level. I conduct a similar analysis using the *MB* dummy as dependent variable in a logistic regression. Panel B of Table 8 presents the results of this analysis.

Based on the results presented in Panel B of Table 8, I find support for the notion that time-varying manager characteristics matter for the propensity to invest into monopoly stocks. As hypothesized, managers who can devote more effort in information production as well as managers with more investment experience place larger monopoly bets. On the other hand, funds managed by larger teams invest less in monopoly stocks, which is consistent with free-riding in information production.

Taken together, results from this section provide strong evidence for a manager-related explanation of why funds differ in their monopoly bet and why these differences predict fund

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

performance. This is consistent with information on product market competition requiring effort and experience in information production and processing.

4 *MB* and fund investment behavior

To further understand the manager's motivation to invest into monopoly firms when incorporating information on the competitive environment and to identify potential channels for the documented outperformance, I finally analyze whether monopoly bets are employed by fund managers to pursue particular investment strategies.

Higher monopoly bets could be the result of long-term trading strategies as monopoly firms generate more stable cash flows. If this is the case, investors should hold on to monopoly stocks for a longer period of time. On the contrary, firms with less market power more often adapt their strategies due to a dynamic competitive environment, e.g. by investing more in R&D or increasing acquisition activity. This leads to a more frequent updating of investors' expectations about the firm's future cash flows (see, e.g., Giannetti and Yu (2016) and Irvine and Pontiff (2009)). Hence, stocks from competitive industries seem to be more appropriate for short-term investors.

To test, whether funds with larger monopoly bets are indeed more long-term oriented, I estimate pooled regressions where the dependent variable is the fund's trading frequency in quarter *t*. I use both the fund's quarterly turnover of the common stock portfolio (*Portfolio turnover*) and the "Simple Horizon Measure" of Lan, Moneta, and Wermers (2016), measured as the value-weighted average number of years that the currently held stocks are kept in the portfolio (*Investment horizon*), as proxies for trading frequency. I annualize *Portfolio turnover* by multiplying it with four. The key independent variable is *MB* or the *MB* 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. Regression results are summarized in Panel A of Table 9.

– Insert TABLE 9 approximately here –

Results from Panel A of Table 9 support the hypothesis that managers with higher monopoly bets keep the stocks for a longer period of time, irrespective of whether I use *Portfolio turnover* or *Investment horizon.* The effect is significant both in statistical (significant at the 1%-level) and economic terms. For example, the portfolio turnover of high-*MB* funds is almost eight percentage points per year lower than the turnover of low-*MB* funds. In addition, the *Investment horizon* is about 0.21 years longer for funds with above median *MB.* Compared to the average *Investment horizon* of low-*MB* funds (3.76 years) this is a difference of about six percent.[24]

In Table A.4 in the Internet Appendix, I additionally present results when calculating *Investment horizon* separately for monopoly- and non-monopoly sub-portfolios. The results provide strong evidence that funds with larger monopoly bets hold both monopoly and non-monopoly stocks for a longer time, while the difference is more pronounced in the monopoly sub-portfolios. This is not surprising considering that high-*MB* funds pick better performing monopoly stocks, as shown in Table 4, and have less incentives to sell monopoly stocks than low-*MB* funds.

The stability and resultant lower trading frequency should further allow the fund manager to pursue riskier strategies and invest more costly, e.g., in more illiquid assets to earn an illiquidity premium (see, e.g., Amihud, Mendelson, and Pedersen (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 run a similar regression as in Panel A of Table 9 using *Portfolio liquidity* as dependent variable. Columns 1 and 2 of Panel B

[24] This result, admittedly, raises the concern that the monopoly bet is just an alternative proxy for the fund's holding horizon. Since Lan, Moneta, and Wermers (2016) document that long-horizon funds outperform, the previously established outperformance of high-*MB* funds could therefore simply stem from a longer investment horizon. However, in unreported tests, I add the fund's investment horizon as control variable in the regression of Table 3 and still find a significant and positive impact of *MB* on fund performance.

in Table 9 present the results. As expected, funds with larger monopoly bets have a significantly (at the 1%-level) lower portfolio liquidity. The difference is almost 0.42 between high- and low-*MB* funds which represents about 5.8 percent of the *Portfolio liquidity* of low-*MB* funds (7.19).

Finally, monopoly stocks might also be used as instruments for mispricing-related trading. As market power could result in safety, growth, and profitability of the firms, monopoly stocks are likely candidates for high quality stocks (Asness, Frazzini, and Pedersen (2014)). I therefore estimate a fund's quarterly loading on the "Quality-Minus-Junk" (QMJ) factor from a Carhart (1997) 4-factor model augmented by the QMJ factor and the "Betting-Against-Beta" (BAB) factor (Frazzini and Pedersen (2014)) using daily gross fund returns within the quarter (*Fund QMJ loading*).[25] The results of the same pooled regression as before, but with *Fund QMJ loading* as dependent variable, are presented in columns 3 and 4 of Panel B. These results provide support for the notion that funds with larger monopoly bets pursue more quality investing. Compared to the *Fund QMJ loading* of below median *MB* funds (-0.13) the loading of high-*MB* funds is by about one-third larger.[26]

In sum, the results from this section suggest that the monopoly character of stocks is exploited for concrete investment strategies. Especially, a higher fraction of monopoly stocks is indicative for profitable trading behavior, such as investments in illiquid stocks and quality investing, which should contribute to the outperformance of high-*MB* funds.

5 Summary and conclusion

Despite the importance of product market competition for asset pricing and corporate decisions, surprisingly little is known about the impact of firm competition on the performance and behavior of professional investors. Only recently, academic research suggests that institutional investors try to avoid rivalry among their portfolio firms and rather push them towards

[25] I obtain daily BAB and QMJ factors from AQR's website: https://www.aqr.com/library/data-sets.

[26] In unreported tests, I replace *Fund QMJ loading* with the loading on the operating profitability factor (RMW) from a Fama and French (2015) 5-factor model. The results remain qualitatively unchanged.

monopolistic behavior (e.g., Azar, Schmalz, and Tecu (2016)). In this paper I study how the incorporation of the product market dimension into stock picking decisions affects the performance of fund managers. A firm's product market environment is more challenging to capture than quantitative information and, thereby, offers valuable information for investors with higher information-processing skills.

I develop the monopoly bet as a simple measure to differentiate managers by their ability to process information on a firm's competitive environment and document that mutual fund managers who place larger bets on firms with the most differentiated products gain information advantages and exhibit a superior performance. Furthermore, my tests based on an exogenous shock to the quality of public information as well as an exogenous demand shock in the military goods industry suggest a causal interpretation of the link between a fund's propensity to overweight monopoly firms and its performance.

Consistent with differences in information-processing ability, I further provide evidence that the tendency to invest into monopoly firms is likely a time-varying manager attribute and strongly depends on her investment experience and effort.

As expected, managers with larger monopoly bets avoid concurrent investment in close rivals and hold stocks for a longer period. Finally, they exploit the monopoly character of the firms to pursue more illiquid and quality investment strategies which are documented to positively affect performance.

Taken altogether, it appears that skilled professional investors can extract valuable information from a firm's product market environment and exploit this hard-to-process information to gain an advantage over their peers.

REFERENCES

Agarwal, V., L. Ma, and K. Mullally. 2016. Managerial Multitasking in the Mutual Fund Industry. Working Paper, Georgia State University and Northeastern University.

Agarwal, V., K. A. Mullally, Y. Tang, and B. Yang. 2015. Mandatory Portfolio Disclosure, Stock Liquidity, and Mutual Fund Performance. *Journal of Finance* 70: 2733-76.

Aguerrevere, F. L. 2009. Real Options, Product Market Competition, and Asset Returns. *Journal of Finance* 64: 957-83.

Akbas, F., E. Boehmer, and E. Genc. 2015. Peer Stock Short Interest and Future Returns. Working Paper, University of Kansas, Singapore Management University, and Erasmus University Rotterdam.

Alldredge, D. M., and A. Puckett. 2016. The Performance of Institutional Investor Trades Across the Supply Chain. Working Paper, Washington State University and University of Tennessee, Knoxville.

Amihud, Y. 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5: 31-56.

Amihud, Y., H. Mendelson, and L. H. Pedersen. 2005. Liquidity and Asset Pricing. *Foundations and Trends in Finance* 1: 269-364.

Antón, M., F. Ederer, M. Giné, and M. Schmalz. 2016. Common Ownership, Competition, and Top Management Incentives. Working Paper, IESE Business School, Yale University, and University of Michigan.

Asness, C. S., A. Frazzini, and L. H. Pedersen. 2014. Quality Minus Junk. Working Paper, AQR Capital Management, Copenhagen Business School, and New York University.

Azar, J., M. C. Schmalz, and I. Tecu. 2016. Anti-Competitive Effects of Common Ownership. Working Paper, University of Navarra, University of Michigan, and Charles River Associates.

Barras, L., O. Scaillet, and R. Wermers. 2010. False Discoveries in Mutual Fund Performance: Measuring Luck in Estimate Alphas. *Journal of Finance* 65: 179-216.

Berk, J. B., and R. C. Green. 2004. Mutual Fund Flows and Performance in Rational Markets. *Journal of Political Economy* 112: 1269-95.

Bernile, G., A. Kumar, and J. Sulaeman. 2015. Home away from Home: Geography of Information and Local Investors. *Review of Financial Studies* 28: 2009-49.

Bhojraj, S., Y. J. Cho, and N. Yehuda. 2012. Mutual Fund Family Size and Mutual Fund Performance: The Role of Regulatory Changes. *Journal of Accounting Research* 50: 647-84.

Forbes, May 16, 2012. 2012. Berkshire Follower? Try These 5 Buffett Wannabe Mutual Funds. May 16, 2012.

The Wall Street Journal, August 2, 2012. 2012. Follow the Buffett Strategy. August 2, 2012.

Bustamante, M. C. 2015. Strategic Investment and Industry Risk Dynamics. *Review of Financial Studies* 28: 297-341.

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

Chen, H.-L., N. Jegadeesh, and R. Wermers. 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: 343-68.

Chen, J., H. Hong, M. Huang, and J. D. Kubik. 2004. Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review* 94: 1276-302.

Cici, G., M. Gehde-Trapp, M.-A. Goericke, and A. Kempf. 2016. What They Did in Their Previous Lives: The Investment Value of Mutual Fund Managers' Experience Outside the Financial Sector. Working Paper, Centre for Financial Research, University of Cologne.

Cohen, R. B., J. D. Coval, and L. Pástor. 2005. Judging Fund Managers by the Company They Keep. *Journal of Finance* 60: 1057-96.

Coval, J. D., and T. J. Moskowitz. 2001. The Geography of Investment: Informed Trading and Asset Prices. *Journal of Political Economy* 109: 811-41.

Cremers, K. J. M., and A. Petajisto. 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. *Review of Financial Studies* 22: 3329-65.

Cremers, M., A. Petajisto, and E. Zitzewitz. 2012. Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation. *Critical Finance Review* 2: 1-48.

Daniel, K., M. Grinblatt, S. Titman, and R. Wermers. 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. *Journal of Finance* 52: 1035-58.

Doshi, H., R. Elkamhi, and M. Simutin. 2015. Managerial Activeness and Mutual Fund Performance. *Review of Asset Pricing Studies* 5: 156-84.

Engelberg, J., A. Ozoguz, and S. Wang. 2013. Know Thy Neighbor: Industry Clusters, Information Spillovers and Market Efficiency. Working Paper, University of California, San Diego, Rice University, and University of North Carolina.

Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2012. How are Shorts Informed?: Short Sellers, News, and Information Processing. *Journal of Financial Economics* 105: 260-78.

Evans, R. B. 2010. Mutual fund incubation. *Journal of Finance* 65: 1581-611.

Fama, E. F., and K. R. French. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics* 33: 3-56.

———. 2010. Luck versus Skill in the Cross-Section of Mutual Fund Returns. *Journal of Finance* 65: 1915-47.

———. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116: 1-22.

Fang, J., A. Kempf, and M. Trapp. 2014. Fund Manager Allocation. *Journal of Financial Economics* 111: 661-74.

Fang, L. H., J. Peress, and L. Zheng. 2014. Does Media Coverage of Stocks Affect Mutual Funds' Trading and Performance? *Review of Financial Studies* 27: 3441-66.

Foucault, T., and L. Frésard. 2016. Corporate Strategy, Conformism, and the Stock Market.

Frazzini, A., and L. H. Pedersen. 2014. Betting Against Beta. *Journal of Financial Economics* 111: 1-25.

Gargano, A., A. G. Rossi, and R. Wermers. 2016. The Freedom of Information Act and the Race Towards Information Acquisition. *Review of Financial Studies* forthcoming.

Giannetti, M., and X. Yu. 2016. The Corporate Finance Benefits of Short Horizon Investors. Working Paper, Stockholm School of Economics, European Corporate Governance Institute, and Indiana University.

Giroud, X., and H. M. Mueller. 2011. Corporate Governance, Product Market Competition, and Equity Prices. *Journal of Finance* 66: 563-600.

Gompers, P. A., W. Gornall, S. N. Kaplan, and I. A. Strebulaev. 2016. How Do Venture Capitalists Make Decisions? Working Paper, Harvard University, NBER, University of British Columbia, University of Chicago, and Stanford University.

Gu, L. 2016. Product Market Competition, R&D Investment, and Stock Returns. *Journal of Financial Economics* 119: 441-55.

Hirshleifer, D., P.-H. Hsu, and D. Li. 2013. Innovative Efficiency and Stock Returns. *Journal of Financial Economics* 107: 632-54.

Hoberg, G., and G. Phillips. 2010. Real and Financial Industry Booms and Busts. *The Journal of Finance* 65: 45-86.

———. 2014. Product Market Uniqueness, Organizational Form and Stock Market Valuations. Working Paper, University of Southern California and Dartmouth College.

Hoberg, G., G. Phillips, and N. Prabhala. 2014. Product Market Threats, Payouts, and Financial Flexibility. *The Journal of Finance* 69: 293-324.
Hoberg, G., and G. M. Phillips. 2015. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy* forthcoming.
Hou, K., and D. T. Robinson. 2006. Industry Concentration and Average Stock Returns. *Journal of Finance* 61: 1927-56.
Hsu, C., X. Li, Z. Ma, and G. M. Phillips. 2015. Does Product Market Competition Influence Analyst Coverage and Analyst Career Success? Working Paper, Hong Kong University of Science & Technology, Peking University, and Dartmouth College.
Huang, L., and J. R. Kale. 2013. Product Market Linkages, Manager Quality, and Mutual Fund Performance. *Review of Finance* 17: 1895-946.
Investment Company Institute. 2015. Investment Company Fact Book 2015. *Investment Company Institute Research Series* 1: 1-296.
Irvine, P. J., and J. Pontiff. 2009. Idiosyncratic Return Volatility, Cash Flows, and Product Market Competition. *Review of Financial Studies* 22: 1149-77.
Jensen, M. C. 1968. The Performance of Mutual Funds in the Period 1945-1964. *Journal of Finance* 23: 389-416.
Jiang, H., and Z. Sun. 2014. Dispersion in Beliefs Among Active Mutual Funds and the Cross-Section of Stock Returns. *Journal of Financial Economics* 114: 341-65.
Jin, L., and A. Scherbina. 2011. Inheriting losers. *Review of Financial Studies* 24: 786-820.
Kacperczyk, M., S. V. Nieuwerburgh, and L. Veldkamp. 2014. Time-Varying Fund Manager Skill. *Journal of Finance* 69: 1455-84.
Kacperczyk, M., and A. Seru. 2007. Fund Manager Use of Public Information: New Evidence on Managerial Skills. *Journal of Finance* 62: 485-528.
Kacperczyk, M., C. Sialm, and L. Zheng. 2005. On the Industry Concentration of Actively Managed Equity Mutual Funds. *Journal of Finance* 60: 1983-2011.
Kim, O., and R. E. Verrecchia. 1994. Market Liquidity and Volume Around Earnings Announcements. *Journal of Accounting and Economics* 17: 41-67.
Lan, C., F. Moneta, and R. Wermers. 2016. Holding Horizon: A New Measure of Active Investment Management. Working Paper, UNSW Business School, Queen's University, and University of Maryland.
Massa, M., and L. Phalippou. 2005. Mutual Funds and the Market for Liquidity. Working Paper, INSEAD and University of Oxford.
Pástor, L., and R. F. Stambaugh. 2003. Liquidity Risk and Expected Stock Returns. *Journal of Political Economy* 111: 642-85.
Patel, S., and S. Sarkissian. 2015. To Group or Not to Group? Evidence from CRSP, Morningstar Principia, and Morningstar Direct Mutual Fund Databases. *Journal of Financial and Quantitative Analysis* forthcoming.
Peress, J. 2010. Product Market Competition, Insider Trading, and Stock Market Efficiency. *The Journal of Finance* 65: 1-43.
Pollet, J. M., and M. Wilson. 2008. How Does Size Affect Mutual Fund Behavior. *Journal of Finance* 63: 2941-69.
Pool, V. K., N. Stoffman, and S. E. Yonker. 2015. The People in Your Neighborhood: Social Interactions and Mutual Fund Portfolios. *Journal of Finance* 70: 2679-731.
Raith, M. 2003. Competition, Risk, and Managerial Incentives. *American Economic Review* 93: 1425-36.
Sirri, E. R., and P. Tufano. 1998. Costly Search and Mutual Fund Flows. *Journal of Finance* 53: 1589-622.
Stein, J. C. 2002. Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *Journal of Finance* 57: 1891-921.

Table 1 – Summary statistics

This table reports summary statistics. In Panel A I report annual summary statistics for the total sample of stocks (All) as well as separately for monopoly and non-monopoly stocks between 1999 and 2012. Monopoly stocks are defined as stocks in the bottom quintile in the number of competitors in a given year. The last column of the table reports the difference in mean stock characteristics for monopoly and non-monopoly stocks. *Number of competitors* is the number of direct rival firms of a given stock according to the Text-based Network Industry Classification (TNIC) as in Hoberg and Phillips (2015). A firm is identified as a rival if its pairwise similarity score of its 10-K product description exceeds a certain threshold. *Product market fluidity* measures competitive threats and changes in the product market competition of a firm based on Hoberg, Phillips, and Prabhala (2014). *Firm size* is the average monthly market capitalization of the firm in a given 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* represents 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, where turnover is defined as the daily number of shares traded divided by total shares outstanding. *Amihud illiquidity* represents the average quarterly stock illiquidity based on a daily Amihud (2002) illiquidity measure. *Annual return* is the annual stock return. Returns are winsorized at the 1st and 99th percentile. *CCP* is the stock quality measure of Cohen, Coval, and Pastor (2005) defined as the average Carhart (1997) 4-factor alpha estimated over the past 24 months of all funds holding the stock. Panel B presents quarterly summary statistics for key variables at the fund level for the total sample (All) as well as for high- and low-*MB* funds, where high-*MB* funds are defined as funds with a monopoly bet (*MB*) above the median over all funds in the respective quarter. The last column of the table reports the difference in fund characteristics for high- and low-*MB* funds. *Fund size* is the total net assets under management in millions of dollars and *Fund age* is shown in years. *Family size* is the 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* represents 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* represents the number of distinct stocks held by the fund. *Raw return* is the gross-of-fee fund return over the quarter. *DGTW-adjusted return* is the value-weighted stock characteristic adjusted quarterly return as in Daniel et al. (1997). *Carhart alpha* represents the quarterly Carhart (1997) 4-factor alpha based on gross-of-fee returns. Both DGTW-adjusted return and Carhart alpha are annualized. ***, **, * denote statistical significance for the difference in means between both groups at the 1%, 5%, and 10% significance level, respectively.

Panel A: Stock characteristics

	All (N=9,452)	Monopoly stocks	Non-monopoly stocks	Difference
Number of competitors	130.42	5.57	163.23	-157.66 ***
Product market fluidity	7.61	5.06	8.28	-3.22 ***
Firm size	2,788	2,109	2,966	-856 ***
Firm age	15.12	17.35	14.53	2.82 ***
Book-to-market ratio	0.82	0.88	0.80	0.08 ***
Quarterly stock turnover (*100)	0.77	0.66	0.80	-0.14 ***
Amihud illiquidity	9.75	15.60	8.21	7.38 ***
Annual return (%)	11.33	10.64	11.50	-0.86
CCP	0.09	0.10	0.09	0.01 **

Table 1 – Summary statistics (continued)

Panel B: Fund characteristics

	All (N=2,561)	**High-*MB***	**Low-*MB***	**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	4.48	2.98	1.50 ***
DGTW-adjusted return (%)	0.19	0.64	-0.27	0.91 ***
Carhart alpha (%), gross	0.23	0.62	-0.16	0.78 ***

Table 2 – *MB* and a fund's reaction to product market competition

This table presents results from pooled OLS regressions that analyze the relation between a fund's response to a firm's product market competition. In Panel A, the dependent variable is *Sensitivity*, the R^2 from the regression of annual changes in a fund's holdings of a given stock on changes in the number of competitors of the stock in the previous two years. The main independent variable is the fund's monopoly bet (*MB*). *MB* is the value-weighted fraction of monopoly firms in the fund portfolio at a given report date adjusted for the average portfolio weight in monopoly firms over all funds in the same investment style. I run separate regressions for the continuous variable as well as for the high-*MB* dummy, which is equal to one if the fund's *MB* is above the median in a given period, and zero otherwise. 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* represents 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* represents 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 *Sensitivity*. If not indicated otherwise, regressions are run with time and style fixed effects and p-values (reported in parentheses) are based on standard errors are clustered at the fund level. 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-monopoly 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-monopoly 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, but now valid as of the end of the quarter preceding the calculation of the dependent variables. 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.

Panel A: Sensitivity to changes in the number of competitors

Dependent variable:	Sensitivity		Sensitivity	
Monopoly bet (MB)	0.0526 ***	0.0197 ***		
	(0.0000)	(0.0047)		
High *MB*			0.0040 ***	0.0017 ***
			(0.0000)	(0.0072)
Fund size		0.0004 *		0.0004 *
		(0.0922)		(0.0903)
Fund age		-0.0008		-0.0008
		(0.1167)		(0.1087)
Turnover ratio		-0.0030 ***		-0.0031 ***
		(0.0000)		(0.0000)
Expense ratio		0.0284		0.0308
		(0.3907)		(0.3405)
Fund flows		0.0023		0.0023
		(0.2550)		(0.2521)
Number of stocks		-0.0192 ***		-0.0193 ***
		(0.0000)		(0.0000)
Family size		-0.0004 ***		-0.0004 ***
		(0.0017)		(0.0011)
Time fixed effects	No	Yes	No	Yes
Style fixed effects	No	Yes	No	Yes
Number of observations	14,507	13,447	14,507	13,447
Adj. R-Squared	0.0070	0.1585	0.0027	0.1580

Table 2 – *MB* and a fund's reaction to product market competition (continued)

Panel B: Concurrent holding and trading of direct competitors

	(Peer-adjusted) Average number of competitors concurrently			
Dependent variable:	Held		Bought	
Monopoly bet (MB)	-2.9878 ***		-1.2959 ***	
	(0.0000)		(0.0000)	
High *MB*		-0.4044 ***		-0.2132 ***
		(0.0000)		(0.0000)
Fund size	0.0337	0.0318	0.0507 ***	0.0495 ***
	(0.3124)	(0.3404)	(0.0003)	(0.0004)
Fund age	-0.3840 ***	-0.3819 ***	-0.2956 ***	-0.2944 ***
	(0.0003)	(0.0003)	(0.0000)	(0.0000)
Turnover ratio	-0.3654 ***	-0.3588 ***	0.1694 ***	0.1688 ***
	(0.0003)	(0.0004)	(0.0000)	(0.0000)
Expense ratio	6.8371	6.4127	-2.3794	-2.5328
	(0.4024)	(0.4270)	(0.3856)	(0.3535)
Fund flows	0.1816 ***	0.1814 ***	0.4151 ***	0.4150 ***
	(0.0002)	(0.0002)	(0.0000)	(0.0000)
Number of stocks	5.4279 ***	5.4440 ***	2.1660 ***	2.1734 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Family size	-0.1377 ***	-0.1352 ***	-0.0309 ***	-0.0303 ***
	(0.0000)	(0.0000)	(0.0006)	(0.0008)
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

Table 3 – Monopoly bet and fund performance

This table presents results from pooled OLS regressions on the relation of quarterly mutual fund performance and the lagged fund monopoly bet *(MB)* 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 monopoly bet (*MB*). I run separate regressions for the continuous variable as well as the *MB* dummy, which is equal to one if the fund's *MB* 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.

	Fund performance			
Dependent variable:	DGTW-adj. return		Carhart alpha	
Monopoly bet (MB)	1.7509 ***		1.0574 ***	
	(0.0000)		(0.0004)	
High *MB*		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

Table 4 – Performance of buys in monopoly and non-monopoly stocks

This table presents results from pooled OLS regressions on the relation of quarterly performance of buy sub-portfolios in monopoly and non-monopoly stocks and the lagged monopoly bet (*MB*). Monopoly stocks are defined as stocks in the bottom quintile according to the number of competitors in a given year. Stocks in the remaining quintiles are part of the non-monopoly stock portfolio. In Panel A, the dependent variable is the next-quarter performance of a sub-portfolio 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. Sub-portfolio 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 sub-portfolio 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 sub-portfolio 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. The main independent variable in both Panels is the fund's monopoly bet (*MB*). I run separate regressions for the continuous variable as well as the *MB* dummy, which is equal to one if the fund's *MB* is above the median in a given quarter, and zero otherwise. Additional independent controls are as in Table 3 and suppressed in Panel B of the table. The independent variables are valid at the end of the quarter preceding the sub-portfolio 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 4 – Performance of buys in monopoly and non-monopoly stocks (continued)

Panel A: Performance of buy sub-portfolios

	Monopoly buys				Non-monopoly buys			
Dependent variable:	DGTW-adj. return		Carhart alpha		DGTW-adj. return		Carhart alpha	
Monopoly bet (MB)	2.3871 ***		1.5400 *		2.0515 ***		1.3095 **	
	(0.0020)		(0.0796)		(0.0000)		(0.0263)	
High *MB*		0.3016 ***		0.2078 **		0.3162 ***		0.2035 ***
		(0.0005)		(0.0337)		(0.0000)		(0.0005)
Fund size	-0.0249	-0.0234	0.0132	0.0143	-0.0536 ***	-0.0523 ***	-0.0528 **	-0.0519 **
	(0.4136)	(0.4434)	(0.7084)	(0.6851)	(0.0021)	(0.0028)	(0.0188)	(0.0206)
Fund age	-0.0099	-0.0121	-0.0208	-0.0223	0.0656	0.0642	0.1022 **	0.1013 **
	(0.8862)	(0.8612)	(0.7893)	(0.7753)	(0.1169)	(0.1252)	(0.0367)	(0.0383)
Turnover ratio	-0.0947	-0.0998	-0.2105 ***	-0.2127 ***	-0.1886 ***	-0.1889 ***	-0.2495 ***	-0.2496 ***
	(0.1672)	(0.1433)	(0.0050)	(0.0047)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fund flows	0.2175 *	0.2195 *	0.0152	0.0166	0.2275 **	0.2300 **	0.1316	0.1332
	(0.0610)	(0.0589)	(0.9036)	(0.8946)	(0.0313)	(0.0309)	(0.2361)	(0.2316)
Number of stocks	-0.0387	-0.0577	-0.1573 **	-0.1694 ***	-0.0596	-0.0710 *	-0.1671 ***	-0.1743 ***
	(0.5025)	(0.3125)	(0.0162)	(0.0095)	(0.1035)	(0.0521)	(0.0002)	(0.0001)
Family size	-0.0050	-0.0076	0.0037	0.0022	-0.0026	-0.0038	-0.0160	-0.0168
	(0.7570)	(0.6396)	(0.8459)	(0.9073)	(0.7986)	(0.7069)	(0.1942)	(0.1708)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	58,331	58,331	58,192	58,192	64,359	64,359	64,335	64,335
Adj. R-Squared	0.0252	0.0252	0.0272	0.0272	0.0408	0.0410	0.0318	0.0319

Table 4 – Performance of buys in monopoly and non-monopoly stocks (continued)

Panel B: Performance relative to a firm's rivals

	Monopoly buys				Non-monopoly buys			
Dependent variable:	Diff. DGTW		Diff. Carhart		Diff. DGTW		Diff. Carhart	
Monopoly bet (MB)	1.8964 **		1.3969		1.1080 **		1.8982 ***	
	(0.0214)		(0.1333)		(0.0169)		(0.0007)	
High *MB*		0.2602 ***		0.2007 *		0.2072 ***		0.2552 ***
		(0.0055)		(0.0627)		(0.0000)		(0.0000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	58,270	58,270	58,025	58,025	64,359	64,359	64,329	64,329
Adj. R-Squared	0.0204	0.0204	0.0340	0.0340	0.0737	0.0738	0.1534	0.1534

Table 5 – Robustness

This table presents robustness checks for the baseline regression of Table 3. For brevity, I only report coefficients of interest and suppress control variables. If not indicated otherwise, fund performance is measured using DGTW-adjusted returns or Carhart (1997) 4-factor alphas based on gross-of-fee returns and reported in percent. The main independent variables are the monopoly bet (*MB*) or the *MB* dummy, defined as in Table 2. In Panel A, I vary the performance measurement. I use the Jensen (1968) 1-factor, the Fama and French (1993) 3-factor, the Pástor and Stambaugh (2003) 5-factor, as well as the Cremers, Petajisto, and Zitzewitz (2012) 4-and 7-factor models to estimate fund performance. I also calculate a fund's Cohen, Coval, and Pástor (2005) alpha, which is the value-weighted average stock quality measure based on the average Carhart (1997) 4-factor alpha of all funds holding a particular stock. In Panel B, I modify the empirical approach by using fund fixed effects, manager fixed effects, family-time fixed effects, or style-time fixed effects. In addition, I report results of a permutation test where the *MB* and the high-*MB* dummy are randomly assigned to funds and the baseline regression of Table 3 is rerun. I repeat the permutation 10,000 times. p-values of this exercise (reported in parentheses) are equal to the fraction of permutations that show an effect that is as strong as the performance difference observed in Table 3. Finally, the last row of Panel B presents results of a weighted matched sample where weights are based on a propensity score matching. To calculate propensity scores, I estimate a logistic regression of the high-*MB* dummy on the same control variables as in the baseline regression as well as time and style fixed effects. In Panel C, I construct alternative measures to capture a fund's tendency to invest in stocks with few competitors and repeat the pooled regression of Table 3 using these alternative proxies. I calculate the equally-weighted instead of the value-weighted fraction of monopoly stocks, the value-weighted average number of competitors of all firms in the portfolio, the value-weighted fraction of stocks in the bottom quintile of product market fluidity, and the value-weighted product market fluidity of all stocks in the portfolio. If not indicated otherwise, 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.

Panel A: Alternative performance measures

	MB	High *MB*
Jensen alpha	2.2015 ***	0.2714 ***
	(0.0000)	(0.0000)
Fama-French alpha	0.8726 ***	0.1413 ***
	(0.0041)	(0.0000)
Pastor-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)

Table 5 – Robustness (continued)

Panel B: Estimation method

	DGTW-adj. return		Carhart alpha	
	MB	High *MB*	*MB*	High *MB*
Fund fixed effects	1.3874 ***	0.1760 ***	0.7687 **	0.1419 ***
	(0.0009)	(0.0000)	(0.0440)	(0.0000)
Manager fixed effects	0.9876 **	0.1749 ***	0.7884 *	0.1294 ***
	(0.0353)	(0.0000)	(0.0526)	(0.0004)
Family-time fixed effects	1.7223 ***	0.1683 ***	0.8317 ***	0.1447 ***
	(0.0000)	(0.0000)	(0.0026)	(0.0000)
Style-time fixed effects	1.7430 ***	0.2293 ***	1.0490 ***	0.1721 ***
	(0.0000)	(0.0000)	(0.0004)	(0.0000)
Permutation	1.7509 ***	0.2286 ***	1.0574 ***	0.1807 ***
	(0.0000)	(0.0000)	(0.0004)	(0.0000)
Matched sample		0.1911 ***		0.2274 ***
		(0.0000)		(0.0000)

Panel C: Alternative proxies

	DGTW-adj. return		Carhart alpha	
	Continuous measure	*Above median cutoff*	*Continuous measure*	*Above median cutoff*
Equally-weighted monopoly stocks	1.7987 ***	0.2186 ***	1.0770 ***	0.1535 ***
	(0.0000)	(0.0000)	(0.0007)	(0.0000)
Value-weighted number of competitors	-0.0074 ***	-0.2519 ***	-0.0051 ***	-0.2143 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Monopoly by product market fluidity	2.6854 ***	0.3462 ***	1.2581 ***	0.1328 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Value-weighted product market fluidity	-0.3349 ***	-0.4464 ***	-0.1924 ***	-0.2122 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 6 – Performance effect around the Sarbanes-Oxley Act

This table presents results from a cross-sectional OLS regression of changes in fund performance around the passage of the Sarbanes-Oxley Act in Q3/2002. The dependent variable is the change in fund performance measured as the difference between average quarterly performance in the four quarters after the event and the average quarterly performance in the four quarters before the event. 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 *Avg. MB*, defined as the average monopoly bet in the four quarters before the event quarter. I use both the continuous variable as well as a *High Avg. MB* dummy equal to one if the fund has an *Avg. MB* above the median, and zero otherwise. Additional independent control variables are *Fund size, Turnover ratio, Fund flows*, and *Number of stocks*, 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. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Change in fund performance			
Dependent variable:	Δ DGTW		Δ Carhart	
Avg. MB	-11.7665 ***		-6.5552 ***	
	(0.0000)		(0.0000)	
High *Avg. MB*		-1.1794 ***		-0.5178 ***
		(0.0000)		(0.0036)
Avg. fund size	-0.0096	0.0009	0.1731 ***	0.1759 ***
	(0.8584)	(0.9864)	(0.0078)	(0.0071)
Fund age	-0.1617	-0.1916 *	-0.1183	-0.1238
	(0.1546)	(0.0951)	(0.4001)	(0.3811)
Avg. turnover ratio	0.6107 ***	0.6391 ***	0.2757 **	0.3023 ***
	(0.0000)	(0.0000)	(0.0137)	(0.0071)
Avg. fund flows	-0.5357 **	-0.7327 ***	-0.6562 **	-0.7840 ***
	(0.0112)	(0.0006)	(0.0232)	(0.0066)
Avg. number of stocks	-0.1634	-0.0809	0.0360	0.0786
	(0.1670)	(0.4972)	(0.7986)	(0.5791)
Avg. family size	-0.0731 **	-0.0694 **	-0.1145 ***	-0.1107 ***
	(0.0112)	(0.0171)	(0.0010)	(0.0015)
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,343	1,343	1,243	1,243
Adj. R-Squared	0.1362	0.1192	0.1027	0.0950

Table 7 – Performance effect around the 9/11 terrorist attacks

This table presents results from a cross-sectional OLS regression of changes in fund performance around the 9/11 terrorist attacks in Q3/2001. The dependent variable is the change in fund performance measured as the difference between average quarterly performance in the four quarters after the event (without the quarter immediately after the attacks) and the average quarterly performance in the four quarters 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 firms in the same quarters for which I measure fund performance. I use both the continuous variable as well as a Δ *Military weight* dummy equal to one if the fund's change in military weight is above the median, and zero otherwise. Additional independent control variables are *Fund size*, *Turnover ratio, Fund flows,* and *Number of stocks*, all defined as in Table 2 but averaged over the last four quarters before the event quarter, as well as F*und age* at the event quarter. The regressions include style fixed effects. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Change in fund performance			
Dependent variable:	Δ DGTW		Δ Carhart	
Δ Military weight	-11.4413 ***		-4.8555 **	
	(0.0000)		(0.0109)	
High Δ Military weight		-1.3721 ***		-0.4673 *
		(0.0000)		(0.0905)
Avg. fund size	0.0551	0.0790	-0.3556 ***	-0.3446 ***
	(0.5470)	(0.3912)	(0.0007)	(0.0010)
Fund age	-0.4051 **	-0.4302 **	0.6538 ***	0.6343 ***
	(0.0229)	(0.0165)	(0.0024)	(0.0032)
Avg. turnover ratio	0.4382 ***	0.4786 ***	-0.1197	-0.0818
	(0.0086)	(0.0044)	(0.5322)	(0.6692)
Avg. fund flows	-0.6845 **	-0.5344	-0.5588	-0.4789
	(0.0406)	(0.1111)	(0.1460)	(0.2113)
Avg. number of stocks	-0.0120	-0.0191	0.0015	-0.0008
	(0.9503)	(0.9220)	(0.9946)	(0.9972)
Avg. family size	0.0592	0.0415	0.1294 **	0.1228 **
	(0.1997)	(0.3724)	(0.0145)	(0.0205)
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	832	832	749	749
Adj. R-Squared	0.1338	0.1195	0.0472	0.0425

Table 8 – Impact of manager changes and manager attributes on *MB*

This table presents results on the influence of the fund manager on a fund's monopoly bet (*MB*). Panel A presents results on changes in monopoly bets around changes in the fund manager for a sub-sample of single-managed funds. The dependent variable is the change in average monopoly bets (Δ *MB)*, measured as the difference of the average quarterly *MB* in the four quarters after the manager change quarter and the average quarterly *MB* in the four quarters before the change quarter. The main independent variables are Δ *MB propensity*, which is the difference between the *MB* propensity of the new manager and the fund's average *MB* in the four quarters before the change, as well as an indicator variable equal to one if this difference is positive, and zero otherwise (*I (*Δ *MB propensity* > 0)). The *MB* propensity of the new manager is defined as the average *MB* in the four quarters before the change across all single- and team-managed funds managed by the new manager. Additional independent controls are as in Table 2. All independent variables are valid as of the end of the quarter of the manager switch. In the first column of Panel B, I present results of pooled OLS regressions where the dependent variable is the monopoly bet for the fund in a given quarter. In the last column of Panel B, I present results of logistic regressions where the dependent variable is the *high-MB* dummy, an indicator variable equal to one if the fund has a monopoly bet above the median of all funds in a given quarter, and zero otherwise. The main independent variables are multiple funds per manager, manager tenure, and # Managers. *Multiple funds per manager i*s an indicator variable equal to one, if the fund 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. 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.

Panel A: Changes in *MB* around manager changes

Dependent variable:	Δ*MB*	Δ*MB*
Δ *MB propensity*	0.3899 ***	
	(0.0000)	
*I (*Δ *MB propensity* > 0)		0.0372 ***
		(0.0001)
Fund size	0.0015	0.0066
	(0.7400)	(0.1787)
Fund age	0.0094	-0.0021
	(0.3273)	(0.8320)
Turnover ratio	0.0035	0.0015
	(0.5698)	(0.8006)
Expense ratio	0.9159	0.8306
	(0.5825)	(0.6437)
Fund flows	0.0141	0.0396
	(0.6945)	(0.3245)
Number of stocks	0.0069	0.0048
	(0.2935)	(0.4918)
Family size	0.0012	0.0001
	(0.6331)	(0.9843)
Style fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Number of observations	140	140
Adj. R-Squared	0.4541	0.3708

Table 8 – Impact of manager changes and manager attributes on *MB* (continued)

Panel B: Determinants of *MB*

Dependent variable:	*Monopoly bet (MB)*	*High MB*
Multiple funds per manager	-0.0060 ***	-0.1100 *
	(0.0074)	(0.0601)
Manager tenure	0.0006 ***	0.0154 ***
	(0.0013)	(0.0003)
# Managers	-0.0009 ***	-0.0378 ***
	(0.0072)	(0.0004)
Fund size	-0.0010	-0.0443 ***
	(0.1816)	(0.0087)
Fund age	-0.0013	-0.0137
	(0.3933)	(0.7223)
Turnover ratio	-0.0120 ***	-0.3057 ***
	(0.0000)	(0.0000)
Expense ratio	0.0937	0.1718
	(0.2526)	(0.9338)
Fund flows	0.0006	0.0015
	(0.7251)	(0.9715)
Number of stocks	-0.0037 **	0.0497
	(0.0172)	(0.1829)
Family size	-0.0022 ***	-0.0396 ***
	(0.0000)	(0.0001)
Time fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Number of observations	52,009	52,009
Adj./Pseudo R-Squared	0.0453	0.0166

Table 9 – Fund investment behavior

This table presents results from pooled OLS regressions that analyze the impact of the lagged monopoly bet on a fund's behavior. In Panel A, I report results of pooled OLS regressions where the dependent variable is *Portfolio turnover*, the minimum of the dollar value of purchases and sales in a given quarter divided by the average of the total portfolio value at the beginning and end of the quarter, defined as in Carhart (1997) (columns 1 and 2) or *Investment horizon*, the value-weighted average number of years that a currently held stock is held in the portfolio, defined as the "Simple horizon measure" in Lan, Moneta, and Wermers (2016) (columns 3 and 4). In Panel B, the dependent variables are *Portfolio liquidity* (columns 1 and 2), and *Fund QMJ loading* (columns 3 and 4). *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. *Fund QMJ loading* represents the fund's loading on the "Quality-Minus-Junk" (QMJ) factor from a Carhart (1997) 4-factor model augmented by the "Betting-Against-Beta" (BAB) and the QMJ factor and using daily returns within the quarter. The main independent variables are the monopoly bet (*MB*) or the *MB* 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 turnover*, *Investment horizon*, *Portfolio liquidity*, and *Fund QMJ loading*. 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.

Panel A: Trading frequency

	Trading frequency			
Dependent variable:	Portfolio turnover		Investment horizon	
Monopoly bet (MB)	-0.7301 ***		1.9431 ***	
	(0.0000)		(0.0000)	
High *MB*		-0.0782 ***		0.2111 ***
		(0.0000)		(0.0000)
Fund size	-0.0404 ***	-0.0410 ***	0.2518 ***	0.2527 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Fund age	0.0255 **	0.0262 ***	0.6571 ***	0.6558 ***
	(0.0103)	(0.0085)	(0.0000)	(0.0000)
Turnover ratio			-1.3910 ***	-1.3993 ***
			(0.0000)	(0.0000)
Expense ratio	1.8185	1.7391	-6.0646	-5.7770
	(0.2003)	(0.2271)	(0.1341)	(0.1556)
Fund flows	-0.0361	-0.0364	0.0278	0.0283
	(0.1155)	(0.1176)	(0.7934)	(0.7914)
Number of stocks	0.0176 *	0.0216 **	0.2150 ***	0.2046 ***
	(0.0807)	(0.0316)	(0.0004)	(0.0006)
Family size	0.0189 ***	0.0199 ***	-0.0786 ***	-0.0809 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	55,126	55,126	54,549	54,549
Adj. R-Squared	0.0774	0.0734	0.4648	0.4638

Table 9 – Fund investment behavior (continued)

Panel B: Investment strategies

	Investment strategy			
Dependent variable:	Portfolio liquidity		Fund QMJ loading	
Monopoly bet (MB)	-4.7907 ***		0.3526 ***	
	(0.0000)		(0.0000)	
High *MB*		-0.4156 ***		0.0429 ***
		(0.0000)		(0.0000)
Fund size	0.0584 ***	0.0573 ***	-0.0057 ***	-0.0055 ***
	(0.0027)	(0.0037)	(0.0039)	(0.0050)
Fund age	0.0080	0.0110	-0.0031	-0.0033
	(0.8577)	(0.8095)	(0.4883)	(0.4588)
Turnover ratio	0.0313	0.0601	-0.0641 ***	-0.0652 ***
	(0.3874)	(0.1032)	(0.0000)	(0.0000)
Expense ratio	-30.6955 ***	-31.4225 ***	-2.5145 ***	-2.4568 ***
	(0.0000)	(0.0000)	(0.0002)	(0.0004)
Fund flows	-0.0969 ***	-0.0992 ***	-0.0054	-0.0049
	(0.0042)	(0.0027)	(0.2825)	(0.3383)
Number of stocks	-0.4523 ***	-0.4270 ***	0.0134 ***	0.0113 ***
	(0.0000)	(0.0000)	(0.0002)	(0.0019)
Family size	0.0757 ***	0.0826 ***	-0.0008	-0.0012
	(0.0000)	(0.0000)	(0.4196)	(0.2551)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	54,755	54,782	66,569	66,569
Adj. R-Squared	0.5585	0.5585	0.1586	0.1572

Market Power in the Portfolio: Product Market Competition and Mutual Fund Performance

Internet Appendix

September 2016

This Internet Appendix presents additional results to accompany the paper "Market Power in the Portfolio: Product Market Competition and Mutual Fund Performance". The contents of the Appendix are as follows.

Table A.1 reports results on logistic regressions of a fund's decision to sell or drop a stock depending on its average similarity with the newly-purchased stocks in a given quarter.

Table A.2 reports performance and performance differences of buy and sell sub-portfolios between high- and low-*MB* funds.

Table A.3 estimates the cross-sectional regression of Table 6 using Q4/2005 as a placebo period and compares the placebo results with the original results of Table 6.

Table A.4 estimates the results of the average investment horizon (Panel A of Table 9) separately for monopoly- and non-monopoly sub-portfolios.

Table A.1 – Replacing competitors

This table presents results of logistic regressions on the relation between a fund's decision to replace rival firms and the monopoly bet (*MB*). The dependent variable is either a *Sell* (column 1) or a *Drop* (column 2) dummy variable equal to one if the fund has decreased the number of shares of a stock in a given quarter or has eliminated the stock from the portfolio, respectively, and zero otherwise. *Sell* and *Drop* are only calculated for non-monopoly stocks. The main independent variable is the *MB* dummy as of the end of the previous quarter. The other main independent variable is *Average similarity,* which is the average pairwise similarity score of the stock with all initiating buys in the same period. A higher score indicates a stronger product similarity. Additional independent controls at the stock level are the annual return, stock turnover, book-to-market ratio, all defined as in Table 1, and return volatility which is defined as the standard deviation of daily stock returns within a given quarter. Additional independent controls at the fund level are the same as in Table 2. Regressions are run with Fama-French-48 industry fixed effects, time fixed effects, and style fixed effects. p-values reported in parentheses are based on standard errors clustered by fund-stock combination. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

	Trade	
Dependent variable:	Sell	Drop
High *MB*	-0.0510 ***	-0.0671 ***
	(0.0000)	(0.0000)
Average similarity	0.6357 ***	0.6692 ***
	(0.0000)	(0.0000)
High *MB* **Average similarity*	0.5065 ***	0.2842 ***
	(0.0000)	(0.0001)
Prior quarter return	-0.0000	-0.4745 ***
	(0.9987)	(0.0000)
Stock turnover	8.5957 ***	13.8996 ***
	(0.0000)	(0.0000)
Market cap	0.0256 ***	-0.1273 ***
	(0.0000)	(0.0000)
Book-to-market ratio	-0.0340 ***	-0.0229 ***
	(0.0000)	(0.0000)
Return volatility	0.2458 ***	0.4818 ***
	(0.0000)	(0.0000)
Fund size	-0.0200 ***	-0.0323 ***
	(0.0000)	(0.0000)
Fund age	0.0568 ***	0.0415 ***
	(0.0000)	(0.0000)
Turnover ratio	0.5350 ***	0.5557 ***
	(0.0000)	(0.0000)
Expense ratio	2.7975 ***	-1.1541 ***
	(0.0000)	(0.0001)
Fund flows	-1.6122 ***	-0.0825 ***
	(0.0000)	(0.0000)
Number of stocks	-0.1977 ***	-0.2637 ***
	(0.0000)	(0.0000)
Family size	0.0505 ***	0.0384 ***
	(0.0000)	(0.0000)
Industry fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Style fixed effects	Yes	Yes
Number of observations	4,930,058	4,930,058
Pseudo R-Squared	0.0616	0.0637

Table A.2 – Performance of buys and sells in monopoly and non-monopoly stocks

This table presents results on the subsequent quarterly performance of trades in monopoly and non-monopoly stocks for funds with above and below median monopoly bets (high- and low-*MB* funds) in the period of the trade. Monopoly stocks are defined as stocks in the bottom quintile according to the number of competitors in a given year. Stocks in the remaining quintiles are part of the non-monopoly stock portfolio. 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. Sub-portfolio 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 sub-portfolio 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 sub-portfolio performance of buys and sells in monopoly and non-monopoly stocks across the two *MB* groups. The third and sixth column report differences in performance of buy (sell) sub-portfolios between high- and low-*MB* funds. The third and sixth row report differences in the performance of buys and sells separately for high- and low-*MB* funds. The last entry in each sub-table of Panel A reports differences-in-differences of buy and sell performance between high- and low-*MB* funds. In Panel B, I present results from a pooled OLS regression where the dependent variable is a fund's performance difference in buy and sell sub-portfolio in a given quarter. I only report differences in sub-portfolios if none of the two is missing. The main independent variable is the high-*MB* dummy, defined as in Table 2 and valid at the end of the quarter preceding the sub-portfolio 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.

Panel A: Performance of sub-portfolios over 3 months

	Monopoly stocks				**Non-monopoly stocks**		
	DGTW-adj. return				DGTW-adj. return		
	High *MB*	Low *MB*	Diff. High - Low		High *MB*	Low *MB*	Diff. High - Low
Buy	0.2735 ***	-0.0572	0.3308 ***	Buy	0.0737 **	-0.2945 ***	0.3682 ***
	(0.0000)	(0.3376)	(0.0001)		(0.0337)	(0.0000)	(0.0000)
Sell	0.0649	-0.0121	0.0771	Sell	0.0188	-0.1232 *	0.1419 ***
	(0.2677)	(0.8406)	(0.3600)		(0.6122)	(0.0627)	(0.0042)
Diff. Buy - Sell	0.2086 ***	-0.0451	0.2537 **	Diff. Buy - Sell	0.0549	-0.1714 ***	0.2263 ***
	(0.0079)	(0.5887)	(0.0292)		(0.2607)	(0.0002)	(0.0005)
	Carhart alpha				Carhart alpha		
	High *MB*	Low *MB*	Diff. High - Low		High *MB*	Low *MB*	Diff. High - Low
Buy	0.2245 ***	-0.0707	0.2952 ***	Buy	0.3522 ***	0.0740 *	0.2782 ***
	(0.0003)	(0.2918)	(0.0016)		(0.0000)	(0.0611)	(0.0000)
Sell	-0.0717	0.0817	-0.1534	Sell	0.1438 ***	0.3613 ***	-0.2175 ***
	(0.2749)	(0.2252)	(0.1028)		(0.0010)	(0.0000)	(0.0002)
Diff. Buy - Sell	0.2962 ***	-0.1525	0.4487 ***	Diff. Buy - Sell	0.2084 ***	-0.2874 ***	0.4958 ***
	(0.0008)	(0.1008)	(0.0005)		(0.0003)	(0.0000)	(0.0000)

Table A.2 – Performance of buys and sells in monopoly and non-monopoly stocks (continued)

Panel B: Difference-in-differences of sub-portfolio performance

Dependent variable:	Difference in buy and sell performance (3 months)	
	DGTW-adj.	Carhart alpha
High *MB*	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

Dependent variable:	Difference in buy and sell performance (3 months)	
	DGTW-adj.	Carhart alpha
High *MB*	0.2256 ***	0.4958 ***
	(0.0005)	(0.0000)
Time fixed effects	Yes	Yes
Number of observations	70,285	70,263
Adj. R-Squared	0.0034	0.0016

Table A.3 – Time-series placebo test on the performance effect around Sarbanes-Oxley

This table presents results from a time-series placebo test using a cross-sectional OLS regression of changes in fund performance around Q4/2005. In Panel A, the dependent variable is the change in fund performance measured as in Table 6. 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 *Avg. MB*, defined in Table 6. I use both the continuous variable as well as a *High Avg. MB* dummy equal to one if the fund has an *Avg. MB* above the median, and zero otherwise. Additional independent control variables are again as in Table 6. The regressions additionally include style fixed effects. In Panel B, I report differences in the coefficient estimates for *Avg. MB and High Avg. MB* between the original results of Table 6 and the placebo results of Panel A. ***, **, * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

Panel A: Placebo period (Q4/2005)

	Change in fund performance			
Dependent variable:	Δ DGTW		Δ Carhart	
Avg. MB	2.3288 ***		0.6977	
	(0.0008)		(0.3199)	
High *Avg. MB*		0.0888		-0.0453
		(0.2881)		(0.5917)
Avg. fund size	0.0145	0.0144	-0.1213 ***	-0.1207 ***
	(0.6558)	(0.6287)	(0.0001)	(0.0001)
Fund age	-0.1070	-0.1119	0.1028	0.1031
	(0.1234)	(0.1064)	(0.1540)	(0.1533)
Avg. turnover ratio	-0.0985	-0.1144 *	-0.0666	-0.0741
	(0.1253)	(0.0753)	(0.3083)	(0.2555)
Avg. fund flows	0.1148	0.1224	-0.4501 ***	-0.4468 ***
	(0.4084)	(0.3793)	(0.0020)	(0.0022)
Avg. number of stocks	0.0717	0.0554	0.0697	0.0594
	(0.2800)	(0.4036)	(0.2997)	(0.3754)
Avg. family size	-0.0182	-0.0201	0.0283 *	0.0260
	(0.4309)	(0.1959)	(0.0763)	(0.1022)
Style fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,399	1,399	1,377	1,377
Adj. R-Squared	0.0817	0.0749	0.0264	0.0259

Panel B: Difference Sarbanes-Oxley (SOX) – Placebo period

	Change in fund performance			
Dependent variable:	Δ DGTW		Δ Carhart	
Around SOX (2002):				
Avg. MB	-11.7665 ***		-6.5552 ***	
	(0.0000)		(0.0000)	
High *Avg. MB*		-1.1794 ***		-0.5178 ***
		(0.0000)		(0.0036)
Placebo period (2005):				
Avg. MB	2.3288 ***		0.6977	
	(0.0008)		(0.3199)	
High *Avg. MB*		0.0888		-0.0453
		(0.2881)		(0.5917)
Difference (2002-2005)	-14.0953 ***	-1.2682 ***	-7.2529 ***	-0.4725 **
F-test (p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0394)

Table A.4 – Investment horizon in monopoly and non-monopoly sub-portfolios

This table presents results from pooled OLS regressions that analyze the impact of the lagged monopoly bet on a fund's investment horizon in its monopoly and non-monopoly sub-portfolios. The dependent variable is the investment horizon measure of a fund in a given quarter, defined as in Table 9. In columns 1 and 2, the investment horizon is measured for the monopoly sub-portfolios and in columns 3 and 4, it is applied to non-monopoly sub-portfolios. In columns 5 and 6, the dependent variable is the difference between the average investment horizons in a fund's monopoly- and non-monopoly sub-portfolios in a given quarter. The main independent variables are the monopoly bet (*MB*) or the *MB* 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 the investment horizons for the sub-portfolios and the horizon differences. 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.

	Investment horizon					
Dependent variable:	Monopoly stocks		Non-monopoly stocks		Horizon difference	
Monopoly bet (MB)	4.3981 ***		1.7650 ***		2.6333 ***	
	(0.0000)		(0.0002)		(0.0000)	
High *MB*		0.4830 ***		0.1784 ***		0.3047 ***
		(0.0000)		(0.0001)		(0.0000)
Fund size	0.2497 ***	0.2519 ***	0.2515 ***	0.2523 ***	-0.0019	-0.0005
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.8864)	(0.9734)
Fund age	0.6843 ***	0.6812 ***	0.6450 ***	0.6438 ***	0.0395	0.0376
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2814)	(0.3037)
Turnover ratio	-1.4163 ***	-1.4329 ***	-1.4098 ***	-1.4177 ***	-0.0066	-0.0153
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.7340)	(0.4330)
Expense ratio	-7.1197	-6.3002	-7.4646	-7.1303	0.3425	0.8281
	(0.1063)	(0.1565)	(0.1057)	(0.1234)	(0.7957)	(0.5247)
Fund flows	0.0312	0.0328	0.0302	0.0309	0.0011	0.0020
	(0.7896)	(0.7828)	(0.7739)	(0.7702)	(0.9554)	(0.9252)
Number of stocks	0.2469 ***	0.2191 ***	0.2477 ***	0.2365 ***	-0.0006	-0.0172
	(0.0001)	(0.0005)	(0.0000)	(0.0001)	(0.9820)	(0.5227)
Family size	-0.0712 ***	-0.0766 ***	-0.0781 ***	-0.0805 ***	0.0069	0.0039
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3514)	(0.6082)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	54,251	54,251	54,246	54,246	54,246	54,246
Adj. R-Squared	0.3903	0.3866	0.4638	0.4628	0.0350	0.0315

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