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# 'Smart' copycat mutual funds: on the performance of partial imitation strategies

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**Abstract**

Using a novel measure of stock-level trade imitation, we uncover 'smart' copycats: fund managers that use their own information when beneficial, and otherwise imitate other managers' better trades. Contrary to previous research, we find that these partial imitation strategies lead to outperformance. Our 'Copycat Score' combines the propensity to imitate and to lead trades. Funds at the high and low ends of the score outperform all others. The Copycat Score is persistent in time, related to other measures of skill, and a good predictor of fund performance. We conclude that smart copycatting is another skill of successful fund managers.

**Keywords:** Copycat portfolios, Mutual funds, Portfolio holdings, Fund performance, Fund manager skill

**JEL Classification:** G21, G23

## Introduction

*"The problem with being a leader is that you're never sure if you're being followed or chased."*
*Claire A. Murray.*

Imitation is a fact of life and its importance in business has been acknowledged as far back as Levitt (1966), often cited as the first paper to call attention to imitation in business. Imitation has been studied in all business disciplines, such as strategy, marketing, organizational behavior, etc. For example, Semadeni and Anderson (2010) look at data from consulting firms to study what they call the 'follower's dilemma', where firms must weigh the uncertainty of imitating the first mover's innovation, versus the uncertainty of not imitating. Hsieh and Hyun (2018) look at imitation in the form of firms matching their competitor's entry into a new geographic region, focusing on the decisions of IT firms in different regions in China. Xie and Li (2017) argue that the actions of perceived peers are more likely to be imitated those of others, and show that cross-border acquisitions by Chinese firms are more likely to be imitated by similar firms, emerging market multinationals, than by developed market multinationals. Posen et al.

(2013) use simulations to show that even imperfect imitation can help underperforming firms improve performance, and even eventually outperform industry leaders. Ross and Sharapov (2015) innovate by ignoring the followers, and instead looking at how market leaders also turn to imitation in a bid to avoid dethronement as a leader. Giachetti et al. (2017) expands on this to show that imitation by some firms in an industry puts pressure on the rest of the competitors to also imitate, and that imitation may not necessarily be an 'all or nothing' strategy, but instead can be a component within a broader corporate strategy.[1] These results combine to show that it is possible for there to be widespread imitation in any industry, as both industry leaders and non-leader firms all incorporate some level of imitation into their strategies in an attempt to improve performance. In this paper we explore these ideas in the context of mutual funds and the imitation of stock trades as a mechanism for some fund managers to improve performance.

In the mutual fund industry, recent work has focused on the imitation of trades by fund managers, usually referred to as "copycatting". However, there are significant gaps in the existing literature. The earliest papers to analyze imitation do not identify actual copycats funds. Instead, they focus on a sample of funds and then estimate what would be the potential performance of hypothetical mimicking portfolios that copy all security holdings of these selected funds. For example, Frank et al. (2004) speculate that the best funds to imitate are those with high expenses, and show that simulated funds that imitate them can match their performance, after expenses. Verbeek and Wang (2013) generate simulated portfolios that imitate every fund in the domestic equity market, and find that the average performance of the mimicking portfolios is a few basis points above that of the real funds.

More recent work introduces actual imitation measures. Based on these measures, funds are labeled as either copycats or non-copycats (see for example, Phillips et al. 2014; Koch 2016). There are important shortcomings in the way these measures are constructed. Existing measures characterize copycatting as an all-or-nothing decision, in which a copycat is modeled as selecting a single fund to imitate, and then attempting to track that manager's portfolio as closely as possible. This view of trade imitation is problematic for various reasons. First, fully tracking a single fund would be easy to detect by fund sponsors, investors, legislators, and anyone who cared to look, potentially triggering negative outcomes for the copycat manager. Second, the management literature provides ample evidence that partial imitation strategies can be superior to full imitation. For example, Posen et al. (2013), Wang et al. (2019), and Gaba and Terlaak (2013) show that imperfect imitation can lead to superior outcomes, in particular when it is combined with a firm's or manager's innate capabilities to innovate in areas where they do not imitate. For example, a fund manager might prefer her own information to trade stocks in which she has an informational advantage, and imitate others' trades where she is at a disadvantage. Likewise, an imitator might find it best to diversify in the fund managers she chooses to follow. For example, she might follow a tech expert when trading technology stocks, and a financial services expert when trading bank stocks.

[1] In addition, see (Lieberman and Asaba 2006; Ordanini et al. 2008) for reviews of theoretical work.

In fact, these strategies that combine innovation with imitation can be so successful that they can sometimes enable followers to outperform the leaders themselves (e.g.: Posen and Martignoni 2018). This last point brings us to the next problem with all-or-nothing measures of trade imitation, which is that they do not allow for a more nuanced approach, one that allows for the possibility that followers may lead in some trades, or that leaders might also engage in partial imitation themselves. This last, industry leaders engaging in imitation, has also received support in the literature as a valid strategy used by incumbents to defend their leadership position (Ross and Sharapov 2015; Aron and Lazear 1990; Sharapov and Ross 2019). Finally, all measures introduced thus far are single period models, which gauge imitation by comparing the trades made by two funds within one quarter of each other. The single period structure renders them particularly sensitive to spurious detection. It is often the case, for example, that two funds alter their portfolios in response to the same exogenous signal, such as index listings, earnings announcements, analyst recommendations, etc. If this signal happens close to the end of a reporting period, we could observe one fund trade before, and the other after the period's cutoff. This, in turn, would incorrectly be taken as evidence of imitation by a single-period measure.

We introduce a novel methodology which measures mutual fund trade imitation at the individual stock level. This approach lends itself to a more precise and nuanced analysis of trade imitation, and reveals a number of previously hidden patterns in imitation and performance in the U.S. domestic mutual fund market. Many of our results on actual imitation behavior are shown to be more intuitive, and consistent with the management literature, than those shown so far in the relevant literature.

Using 5 years of trading data in a VAR-Granger framework, we label each stock in a fund's portfolio as one in which the fund manager imitates another fund's trades ('follows'), or is imitated ('leads'). We then aggregate this data at the fund level obtaining a "Copycat Score" for each fund, which consists of the sum of portfolio weights of stocks in which the fund imitates someone elses trades, minus those in which it leads.

Our measure can identify fund managers who imitate trades of different funds for each stock in their portfolio, or avoid imitation in favor of their own information. One advantage of this approach is that it is able to identify imitation even if it is highly diversified among peer funds. "All-or-nothing" measure would not identify this as copycatting, as the amount of imitation of a single fund would be very low. Also, by using a time series of trades in a VAR-Granger setting, our measure is far less likely to identify a spurious trade pattern as imitation. Finally, our approach does not produce a binary variable, "copycat" or "not copycat", but rather a continuous measure that gauges not just the general direction of the fund manager's behavior, as tilted towards leading versus following, but also the intensity in either direction.

Our results show that the increased precision of our copycat analysis pays off. We show that imitation is pervasive in the mutual fund industry. Almost every fund in our sample imitates another fund's trades to some degree. However, for most funds trade imitation does not lead to outperformance. In fact, the average return of these imitated trades is equal to, and in some cases inferior to, the return of the average stock in our sample. Only a small number of fund managers appear to posses the skill of picking the best funds and stock trades to emulate, so that their copycat trades actually outperform. We consider this

'smart imitation' as a hitherto unreported form of fund manager skill. Within this framework, we define a 'smart copycat' as a fund manager who trades on her own private information when it is superior, but can choose the best managers to imitate their trades where they have an advantage. The result is a fund that benefits from a partial imitation strategy: performance is aided by the manager's skill to select stocks investments by herself, as well as the best trades made by other managers which are worth imitating.

With the U.S. mutual fund industry managing 22% of all household assets at the end of 2016 (assets in excess of 16 trillion dollars, 52% invested in equity funds), the question of the skill of fund managers has become one of the most important open issues in modern financial research. The performance and skill of active money managers has important implications for retail investors, financial markets, and for the economy as a whole. So far, evidence of persistent outperformance in mutual funds, or fund manager skill, has been mixed. While some authors find that most mutual funds underperform their benchmark (see for example, Jensen 1968; Malkiel 1995; Fama and French 2010), others find that a small group actually outperforms (Chen et al. 2000; Avramov and Wermers 2006; Kosowski et al. 2006; Cuthbertson et al. 2008). Our results contradict the assumption of past research in this area, that imitation is solely employed by fund managers with inferior skill. We find that smart partial imitation is correlated to measures of fund manager skill. In our sample, smart imitators do not just pick good stock trades to emulate, but also outperform with their own stock picks, and manage all around superior funds. Funds with high values of the Copycat Score are those with a strong tendency to imitate others with their trades, while funds with low values of the score tend more towards leading. However, funds observed at both extremes of the measure's scale are highly active in both, leading and following trades. It is precisely these funds that outperform all others in the sample, particularly those with a Copycat Score of zero, which indicates they lead about as much as they imitate. Funds that tend the most towards leading outperform the zeros by 16 basis points per month, while those that tend towards imitation do so by 27 bps. In brief, these fund managers show signs of a combination of talents, including smart imitation, which they employ to outperform their peers.

Further tests show that both types of funds at the extreme ends of the Copycat Score scale, leaders and imitators, employ strategies which are persistent in time, as is their outperformance. We also show that the Copycat Score is a good predictor of long term mutual fund performance, matching, and sometimes surpassing, the predictive power of other measures of performance and skill. However, this is not the case for the measure's components individually, the amount of leading and following. This result highlights the importance of our methodology which takes into account partial imitation strategies, compared to those which measure imitation only.

The rest of this paper is organized as follows. Section "Data, methodology and summary statistic" presents the VAR-Granger methodology and the data employed. Section "Empirical results" shows our empirical results, and section "Conclusions" offers concluding remarks.

## Data, methodology and summary statistic

### Data and sample selection

We obtain summary and performance data from CRSP for all actively managed, open ended mutual funds that invest primarily in domestic (U.S.) equities.[2] Characteristics such as investment style, fees and turnover are available at quarterly frequency, while returns and total net assets are observed every month. Table 1 shows descriptive statistics for the sample. Panel A depicts the aggregate characteristics of the sample, which are consistent with datasets used in previous research. In brief, we observe that the distributions of fund size, expense ratio and gross return are highly skewed. While the mean of total net assets is close to a billion dollars, the median fund is far smaller, below $100 million in assets. Less extreme is the cross-sectional variation in turnover, where the average ratio is about 87%, and the median is only 62%. Gross returns are estimated by taking CRSP-reported net returns, and adding back 1/12th of the fund's annual expenses (see Cremers and Petajisto 2009). The median return is about 1% per month, consistent with previous findings on the performance of the U.S. equity mutual fund industry. Finally, it is worth noting that the mean percentage of fund assets invested in equities is close to 94%, with a significant part of the remaining capital held in cash and equivalents.

Mutual fund portfolio holdings are obtained from the Thompson Financial CDA/Spectrum database.[3] We obtain inferred trades as the percentage change in the number of shares held by each fund in each stock between one filing and the one that follows. The data is based on mutual fund SEC filings. Before 2004, funds were required to disclose their portfolios semiannually, whereas an SEC regulation change increased the mandated disclosure frequency from semiannual to quarterly (the change became effective in May, 2004). However, anecdotal evidence shows that a large percentage of funds were voluntarily disclosing portfolio holdings at quarterly intervals before the regulation change.

Portfolio holdings data is available starting in the 1970s. However, the number of funds remains small until the late 1990s. After that, we see a marked increase in mutual funds, the portion of the equity market held by them, as well as traded volumes and their impact in asset pricing. Thus, we restrict the time series of our measures to the post-2000s period. However, to obtain our measure we require a 5 year window, which is why we use data starting in 1996. Therefore, all results are presented for the 2000–2016 period.

### The copycat score

Copycat investing is defined as the strategy in which a mutual fund manager replicates the positions or trades of another, presumably, skilled manager. Existing measures of copycatting compare the holdings of one fund in period $t-1$ to those of another in period $t$. The period $t$ fund is labeled a 'copycat' if the holdings match above a certain

[2] To generate this sample we follow the descriptions in Verbeek and Wang (2013), Additional file 1: Appendix A, and Kacperczyk et al. (2008), Additional file 1: Appendix A. The only deviation from these methodologies is the use of CRSP investment objectives to identify the desired funds, instead of Lipper and Wiesenberger codes used by other authors. The resulting sample has characteristics which are consistent with those reported in previous research.

[3] CDA/Spectrum data is screened so that the remaining portfolio holdings correspond to the first vintage of reported data.

arbitrary threshold. Those measures' potential shortcomings include identifying 'copycatting' spuriously as both funds trade in similar patters with no imitation involved (for example, if both react to the same exogenous signals, such as earnings announcements), and failing to identify copycats if they imitate more than one manager, so that their holdings do not match a single fund's enough to clear the threshold. In addition, it seems that this 'all-or-nothing' approach would be a particularly poor choice for a copycat manager, as it would be far easier to detect. Thus, it is unlikely to be implemented by money managers in general, and so measures that rely on this behavior would be unlikely to capture the full extent of imitation in the mutual fund industry.

Our approach improves on existing measures in two ways. First, we look for evidence of imitation in trades of each stock in a fund's holdings. Thus, we can detect copycatting behavior even if a fund manager imitates the trades of various other managers, instead of simply replicating a single manager's portfolio. Second, we use a time-series of trades to establish if there is persistent imitation, as opposed to a single period comparison. This reduces the concern of falsely identifying a fund manager as a copycat if her portfolio happens to look like someone else's during a single period of time.

We start by using a 5 year time window of quarterly inferred trades, obtained from the Thompson Reuters holdings dataset. We select a single fund $i$, and list all stocks traded. We then focus on the trades made by fund $i$ of stock $s$, and look for all other funds which also traded stock $s$ within the same 5 year period. For each fund $j$ that traded stock $s$, we estimate the following Vector Auto Regression (VAR) model:

$$\begin{cases} Trades^s_{i,t} = \beta^s_{i,i} Trades^s_{i,t-1} + \beta^s_{i,j} Trades^s_{j,t-1} + \varepsilon^s_{i,t} \\ Trades^s_{j,t} = \beta^s_{j,j} Trades^s_{i,t-1} + \beta^s_{j,i} Trades^s_{j,t-1} + \varepsilon^s_{j,t} \end{cases}, \tag{1}$$

where $Trades^s$ is the percentage change in shares held by fund $i$ of stock $s$ between reports filed on periods $t-1$ and $t$.

In the model above, trades made by fund $i$ at time $t$ are regressed on the lagged trades made by the same fund, as well as the lagged trades made by fund $j$, and vice versa. In essence, we try to explain the contemporaneous trades of one fund in terms of its own lagged trades and those of another fund. Our focus is on the coefficients ${\beta^s}_{i,j}$ and ${\beta^s}_{j,i}$, which show how much of a fund's contemporaneous trading of stock $s$ can be attributed to another fund's lagged trades of the same stock. To formally establish the significance of this relationship, we use the Granger causality test.

For example, suppose that funds A and B hold stock XYZ. We use the time series of XYZ trades made by funds A and B as inputs for the VAR model. We then test Granger-causality in both directions. We consider a Granger-causality test to be statistically significant if it rejects the null hypothesis, that there is no evidence of trades imitation, at the 10% level. The result can be that fund A follows fund B in trades of XYZ, or that B follows A, or that neither imitates the other. Stock trade matches will be made as long as both funds, A and B, report at least one trade of stock XYZ within the same 5 year period. This means it is likely for some matches to be made when there is no evidence of one fund following the other. An extreme example would be if fund A trades stock XYZ during the first year of the time period, while fund B trades it only in the fifth year. While these models will be estimated, the combined requirements of the VAR model

and Granger test significance will result in this data not generating a leading or following signal, which is the same as if the matched data had been ignored.

We repeat the VAR-Granger test described above for each stock in fund *i*'s portfolio, before moving on to the next fund and repeating the process, stock by stock. This process continues until all funds in the sample have been analyzed, and each stock in each portfolio can be labeled as one in which the a fund imitates another fund's trades, is in turn imitated, or neither of these is true.

Finally, we aggregate the individual stock data for each fund into the "Copycat Score". We merge the output from the VAR-Granger process described above with the last set of portfolio holdings reported by each fund within the estimation period, which corresponds to the final quarter of the five year sample. We then label each stock held by the fund in terms of the fund's imitation behavior. If the fund is following another fund's trades of the security, we label that stock as "following". If the fund's trades in one stock indicate that it's actually being followed by another fund, then we apply the label of "leading" to that stock. We omit stocks that fall in either alternative situation: no imitation is detected, or funds seem to follow each other. The Copycat Score is constructed by taking the aggregate portfolio weight of the stocks in which the fund follows in trades, and subtracting those in which it leads. The Copycat Score can be expressed as follows:

$$Copycat_i^t = \sum_s w_{s,Follow}^t - \sum_s w_{s,Lead}^t, \tag{2}$$

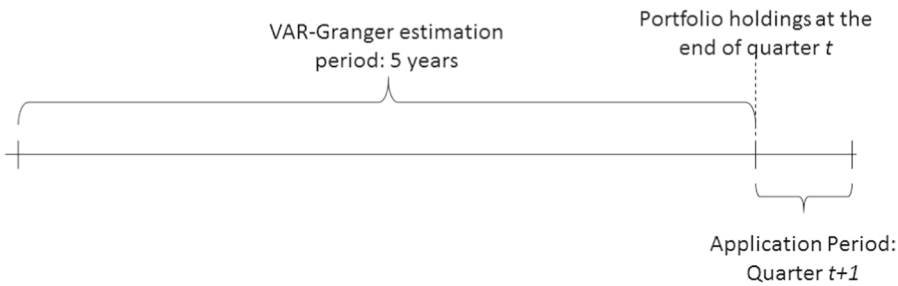
where $Copycat_i^t$ is the Copycat Score for fund *i* at the end of quarter *t*, and $\sum_s w_{s,Follow}^t$ & $\sum_s w_{s,Lead}^t$ represent the total portfolio assets in which the fund follows and leads others trades, respectively, at the end of quarter t. The Copycat Score can take values in a range from −1, meaning that the fund manager leads other managers' trades for all stocks in his portfolio, to 1, which means the manager imitates others in trades of all its stocks. Since the data used in the VAR model is percentages and therefore has been differenced, there is little concern about stationarity of the time series of stock trades. Regardless, we conduct stationarity tests on the 18.4 million individual time series of fund stock trades used to estimate the Copycat Score for all funds and time periods in the sample. About 1.3% of the time series tested report any potential stationarity issue. Not only is this a minor portion of the sample, the impact of such issues is even smaller as many VAR-Granger results are discarded (statistically insignificant results, as well as instances in which a manager seems to lead and follow in trades of the same stock).[4]

For example, let's assume that a certain fund has 10 stocks in its portfolio, labeled A to J, and at the end of the 5 year time window its capital is equally distributed between them. In addition, each stock has been labeled as Leading, Following, or Neither (see table below). In this case, the sum of portfolio weights of stocks in which the fund leads would be 20%, the sum of stocks in which it follows is 40%, and thus the Copycat Score for this fund at this point in time would be 20%.

[4] Financial markets research often requires the use of very large datasets. Other than our econometrics derived model, another popular methodology to process this data is the use of machine learning (see, for example, Kou et al. 2019).

A. VAR-Granger estimation timeline.

This image depicts the time line of the estimation and use of VAR-Granger data. A five year ("estimation period") sample of inferred stock trades is used to estimate VAR-Granger models for all stocks held in common by each pair of funds in the sample. To aggregate data into the Copycat measure, the portfolio weights obtained using the most recently available fund holdings in the five year period, which often correspond to the fund's disclosed portfolio in the final quarter of the five year period. The Copycat measure obtained using this five year sample is then associated with the fund for the ensuing quarter ("Application Period"), until it is updated with new information estimated rolling the five year window forward by one quarter.




B. Copycat Score quantiles and labels

The schema pictured below shows the uneven quantiles used to group data using the Copycat Score in many of the tests and tables presented throughout this paper. Funds with a positive Copycat Score (those whose trading is tilted towards imitation over leading) are divided into equal-sized quintiles numbered 1 to 5 in order of increasing Copycat Score. Funds with negative scores (tilted in the opposite direction, thus more towards being imitated) are also split into quintiles, numbered -1 to -5, in order of increasing absolute value of their negative score. Funds with a score of zero are grouped into the middle quantile. Throughout the analysis attention is focused on the middle and extreme groups. Thus, we label the extreme quantiles as "Followers" and "Leaders", respectively, and the middle quantile as "Zeros".

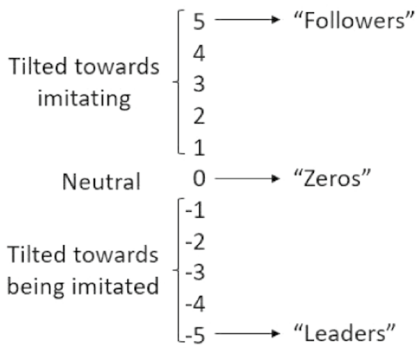



**Fig. 1** Copycat Score estimation timeline and resulting quantiles

| Stock | Weight | Imitation |
|---|---|---|
| A | 10% | Leading |
| B | 10% | Following |
| C | 10% | Following |
| D | 10% | Neither |
| E | 10% | Neither |
| F | 10% | Neither |
| G | 10% | Following |
| H | 10% | Neither |
| I | 10% | Leading |
| J | 10% | Following |

Figure 1A depicts the time line for the estimation and application of the Copycat measure. To avoid applications of the measure that might overlap with the estimation period (i.e.: 'look-ahead' bias), a Copycat Score estimated using a five year sample ending on quarter $t$ is then assigned to a fund for the duration of quarter $t+1$ (see 'Application Period' in Fig. 1). At the end of quarter $t+1$ new information is received on both, the structure of the portfolio and the output of VAR-Granger data for a new 5-year period (similar to the previous time window, but rolled forward by one quarter). The measure is then updated and applied to quarter $t+2$, and so on. For example, if the five year window used to generate VAR-Granger estimates ends in December of a given year, then the portfolio data used to estimate the Copycat measure will correspond to holdings reported during Q4 of that same year.[5] Once the Copycat Score is estimated using data from Q4, it will be assigned to the fund for the duration of Q1 of the following year. Thus, in all analyses that follow the use of the Copycat Score is predictive.

In both, summary statistics presented below, as well as empirical tests depicted in the section that follows, we show that funds at both ends of the spectrum, those that lean towards net imitation or net leading, actually have much in common between them, and are very different to those in the middle of the measure's scale. Specifically, funds in the extreme groups engage in a high level of both, leading and imitating trades. Any imbalance between these two activities is what results in them being classified as net leaders or net followers. By contrast, funds in the middle of the scale (with a score equal to zero), engage in comparatively little of both, leading and imitation. The inference from various tests shows that funds at both ends of the Copycat measure behave in similar ways, in that they employ partial imitation strategies, with relatively small variations resulting in their differing scores. Due to this similarity between funds separated seemingly only by the sign of their resulting Copycat score, in some tests we use instead the absolute value of the score. This allows us to study the effects of partial imitation strategies in, for example, fund performance in a way that results in a linear relationship, instead of the U-shaped pattern that can be observed when using the 11 quantiles described above.

The methodology used to construct the Copycat Score involves a number of arbitrary decisions, such as the length of each time series of trades to use, or the threshold used to consider a Granger test result as statistically significant. While we present most results in this paper using the baseline specification described above, in an Additional file 1: Appendix available online we show robustness tests where these conditions are altered in various ways. The inferences obtained from the baseline results remain unchanged using these alternate specifications of the Copycat Score.

### Summary statistics

In Fig. 2 we can see the time series of the monthly average of the Copycat Score components. Specifically, we plot the equal- and value-weighted means of wLead, wFoll, as defined in the previous section, and wNeither, which is the percentage of fund assets in which the fund manager doesn't follow nor leads others trades. As we can observe, not

[5] While a majority of funds in the sample report their holdings at the end of each calendar quarter, a small number do not. In our main tests we ignore these asynchronous reporting dates, and these funds are simply assigned a Copycat Score following their own reporting dates. For example, a fund that reports in October will have the same Copycat Score from November to January, and then have it updated. In unreported robustness tests, we lag all report dates for these funds to match calendar quarters. Results remain unchanged.

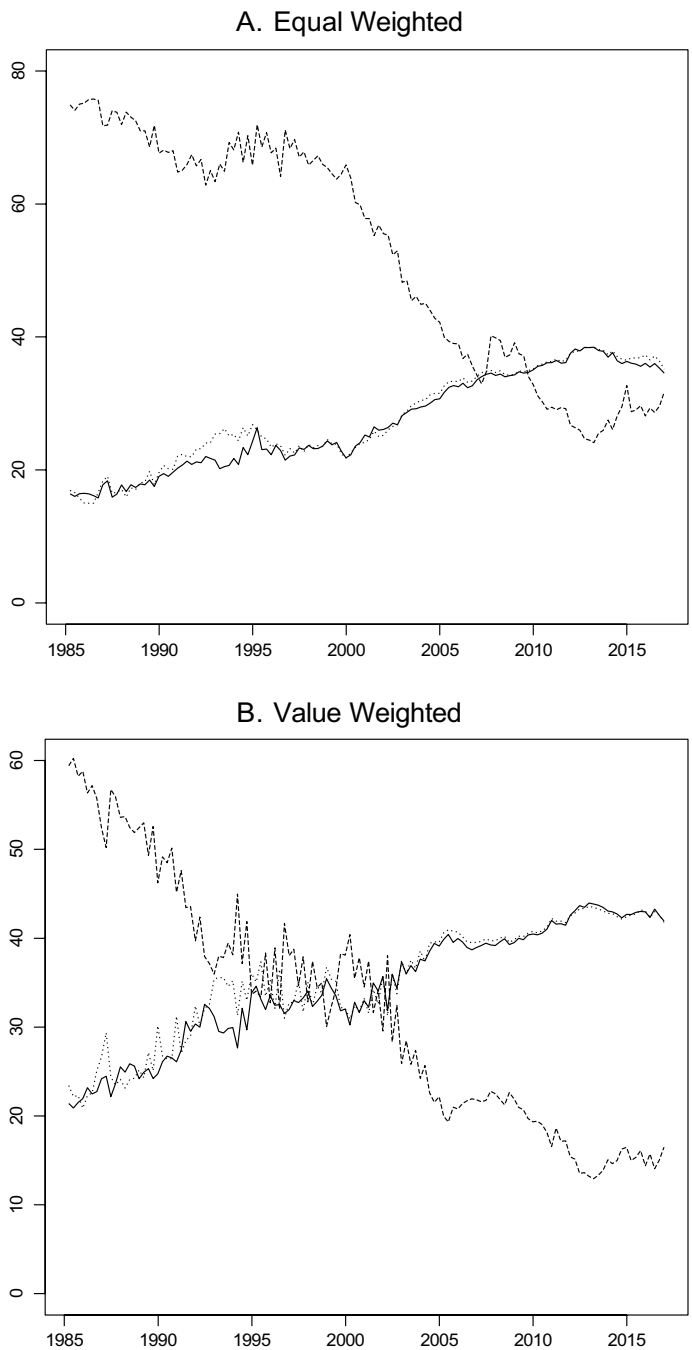



**Fig. 2** Time series of imitation measures. Each quarter, every funds' equity holdings are classified into stocks in which a fund Leads, Follows or does neither, and portfolio weights are added within each category. The percentage of Leading, Following, and neither, is then averaged for all funds. The resulting time series of each classification is depicted in the figures below. **A** shows equal-weighted averages, while in **B** the categories are averaged using fund size (TNA) as weights. In both figures the solid line shows the quarterly average of the percentage of fund assets in which funds Lead, whereas the dotted and dashed lines show the percentage in which they Follow and do neither, respectively

**Table 1** Summary statistics.

**Panel A: Full sample statistics**

| | Mean | 25th perc | Median | 75th perc | St. Dev |
|---|---|---|---|---|---|
| CopyScore | − 0.38 | 0.00 | 0.00 | − 0.87 | 3.52 |
| wLead | 32.85 | 25.75 | 37.57 | 43.88 | 14.39 |
| wFoll | 32.48 | 25.40 | 36.97 | 43.39 | 14.30 |
| TNA | 871.50 | 16.70 | 84.70 | 422.80 | 3616.78 |
| ExpRatio | 1.28 | 0.95 | 1.20 | 1.49 | 1.08 |
| TurnRatio | 86.69 | 33.00 | 62.00 | 107.00 | 107.35 |
| 12b1 | 0.38 | 0.25 | 0.25 | 0.40 | 0.28 |
| PerCom | 93.76 | 92.01 | 95.84 | 98.17 | 8.58 |
| PerCash | 3.15 | 0.44 | 1.96 | 4.23 | 6.24 |
| Fund Age | 12.60 | 4.41 | 9.00 | 15.73 | 12.91 |
| Gross Return | 0.60 | − 2.04 | 1.04 | 3.68 | 5.33 |

**Panel B: Statistics of funds sorted into Copycat Score groups**

| group | CopyScore | wLead | wFoll | Funds | TNA | PerCom | PerCash | ExpRatio | TurnRatio | Age | Following |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 7.92 | 31.67 | 39.59 | 59 | 975 | 92.46 | 3.21 | 1.43 | 95.59 | 12.26 | 67.55 |
| 4 | 2.71 | 33.56 | 36.26 | 60 | 1089 | 93.53 | 3.05 | 1.31 | 87.76 | 13.26 | 69.30 |
| 3 | 1.43 | 34.66 | 36.09 | 60 | 1248 | 94.28 | 2.67 | 1.31 | 87.24 | 13.41 | 71.86 |
| 2 | 0.73 | 35.78 | 36.51 | 60 | 1402 | 94.11 | 2.60 | 1.25 | 83.15 | 14.42 | 83.74 |
| 1 | 0.23 | 38.01 | 38.24 | 60 | 1423 | 94.48 | 2.51 | 1.18 | 88.20 | 14.77 | 85.50 |
| 0 | 0.00 | 23.43 | 23.43 | 430 | 460 | 94.21 | 3.12 | 1.38 | 94.91 | 11.88 | 19.60 |
| − 1 | − 0.31 | 38.32 | 38.01 | 95 | 1460 | 94.67 | 2.40 | 1.18 | 86.84 | 14.98 | 78.58 |
| − 2 | − 0.93 | 37.12 | 36.19 | 93 | 970 | 94.29 | 2.39 | 1.24 | 86.97 | 13.98 | 70.80 |
| − 3 | − 1.76 | 36.70 | 34.93 | 94 | 971 | 93.96 | 2.79 | 1.27 | 80.54 | 13.78 | 60.34 |
| − 4 | − 3.17 | 37.58 | 34.41 | 94 | 668 | 93.91 | 2.85 | 1.29 | 80.03 | 13.00 | 59.01 |
| − 5 | − 7.24 | 39.58 | 32.34 | 94 | 507 | 92.89 | 3.07 | 1.37 | 76.71 | 12.22 | 49.55 |
| Mean | − 0.36 | 29.55 | 29.19 | 1086 | 790 | 94.08 | 2.78 | 1.33 | 93.37 | 12.30 | 60.08 |

In Panel A, summary statistics are presented for the full sample, which contains all actively managed mutual funds that invest primarily in U.S. equity, for the period 2000–2016. In Panel B, mutual funds are sorted every quarter into uneven quantiles by their Copycat Score. Funds with a score of zero are placed in quantile 0, and those with negative and positive scores are separately ranked into quintiles. Summary statistics for each resulting group is presented. The copycat score ('CopyScore') is the difference of the fund's aggregate portfolio weight in stocks in which is imitates trades ('wFoll'), minus those in which it leads ('wLead'). 'Funds' is the average number of funds in each group. 'TNA' is fund Total Net Assets. Expense ratio, turnover ratio, actual 12b1 expenses and percentages of common equity ('PerCom') and cash ('PerCash') are obtained from quarterly data. Monthly gross returns are obtained by adding back 1/12th of annual expenses to CRSP reported net monthly returns. 'Following' is the average number of funds followed by each imitator.

only is trade imitation, depicted by wFoll, a pervasive component in the mutual fund industry, but also this practice shows a steady upward trend throughout our sample period. In the 1980s the average fund imitates trades in about 20% of its stocks, whereas by the 2010s this number just about doubles, with the most dramatic increases happening after the year 2000. While this need not be the case, we see that the rate of imitation, wFoll, is always very close to that of leading, wLead, indicating that the lead-follow relationship in mutual funds is close to one-to-one. Since, mechanically, for each fund these measures (wFoll, wLead and wNeither) add up to 100% of the equity portion of the portfolio, the increase in leading-following is accompanied by an equally drastic reduction in average wNeither, that is, the propensity for funds to trade stocks without imitating or being imitated. These images describe the average behavior of the mutual fund industry. As we discover below, there are important variations in the cross-section of the Copycat Score.

In Panel B of Table 1, and in other tables in this analysis, we rank funds by their Copycat Score into uneven quantiles as follows. Every month $t$, funds with a Copycat Score of zero are grouped into a single quantile. Funds with positive and negative Copycat Score are separately ranked into quintiles in ascending order. Thus, we obtain 11 groups, where quantiles labeled 1 to 5 contain funds with positive Copycat Score, quantiles − 1 to − 5 contain funds with negative Copycat Score, and the middle quantile contains those funds with a score of zero. As we go from quantiles 5 to − 5, the Copycat Score goes from being large and positive, becomes smaller in absolute value until it reaches zero, then becomes negative, and then grows (in absolute value) until it reaches a maximum in the last group. The reason for this choice of sorting is that, as we can see in Panel B of Table 1, there is a disproportionately large number of funds with a Copycat Score of zero. Throughout our sample time span (years 2000 to 2016), the total number of actively managed U.S. equity mutual funds in our sample exceeds 3000. However, the monthly average number of funds with a Copycat measure of zero is 430, whereas the number of funds with negative/positive measures is 470/300. This makes more traditional grouping (quintiles, deciles) impractical, as it is not possible to split a large group with a measure that does not vary.

For convenience, throughout this analysis we single out three particular groups out of these 11 quantiles. Funds in quantile 5, those with the highest Copycat Score and therefore those who tend to imitate others' trades the most, we call "Followers". On the other side of the scale, in quantile − 5, we find the funds which have their trades imitated the most, whom we call "Leaders". Finally, funds with zero Copycat Score we simply call "Zeros". Image 1.B shows the quantile schema, and the labels of these specific quantiles singled out.

Panel B of Table 1 shows the average Copycat Score for each quantile. We also show group averages for the components of the measure (wLead and wFoll), with the remainder held in stocks in which the manager does not seem to lead nor follow. While we are able to rank funds by their Copycat Score, we also note that this does not mean that funds have unique strategies based on imitation. Rather, portfolio holdings show that all funds in the sample seem to incur in some level of copycatting, with about 29% of all capital invested in imitated stocks. However, imitation is a larger component for funds in the extreme quantiles, with Leaders and Followers maintaining an average of 39% and 32% of their capital, respectively, in stocks in which they imitate trades. By contrast, Zeros have the lowest incidence of imitation, only 23% of their assets, but they also seem to lead in trades of another 23% of the value-weighted stocks, which results in their zero net score. In essence, determining who is a true 'copycat' is relative, and we choose to apply this designation to funds in which holdings in imitated stocks dominate all others.

In panel B of Table 1, we also report group averages for a number of fund characteristics which include the funds' total net assets, the percentages of common stock and cash in the portfolio, expense ratio, turnover ratio, fund age, and the average number of funds that each imitator follows. A number of these characteristics have previously been shown to be related to mutual fund performance. Chen et al. (2004) show that size affects performance, and that larger funds underperform their smaller competitors. Simutin (2013) argues that funds that hold an excess of cash are better equipped to face redemptions without recurring to costly fire sales, and show better judgement

in stock picking. Cremers and Pareek (2016) argue that it is 'patient active managers' the ones with the highest skill. 'Active' in this respect refers to managers of funds with a high 'Active Share' measure, introduced in Kacperczyk et al. (2008), which indicates the amount by which the fund's portfolio deviates from that of their benchmark. On the other hand, the 'patient' part comes from trading less often than their peers, as shown by the 'Stock Duration' measure introduced in Cremers and Pareek (2016). While we do not estimate Stock Duration for our sample of funds, we note that Cremers and Pareek (2016) find that their measure has a correlation of − 70% with fund turnover.

Looking at size, Leader and Zero funds are among the smallest funds in the sample, with average TNAs of 507 and 460 billion dollars, respectively. In contrast, Follower funds are far larger, with about 975 billion in assets under management. On the other hand, both Leader and Follower funds have below average equity holdings, equal to 92% of assets of both groups, while Zeros have just about the average, 94%. However, all three groups have above average cash holdings, at just over 3% of their portfolios. Finally, in terms of turnover, the sample average ratio is about 93%. For this measure we have Leader, Zeros and Followers with ratios which are below, at, and above the mean, respectively. If we were to use the data in panel B of Table 1, predicting which funds should have the highest performance would be a hard task, as we obtain conflicting ranks depending on the measure we employ.

With respect to imitation behavior, we can see that the 'Zeros' follow the lowest number of other funds in their trades, which is consistent with their low overall copycat score. However, it is also interesting to see that both extreme quantiles, 5 and − 5, have the lowest number of funds they follow, except for the Zeros. This could be evidence of a more focused approach to imitation, in that these managers have better information about whom it is more profitable to imitate.

## Empirical results

In this section we look at the performance implications of imitation, and how the Copycat Score reveals previously unobserved outperformance for both, the funds that tend to lead most in trades, as well as those that tend to imitate the most. In addition, we establish that the Copycat Score is persistent in time, and is related to other measures of fund manager skill.

### The Copycat Score and fund performance

Previous studies of copycat funds provide evidence that this strategy leads funds to underperform their peers. In Table 2 we show various fund performance and risk measures, estimated for the 'fund of funds' portfolios made by sorting mutual funds into quantiles as described in the previous section. In terms of both gross return and four-factor model alpha, the worst performers are the Zeros. Their average monthly return is 52 basis points, with a statistically insignificant Carhart (1997) four factor alpha of -0.005%. Performance steadily increases as we move away from this central group, until it peaks at both ends of the scale. Indeed, Leaders and Followers (deciles − 5 and 5) obtain monthly gross return of 68 and 78 bps, respectively. These returns are higher than those of Zeros by 16 bps for Leaders and 27 bps for Followers, both differences statistically significant. The Leader group's four-factor alpha is positive but statistically insignificant,

**Table 2** Copycat Score and mutual fund performance

| Quantile | CopyScore | Return | StDev | Alpha | MktRf | SMB | HML | MOM |
|---|---|---|---|---|---|---|---|---|
| 5 | 9.81 | 0.78 | 4.84 | 0.136* | 0.981*** | 0.273*** | 0.177*** | − 0.020 |
| 4 | 3.17 | 0.74 | 4.84 | 0.099 | 1.000*** | 0.284*** | 0.121*** | 0.003 |
| 3 | 1.69 | 0.65 | 4.77 | 0.053 | 1.022*** | 0.162*** | 0.101*** | 0.001 |
| 2 | 0.86 | 0.62 | 4.66 | 0.044 | 1.017*** | 0.127*** | 0.066*** | 0.013 |
| 1 | 0.27 | 0.61 | 4.61 | 0.061 | 1.015*** | 0.088*** | 0.044*** | 0.008 |
| 0 | 0.00 | 0.52 | 4.53 | − 0.005 | 0.999*** | 0.087*** | − 0.014 | 0.016** |
| − 1 | − 0.33 | 0.57 | 4.57 | 0.019 | 1.007*** | 0.103*** | 0.025** | 0.016** |
| − 2 | − 0.99 | 0.59 | 4.69 | 0.017 | 1.016*** | 0.154*** | 0.039*** | 0.005 |
| − 3 | − 1.88 | 0.59 | 4.80 | 0.009 | 1.021*** | 0.194*** | 0.039** | − 0.001 |
| − 4 | − 3.38 | 0.60 | 4.86 | − 0.007 | 1.024*** | 0.219*** | 0.081*** | − 0.005 |
| − 5 | − 8.42 | 0.68 | 5.01 | 0.036 | 1.018*** | 0.313*** | 0.106*** | − 0.025** |
| 5–0 | | 0.27*** | 0.31 | 0.141** | − 0.018 | 0.186*** | 0.190*** | − 0.037*** |
| (− 5)− 0 | | 0.16** | 0.48 | 0.042 | 0.020* | 0.226*** | 0.119*** | − 0.042*** |

Mutual funds are sorted every quarter into uneven quantiles by their Copycat Score, and the subsequent quarter's funds' returns are recorded. Funds with a score of zero are placed in quantile 0, and those with negative and positive scores are separately ranked into quintiles. For each fund, gross returns are estimated by adding reported expenses to net returns. For funds with more than one share class, data is aggregated using lagged total asset size as weights. Monthly portfolio returns are calculated as the equally-weighted return of all funds within each quantile. The data spans the years 2000 to 2016. Average monthly return for each quantile is presented, as well as standard deviation of returns, and the output from a Carhart (1997) four-factor model, which includes the factor model alpha, as well loadings in the market, SMB, HML and MOM factors. Statistical significance of the regression results is denoted by ∗∗∗, ∗∗ and ∗ for significance at the 1%, 5% and 10% levels, respectively

whereas it's positive and significant for Followers, who attain an average monthly alpha of 13.6 bps. The differences in alphas between the high-performing extreme quantiles and low-performing Zeros are positive and, at least for Followers vs Zeros, a statistically significant 14.1 bps per month.

In addition to performance, we also look at the riskiness of each group. As with returns and alphas, standard deviation of returns is lowest for Zeros and increases towards the higher and lower Copycat Score groups. However, the differences between the extremes and Zeros are statistically insignificant. In terms of loadings on risk factors, Leader funds tend to have higher market betas than Zeros, whereas Followers' betas are similar to those of the middle quantile. Both Leaders and Followers tend to load on stocks which are smaller and have higher B/M ratios. Finally, while the momentum loading tends to be insignificant for most individual groups, middle quantiles (including Zeros) have positive momentum coefficients, whereas extreme high and low quantile groups have negative loadings. The difference in momentum loading between extremes and Zeros is negative and significant, indicating that extreme quantile funds tend to have slightly more contrarian investment patterns than the Zeros.

As we can see, Leaders and Followers clearly outperform other mutual funds in our sample, with the largest difference observed between these groups and the Zeros. In what follows we explore the sources of these differences in performance.

**Table 3** Returns of stocks held by mutual funds

| | Portfolio weights | | | Stock returns | | | | |
|---|---|---|---|---|---|---|---|---|
| **copyQ** | **wFoll** | **wNeither** | **wLead** | **rFoll** | **rNeither** | **rLead** | **rLead-rFoll** | **rLead-rNeither** |
| 5 | 36.26 | 35.58 | 29.85 | 1.17 | 1.17 | 1.04 | − 0.12*** | − 0.12** |
| 4 | 33.96 | 34.87 | 31.77 | 1.07 | 1.07 | 1.06 | − 0.01 | − 0.01 |
| 3 | 33.87 | 34.02 | 32.80 | 0.96 | 0.99 | 0.97 | 0.00 | − 0.03 |
| 2 | 34.78 | 31.88 | 34.33 | 0.94 | 0.99 | 0.90 | − 0.03* | − 0.09 |
| 1 | 36.25 | 28.49 | 36.16 | 0.92 | 0.96 | 0.90 | − 0.02 | − 0.06 |
| 0 | 28.32 | 53.45 | 28.39 | 0.69 | 0.86 | 0.68 | − 0.01 | − 0.17** |
| − 1 | 36.06 | 28.25 | 36.39 | 0.87 | 0.92 | 0.87 | 0.00 | − 0.05 |
| − 2 | 34.58 | 30.76 | 35.41 | 0.89 | 0.95 | 0.87 | − 0.02 | − 0.08 |
| − 3 | 33.30 | 32.58 | 34.73 | 0.91 | 0.93 | 0.91 | 0.00 | − 0.01 |
| − 4 | 32.42 | 33.48 | 34.90 | 0.89 | 0.95 | 0.94 | 0.05** | 0.00 |
| − 5 | 30.71 | 33.61 | 36.61 | 0.95 | 1.03 | 1.06 | 0.1*** | 0.03 |
| 5–0 | | | | 0.47*** | 0.31*** | 0.36*** | | |
| (− 5)− 0 | | | | 0.26** | 0.17** | 0.37*** | | |

Mutual funds are sorted every quarter into uneven quantiles by their Copycat Score. Funds with a score of zero are placed in quantile 0, and those with negative and positive scores are separately ranked into quintiles, in ascending order. Every quarter, each fund's holdings are separated into stocks in which the fund Follows other fund's trades, those in which it Leads, and those in which it does Neither. The first three columns of the table show the total portfolio weight of each type of stock, whereas the next three columns depict the average return of stocks in each category. The final two columns show the difference in returns between stocks in which the fund Leads minus those in which it Follows, and between stocks in which it Leads minus those in which it does Neither. The data spans the years 2000–2016. Statistical significance of return differences is denoted by ∗∗∗, ∗∗ and ∗ for significance at the 1%, 5% and 10% levels, respectively

In the first three columns of Table 3 we report the average percentage of fund assets classified into stocks in which a fund follows others' trades, leads, or does neither.[6] In the three columns that follow we show the equal-weighted return of the stocks in each of the three groups, while the last two columns show differences between these returns.

While the previous literature separates mutual funds into two categories, imitators and imitated, our measure allows for a more nuanced analysis. Not only do we observe that imitation is pervasive, but we can now see that some funds are better at it than others. For example, the amount of imitation is similar between the extreme Followers in decile 5, and decile 1, which tilts towards imitation but is close to the central quantile, the Zeros. Both invest about 36% of their capital in stocks in which they imitate other funds' trades. However, the average return of these imitated stocks is 0.92% per month for decile 1, far lower than the 1.17% obtained by the Followers. In this respect, we can consider imitation not as a binary classification but as a spectrum, where many fund managers do it but only some do it successfully. We can think of these as 'smart copycats', and here we can see that they outperform their peers, contradicting past results. Moreover, the evidence in Table 3 contradicts another previous assumption, that managers who engage in copycat investing do so because they lack the skills to pick their own stocks. As we can see, the returns of stocks selected by Follower funds (decile 5) outperform those of others, with few exceptions. On average, stocks in which Followers lead other's trades obtain a return of 1.04% per month, barely below the return obtained by quantiles

[6] This is essentially the same data shown in columns 3 and 4 of Table 1, Panel B. The patters.
remain the same, even though each specific number is slightly different. These differences are due to sample selection, as in Table 1 the copycat data is merged with quarterly portfolio characteristics, while in Table 3 it is used in conjunction with monthly stock data.

− 5 (Leaders) and 4, and stocks in which they neither lead nor follow have returns of 1.17%, matching the returns of the stocks in which they follow, and again outperforming all other funds in the sample. Thus, funds which do gain an advantage from this "smart imitation" are not managed by executives that lack skill, as they do not depend solely on imitation for their overall performance. Rather, imitation is one of many skills they seem to possess, as their performance when leading and doing neither (that is, relying on their own information to trade) is equally impressive as when they imitate. On the other hand, the underperforming managers are revealed as those who are not able to compete based on their own trades, nor are they capable of implementing successful imitation strategies.

As would be expected, Leader funds (quantile − 5) outperform all others in stocks in which they lead, with a return of 1.06% per month. However, just as Follower funds, the performance in stocks in which they imitate and in which they do neither is also among the highest in the sample, indicating that the fund managers of these portfolios are also highly skilled when choosing whose trades to imitate.

Thus, managers of both, Leader and Follower funds, seem to be more skilled than others. Moreover, these skills do not manifest in one strategy only, leading or following, but are present across all. The picture that emerges is of different types of imitation. For most funds, and especially those in the Zeros quantile which contain a larger number of funds than others, managers seem to lack any skill and engage in imitation with poor results. However, at both ends of the Copycat Score spectrum, we find skilled managers who can not only pick good stocks by themselves, but can also pick better trades to imitate than their peers. If the absolute value of the Copycat Score is indeed a measure of skill, then this would explain the U-shaped performance measures observed in Table 3. We explore the relationship between the Copycat Score and skill in more detail in what follows in this and the next subsection.

Given the evidence presented so far, we would expect the Copycat Score to be a good predictor of mutual fund performance. We put this to the test in Table 4, by regressing measures of long-term mutual fund performance on the lagged (absolute value) Copycat Score.

In all tables so far, the Copycat Score is lagged by one month with respect to returns data. Following the fund manager skill literature, we speculate on the longer term predictive power that the measure might have for fund performance. In Table 4 we regress the one-year-ahead gross return (Panel A), calculated as the annual return for the period between months $t+1$ and $t+12$, or four factor alpha (Panel B), obtained from a Carhart (1997) four-factor model estimated using the same future returns, of each fund on the absolute value of it's Copycat Score,[7] as well as measures of manager skill introduced in the past, as well as control variables.

Skill measures include the following: each fund's industry concentration, estimated as the standard deviation of the percentages of assets allocated by each fund to 10 industry groups, as tabulated in Kacperczyk et al. (2005), past $R^2$ and fund alpha obtained from

[7] We use the absolute value of the Copycat Score due to the U-shaped relationship between the Copycat Score and performance observed above. Using the absolute value of the measure turns this into a linear relationship. See section "Data, methodology and summary statistic" for a more extensive motivation.

**Table 4** Mutual fund Copycat Score and future performance

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Panel A: 1 Year ahead gross return** | | | | | | | | |
| absCopy | 22.922*** | 7.710*** | − 6.487* | 76.215* | 1.588 | 4.466* | − 12.525*** | 15.350*** |
| Active | | | | | | | | 9.418*** |
| R2 | | | | | | | | − 4.946 |
| Alpha | | | | | | | | 116.829*** |
| Tracking | | | | | | | | − 16.427** |
| IC | | | | | | | | − 15.492** |
| Peers | | | | | | | | − 6.404* |
| PerCom | − 0.001 | − 0.017 | 0.000 | − 0.009 | − 0.027 | − 0.009 | − 0.028 | − 0.008 |
| PerCash | − 0.016 | − 0.076*** | − 0.023 | − 0.026 | − 0.047*** | − 0.026 | − 0.008 | − 0.052** |
| logTNA | − 0.178* | − 0.085 | − 0.086 | − 0.122 | − 0.115 | − 0.161 | − 0.170 | − 0.013 |
| Fund Age | 0.045 | − 0.158 | − 0.052 | − 0.037 | − 0.286* | − 0.021 | − 0.009 | − 0.035 |
| Turn Ratio | − 0.513* | − 0.526 | − 0.578* | − 0.413 | − 0.470 | − 0.553** | − 0.873** | − 0.401 |
| Exp Ratio | − 103.016*** | − 145.326*** | − 112.309*** | − 79.032** | − 41.121 | − 97.829*** | − 104.711*** | − 101.53*** |
| Obs | 221,226 | 136,492 | 210,891 | 210,891 | 136,492 | 219,945 | 147,031 | 100,130 |
| Adj. $R^2$ | 0.63 | 0.68 | 0.64 | 0.63 | 0.67 | 0.63 | 0.69 | 0.74 |
| **Panel B: 1 year ahead alpha** | | | | | | | | |
| absCopy | 0.574*** | 0.136** | − 0.380* | | | | | 0.445* |
| Active | | | | | | | | 0.187** |
| R2 | | | | | | | | − 0.287 |
| Alpha | | | | 5.851* | | | | 13.198*** |
| Tracking | | | | | − 0.315 | 0.550*** | | − 1.110** |
| IC | | | | | | | | − 0.380 |
| Peers | | | | | | | − 0.225 | − 0.094 |
| PerCom | − 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 |
| PerCash | 0.001 | 0.000 | 0.002 | 0.001 | 0.001 | 0.001 | 0.002** | 0.002 |
| logTNA | − 0.004 | 0.000 | − 0.003 | − 0.004 | 0.000 | − 0.005 | − 0.005 | − 0.003 |
| Fund Age | 0.016* | 0.004 | 0.017** | 0.018** | 0.001 | 0.014* | 0.007 | 0.008 |
| Turn Ratio | − 0.042*** | − 0.051*** | − 0.044*** | − 0.039*** | − 0.047*** | − 0.042*** | − 0.059*** | − 0.054*** |
| Exp Ratio | − 10.493*** | − 11.125*** | − 11.613*** | − 9.389*** | − 8.532*** | − 11.874*** | − 11.448*** | − 9.660*** |
| Obs | 221,226 | 136,492 | 210,891 | 210,891 | 136,492 | 219,945 | 147,031 | 100,130 |
| Adj. $R^2$ | 0.10 | 0.13 | 0.14 | 0.12 | 0.13 | 0.12 | 0.14 | 0.20 |

Mutual fund performance measures are regressed on lagged fund characteristics and measures previously identified as predictors of future fund performance or fund manager skill. In Panel A the dependent variable is the fund's annual gross return calculated using monthly data from month $t+1$ to $t+12$, while in Panel B it's the fund's alpha obtained from a Carhart (1997) four-factor model estimated using the same data span. Regressors are obtained using data available at the end of month t or before. 'absCopy' is the absolute value of the fund's Copycat Score. IC is the fund's industry concentration, estimated as the standard deviation of the percentages of assets allocated by each fund to 10 industry groups, as tabulated in Kacperczyk et al. (2005). Past $R^2$ and fund Alpha are obtained from a four-factor model following Amihud and Goyenko (2013). Active Share and Tracking Error are used as in Cremers and Petajisto (2009). The number of Peers or competing funds (Hoberg et al. 2017) is included as a percentage of all mutual funds in each period of time. Control variables include fund characteristics, such as the percentages of fund assets invested in common equity (PerCom) and cash (PerCash), the log of Total Net Assets ('logTNA'), the fund's age, Turnover Ratio, and Expense Ratio. For most models and variables the data spans 2000–2016. Data for Active Share and Tracking Error ends in 2009. Data on Peers runs through 2012. The Fama-MacBeth regression methodology is used, with Newey-West standard errors. Statistical significance is denoted by ∗∗∗, ∗∗ and ∗ for significance at the 1%, 5% and 10% levels, respectively.

a fourfactor model following (Amihud and Goyenko 2013), Active Share and Tracking Error used as in Cremers and Petajisto (2009). We also include the number of 'Peers' or competing funds, introduced in Hoberg et al. (2017), as a percentage of all mutual funds in each period of time. While not a measure of skill, Hoberg et al. (2017) show that funds that face higher levels of buy-side competition for stocks obtain lower returns. For each

fund in their sample, 'NPeers' is the number of funds which are considered to be direct competitors, in the sense that their investment styles are close enough that they compete for the same stocks. The level of buy-side competition is gauged by first estimating the pair-wise style distance between all funds.[8] Then, for each fund, all other funds which are closer than a certain threshold are considered peers, or competitors. In our tests, we include this measure, expressed as a percentage of all mutual funds in each period of time. Control variables include fund characteristics, such as the percentages of fund assets invested in common equity and cash, the log of total net assets (TNA), the fund's age, turnover ratio, and expense ratio.

In panel A of Table 4 we observe that, as expected, the Copycat Score is a strong predictor of mutual fund performance. Whether modeled just with controls, as in specification (1), or including competing measures and controls, as in model (8), the coefficient of the Copycat Score is positive and significant. Moreover, the size of the coefficient shows little change in the presence of other variables previously used to identify fund outperformance or skill, going from 22.92 in model (1) to 15.35 in model (8). In contrast, some of the other measures of skill show more variability between a model which only includes control variables and the full specification, model (8). For example, $R^2$ in model (3) has the right sign and is statistically significant, with a coefficient of -6.49. However, in model (8), $R^2$ ceases to be significant. The opposite is true for the coefficient of the tracking error, which goes from having the correct sign but being insignificant, to a result which is statistically significant, but has the opposite sign to that expected in theory. Finally, industry concentration is significant in both, models (6) and (8), although it switches sign in model (8). The results in Panel B are similar, with the Copycat Score remaining a significant predictor of future alpha, independent of the explanatory variables included in each model.

### Characteristics of the Copycat Score and copycat behavior

The evidence presented above establishes that funds with extreme (high or low) Copycat Scores outperform their peers. In what follows, we explore the characteristics of the Copycat Score and what it can tell us about fund manager behavior. First, we look at the persistence of the classifications based on the score. It could be the case that the strategy that results in these scores is highly variable, and funds frequently move into and out of these groups. If that were the case, then the Copycat Score would not be a persistent characteristic of the fund (or its manager), and should not be considered as evidence of skill.

In Table 5 we estimate switching probabilities between the Copycat Score quantiles over varying periods of time. Specifically, every quarter $t$ we identify the funds in each quantile, $-5$ to 5. We then count the number of funds that are still in the same quantile after $n$ quarters, and express it as a percentage of the original number of funds. These percentages represent the probability of staying in the same group, and can be interpreted as the persistence of a group's members. Persistence probabilities are arrayed

[8] The distance between two funds is calculated as the euclidean distance between vectors of fund characteristics. While Hoberg et al. (2017) use a variety of characteristics and specifications, we use data provided by Gerard Hoberg in which peers are identified using their main model, which is based on fund size, book-to-market, and momentum.

**Table 5** Mutual fund copycat measure switching probability matrices

| From\To | 5 | 4 | 3 | 2 | 1 | 0 | − 1 | − 2 | − 3 | − 4 | − 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Switching Probabilities 1 Quarter After Initial Fund Classification* | | | | | | | | | | | |
| 5 | 59.06 | 16.71 | 6.20 | 2.82 | 1.48 | 4.69 | 1.66 | 1.60 | 1.66 | 1.58 | 2.54 |
| 4 | 17.30 | 33.45 | 16.45 | 8.13 | 4.60 | 5.94 | 4.41 | 2.84 | 2.77 | 2.50 | 1.61 |
| 3 | 5.55 | 16.81 | 25.85 | 15.09 | 7.68 | 8.84 | 5.72 | 4.59 | 4.49 | 3.34 | 2.04 |
| 2 | 2.96 | 7.55 | 14.19 | 25.20 | 14.61 | 10.77 | 8.65 | 6.71 | 4.55 | 3.21 | 1.60 |
| 1 | 2.07 | 4.33 | 7.70 | 13.48 | 27.25 | 10.11 | 15.75 | 8.44 | 5.54 | 3.50 | 1.84 |
| 0 | 1.55 | 1.85 | 2.34 | 2.74 | 2.38 | 75.66 | 3.48 | 3.54 | 2.79 | 2.16 | 1.51 |
| − 1 | 1.16 | 2.87 | 4.53 | 5.64 | 10.54 | 10.55 | 32.95 | 15.77 | 8.66 | 4.90 | 2.42 |
| − 2 | 1.22 | 2.55 | 3.94 | 4.56 | 5.67 | 9.78 | 16.12 | 27.36 | 16.75 | 8.39 | 3.66 |
| − 3 | 1.27 | 2.31 | 3.00 | 3.50 | 4.24 | 7.66 | 8.18 | 16.63 | 29.23 | 17.33 | 6.65 |
| − 4 | 1.13 | 1.70 | 2.45 | 2.07 | 2.58 | 5.22 | 4.41 | 8.18 | 18.51 | 35.16 | 18.58 |
| − 5 | 1.68 | 1.14 | 1.19 | 1.40 | 1.45 | 3.82 | 2.03 | 3.73 | 6.03 | 18.81 | 58.70 |
| *Panel B: Switching Probabilities 2 Quarters After Initial Fund Classification* | | | | | | | | | | | |
| 5 | 47.84 | 16.72 | 7.52 | 4.27 | 2.39 | 7.00 | 2.45 | 2.33 | 2.38 | 3.08 | 4.02 |
| 4 | 16.25 | 24.44 | 15.10 | 8.33 | 5.78 | 8.93 | 5.03 | 4.71 | 4.38 | 3.89 | 3.16 |
| 3 | 7.17 | 14.21 | 18.11 | 13.49 | 8.50 | 11.09 | 7.21 | 6.41 | 6.14 | 4.63 | 3.04 |
| 2 | 4.13 | 8.56 | 12.43 | 18.16 | 12.60 | 13.36 | 9.73 | 7.74 | 5.57 | 4.86 | 2.86 |
| 1 | 2.30 | 5.37 | 8.17 | 12.84 | 21.82 | 13.13 | 13.42 | 8.87 | 6.59 | 4.77 | 2.74 |
| 0 | 2.31 | 2.71 | 3.09 | 3.38 | 3.03 | 67.58 | 4.53 | 4.48 | 3.76 | 2.95 | 2.18 |
| − 1 | 1.84 | 3.62 | 4.78 | 6.99 | 10.07 | 13.61 | 26.09 | 14.50 | 9.33 | 5.79 | 3.38 |
| − 2 | 1.76 | 3.25 | 4.74 | 4.99 | 6.58 | 13.58 | 15.58 | 19.94 | 14.98 | 9.66 | 4.94 |
| − 3 | 1.82 | 3.20 | 4.37 | 4.06 | 4.79 | 10.74 | 9.67 | 15.04 | 21.88 | 15.98 | 8.45 |
| − 4 | 1.81 | 2.80 | 3.20 | 2.96 | 3.43 | 8.08 | 5.73 | 10.28 | 16.58 | 26.44 | 18.68 |
| − 5 | 2.87 | 2.22 | 2.30 | 1.70 | 1.74 | 5.75 | 2.99 | 5.50 | 8.21 | 18.87 | 47.86 |
| *Panel C: Switching Probabilities 3 Quarters After Initial Fund Classification* | | | | | | | | | | | |
| 5 | 41.19 | 15.99 | 8.19 | 4.85 | 2.56 | 7.92 | 3.31 | 2.95 | 3.73 | 3.80 | 5.52 |
| 4 | 15.73 | 20.33 | 13.31 | 8.40 | 6.33 | 10.08 | 5.53 | 5.76 | 5.40 | 4.81 | 4.32 |
| 3 | 7.03 | 13.72 | 14.97 | 11.17 | 8.26 | 13.19 | 7.31 | 7.62 | 6.68 | 5.67 | 4.37 |
| 2 | 4.42 | 7.74 | 11.31 | 14.33 | 12.29 | 15.22 | 9.93 | 8.58 | 7.29 | 5.64 | 3.25 |
| 1 | 2.70 | 5.07 | 8.12 | 12.16 | 18.30 | 13.48 | 13.62 | 9.14 | 7.22 | 6.02 | 4.16 |
| 0 | 3.20 | 3.34 | 3.89 | 3.95 | 3.52 | 59.80 | 5.17 | 5.42 | 4.82 | 3.84 | 3.04 |
| − 1 | 2.11 | 3.58 | 5.53 | 6.56 | 9.84 | 15.25 | 22.07 | 13.26 | 10.38 | 6.95 | 4.47 |
| − 2 | 2.11 | 4.05 | 4.61 | 5.70 | 6.46 | 15.58 | 14.87 | 16.89 | 13.50 | 10.28 | 5.96 |
| − 3 | 2.64 | 3.76 | 4.18 | 5.00 | 5.23 | 12.46 | 9.93 | 14.50 | 18.26 | 14.15 | 9.89 |
| − 4 | 2.70 | 3.55 | 3.41 | 3.93 | 3.90 | 9.35 | 6.85 | 9.75 | 15.45 | 22.95 | 18.16 |
| − 5 | 3.73 | 2.65 | 3.15 | 2.24 | 2.40 | 7.24 | 3.95 | 6.43 | 9.58 | 18.17 | 40.46 |
| *Panel D: Switching Probabilities 4 Quarters After Initial Fund Classification* | | | | | | | | | | | |
| 5 | 36.71 | 15.74 | 8.63 | 4.94 | 2.77 | 8.57 | 3.34 | 3.38 | 4.26 | 4.66 | 7.01 |
| 4 | 14.80 | 17.11 | 12.43 | 8.85 | 5.93 | 11.42 | 5.53 | 6.11 | 6.28 | 5.84 | 5.69 |
| 3 | 7.78 | 12.38 | 12.93 | 10.81 | 7.38 | 14.56 | 8.07 | 7.79 | 7.59 | 6.15 | 4.57 |
| 2 | 4.56 | 8.23 | 10.26 | 13.85 | 11.77 | 15.92 | 9.62 | 8.18 | 7.48 | 6.23 | 3.90 |
| 1 | 2.95 | 5.47 | 7.80 | 11.84 | 16.76 | 14.56 | 13.15 | 10.27 | 7.54 | 5.54 | 4.11 |
| 0 | 3.24 | 3.67 | 4.15 | 3.98 | 3.65 | 57.25 | 5.66 | 5.53 | 5.11 | 4.37 | 3.40 |
| − 1 | 2.34 | 3.84 | 4.81 | 6.51 | 9.88 | 16.37 | 20.70 | 14.17 | 9.99 | 6.88 | 4.52 |
| − 2 | 2.50 | 3.70 | 5.25 | 5.47 | 7.16 | 16.81 | 14.21 | 14.94 | 12.75 | 10.20 | 7.02 |
| − 3 | 2.59 | 4.21 | 4.78 | 4.88 | 5.41 | 14.41 | 10.01 | 13.77 | 16.38 | 14.04 | 9.52 |
| − 4 | 3.07 | 3.83 | 3.88 | 4.28 | 3.60 | 11.43 | 6.83 | 10.42 | 14.74 | 20.77 | 17.17 |
| − 5 | 4.42 | 3.51 | 3.13 | 2.62 | 2.57 | 8.95 | 4.26 | 6.51 | 9.40 | 17.50 | 37.14 |

**Table 5** (continued)

| From | To follower | To zero | To leader |
|---|---|---|---|
| *Panel E: 4 Quarters* | | | |
| Follower | 54.51 | 12.98 | 32.51 |
| Zero | 18.70 | 57.21 | 24.09 |
| Leader | 21.68 | 13.60 | 64.72 |
| *Panel F: 8 Quarters* | | | |
| Follower | 46.00 | 15.26 | 38.74 |
| Zero | 21.39 | 50.24 | 28.37 |
| Leader | 23.15 | 17.09 | 59.76 |
| *Panel G: 20 Quarters* | | | |
| Follower | 35.46 | 21.28 | 43.26 |
| Zero | 23.79 | 45.53 | 30.69 |
| Leader | 24.46 | 24.77 | 50.77 |

Mutual funds are sorted into groups every quarter, ranked by their Copycat measure. The dataset spans 2000 to 2016. Transition probabilities are calculated as the percentage of funds that switch from one group to another between quarters $t$ and $t+n$. Panels A to D show transition matrices for groups sorted as follows: funds with a Copycat measure of zero are put together, while those with negative and positive measures are sorted into quintiles, ranked in ascending order by their Copycat measure. This results in 11 uneven quantiles. Panel A shows transition probabilities after one quarter, while Panels B, C and D show differences after 2, 3, and 4 quarters, respectively. In panels E and F funds are sorted into three groups, for those with negative, zero and positive Copycat measures. Panel E shows switching probabilities 1 year (4 quarters) after initial fund classification, and Panel F depicts probabilities of switching after 2 years.

on the diagonal of the switching matrix. We repeat this calculation for those funds that have moved from one quantile to another, and obtain the probabilities of switching between groups. These are the off-diagonal terms. Panels A to D of Table 5 show the switching probability matrices for funds 1, 2, 3 and 4 quarters after initial group formation. In Panel A we can see that there is a high degree of persistence in the Zeros group. The probability of still being in that group one quarter after initial sorting is over 75%. This probability decays over longer periods of time, but after a full year (Panel D), is still about 57%. On the other hand, it would appear that there is less persistence in the rest of the groups. In Panel A we see that there is a relatively strong level of persistence in the extreme groups, Leaders and Followers. These funds have better than 58% probability of remaining in their respective groups after one quarter. However, probabilities are far lower for the rest of the quantiles, indicating a large amount of movement between groups, particularly between contiguous ones.

Initially it would seem as though there is little persistence in all groups other than the Zeros, which would indicate that leading and following are short term tactics, and can change in time. However, the movements between adjoining groups with similar strategies masks the real pattern. To alleviate this problem, we use a simpler three-way sort in Panels E and F of Table 5, where the Zeros remain as before, but now 'Leaders' refers to all funds with a positive Copycat Score, and 'Followers' now encompasses all those with a negative measure. To further illustrate the point, we skip the smaller time periods, and show the switching probabilities between these three groups after one year (Panel E), and two years (Panel F). It now becomes much clearer that the levels of persistence in the overall behavior of fund managers are higher than those hinted at before. In fact, a year after sorting the probability of remaining in the Zeros group is about 57%, similar to the probability of remaining in the Follower group (54%), and actually lower than that of the Leader group, which is close to 65%. The evidence shows that while, for example,

**Table 6** Imitation by fund quantile

| CopyQ | 5 | 4 | 3 | 2 | 1 | 0 | − 1 | − 2 | − 3 | − 4 | − 5 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 8.58 | 5.52 | 4.67 | 4.30 | 4.26 | 13.17 | 7.80 | 8.69 | 10.02 | 11.93 | 21.04 |
| 4 | 6.94 | 5.16 | 4.60 | 4.30 | 4.50 | 17.19 | 8.98 | 9.39 | 10.45 | 11.19 | 17.30 |
| 3 | 6.05 | 4.79 | 4.53 | 4.38 | 4.57 | 20.25 | 9.38 | 9.82 | 10.54 | 10.79 | 14.90 |
| 2 | 5.04 | 4.51 | 4.45 | 4.41 | 4.74 | 23.62 | 10.13 | 10.12 | 10.48 | 10.10 | 12.41 |
| 1 | 4.65 | 4.22 | 4.39 | 4.38 | 4.83 | 26.03 | 10.32 | 10.20 | 10.41 | 9.68 | 10.89 |
| 0 | 4.06 | 4.53 | 4.78 | 4.95 | 5.02 | 37.58 | 9.44 | 8.42 | 8.10 | 7.18 | 5.96 |
| − 1 | 4.85 | 4.61 | 4.47 | 4.62 | 4.70 | 29.58 | 10.43 | 9.40 | 9.19 | 8.65 | 9.51 |
| − 2 | 5.55 | 4.72 | 4.38 | 4.48 | 4.45 | 27.69 | 10.22 | 9.34 | 9.37 | 9.14 | 10.66 |
| − 3 | 6.65 | 5.18 | 4.44 | 4.41 | 4.41 | 24.59 | 9.79 | 9.16 | 9.51 | 9.80 | 12.06 |
| − 4 | 8.26 | 5.50 | 4.51 | 4.52 | 4.25 | 20.88 | 9.17 | 8.76 | 9.34 | 10.44 | 14.35 |
| − 5 | 10.45 | 6.22 | 4.67 | 4.57 | 4.04 | 16.77 | 8.13 | 8.12 | 9.01 | 10.95 | 17.06 |

Each quarter, all stocks from a fund's portfolio in which the fund manager is identified as imitating another manager's trades are classified on two dimensions: the copycat quantile of the fund which holds them, and the quantile of the fund whose trades are imitated. The average group portfolio weight is calculated as the mean of the weight of each stock in its portfolio. The imitating fund's classification is located on the Y axis, while the quantiles of the funds whose trades they copy are arrayed on the X axis. The table data is normalized so that each row (imitation weights for all funds in a certain quantile) adds up to 100%. The resulting table depicts the intensity with which funds from each quantile tend to imitate funds in every quantile, including their own. For example, of all stocks in which they imitate other funds, managers in quantile 5 tend to devote 8.58% to imitating trades of managers in the same group (5), whereas they follow trades of funds in quantile − 5 21.04% of the time

Followers may increase or decrease the relative levels of leading and following, the balance tends to remain negative for long periods of time. The same is true for Leaders, albeit with a resulting positive Copycat Score. Thus, we establish that the Copycat Score reveals a persistent behavior, or strategy.

But what exactly does this strategy entail, and why is it that only some fund managers seem to reap a performance benefit out of imitation, while others do not? We propose that the fund managers who outperform partly due to imitating others' stock picks posses a specific skill in that regard. We can define this skill as the ability to identify other fund managers who make superior stock picks, which they then imitate. As we've shown before, outperforming managers do not rely entirely on imitation, but are also capable of picking good stocks by themselves. We refine our theory by proposing a model of complementing skills. For example, fund manager A might be very good at selecting stocks in the tech sector, but may not be knowledgeable enough to make good picks in the banking industry. Conversely, manager B might be very good at picking bank stocks, but make poor choices when it comes to tech. The best performance for both managers would then be obtained if manager A uses her private information when trading tech stocks, but imitates manager B's trades when trading bank stocks, and vice versa.

In Table 6 we look at the average fund loading for each quantile group, in terms of which funds they tend to imitate. That is, we look at all stocks in a fund's portfolio in which the manager is identified by the VAR-Granger methodology as following another manager's trades. We sort these imitated stocks into groups on two dimensions: the quantile of the fund that holds the stock, and the quantile of the fund whose trades are imitated. Under the null hypothesis of uninformed imitation, managers should imitate trades of all funds in the sample indiscriminately. This should result in an imitation distribution that resembles a uniform distribution, albeit weighted by

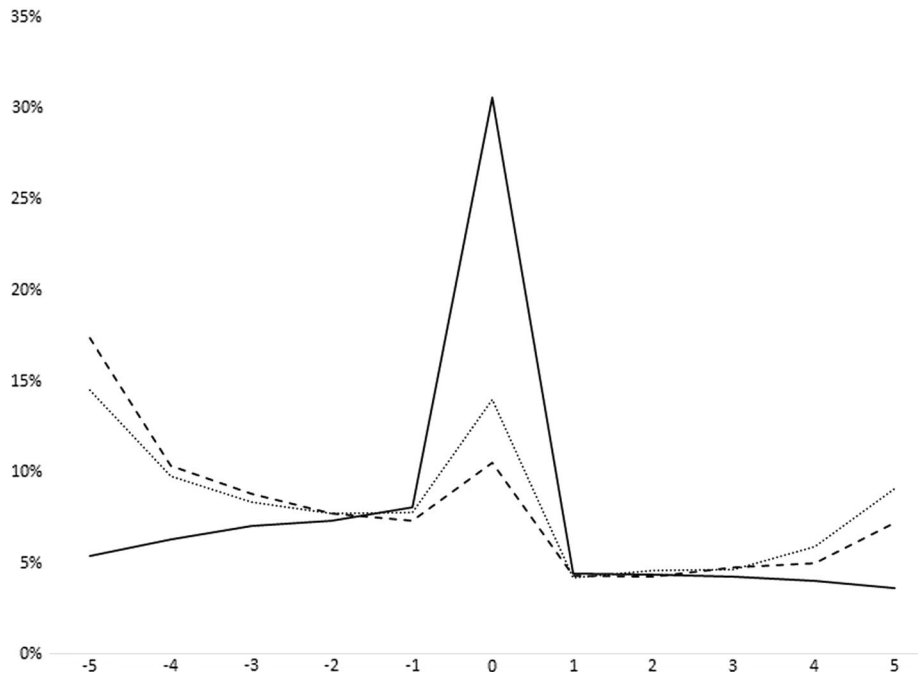



**Fig. 3** Imitation by copycat quantile distributions. Each quarter, all stocks from a fund's portfolio in which the fund manager is identified as imitating another manager's trades are classified on two dimensions: the copycat quantile of the fund which holds them, and the quantile of the fund whose trades are imitated. The average group portfolio weight is calculated as the mean of the weight of each stock in its portfolio. The figure depicts the percentage of stocks in which fund managers imitated the trades of other managers in each copycat quantile. The continuous line shows the propensity to imitate in each group by fund classified into quantile 0 ('Zeros'), whereas the dotted and dashed lines show the same data for funds in quantiles 5 ('Copycats') and − 5 ('Leaders')

the number of funds in each group. Specifically for our sample, the null distribution of imitation would show a disproportionate amount of imitated stocks in the central, or Zero, quantile, simply because this group contains the largest number of funds in the sample. Additionally, the weights for the positive quantiles should be roughly the same for each group, as these quantiles contain the same number of funds, with the same being the case for the negative quantiles, albeit with a lower loading, as these groups are smaller than their positive counterparts.

The null distribution described above is, indeed, what we observe in Table 6 for the Zero quantile funds. By far the most imitated quantile for these funds is their own, with 37.58% of imitated fund assets. Imitation again follows our conjectured null distribution, with similar and lower numbers for the negative quantiles, ranging between 9.44 and 5.96% for quantiles − 1 to − 5, and again lower but similar numbers for the positive quantiles, from 5.02 to 4.06% for quantiles 1 to 5. However, as we move away from the central group the distribution changes dramatically. In particular, for the extreme quantiles, funds in groups − 5 and 5, we see the seemingly bell-shaped curve transform into a pronounced 'W' shape. That is, while there is still a noticeable concentration of imitation of the Zero quantile, the extreme quantiles themselves now attract a larger portion of overall imitation. In fact, funds in quantile 5, the Followers, devote on average 21.04% of imitated fund assets to following trades of the Leaders

(group − 5), and 8.58% to imitating funds in their own group (a figure that more than doubles the same loading for funds in the Zero group). For funds in quantile − 5, Leaders, the largest source of imitation information is their own group, with 17.06% of fund assets of all imitated stocks, and 10.45% devoted to imitating stocks of the Followers, quantile 5. This last result seems surprising, given the labels of 'leader' and 'follower', but it is consistent with the literature on partial imitation strategies, in particular previous results such as Ross and Sharapov (2015) that show that leaders can benefit from imitating followers to help them stay ahead of the pack.

The information contained in this table can also be observed in Fig. 3, where the imitation percentages by quantile have been plotted for the Zero, Follower and Leader groups, and where the differences between distributions are observably large. Unreported tests strongly reject the null hypothesis that the data observed for the Zeros vs that of Leaders and Followers stems from the same distribution.[9]

The evidence observed in Table 6 supports the idea of an 'imitation ecosystem'. In this context, informed fund managers are those who know whom to imitate to obtain superior information. In particular, it shows how both, extreme Followers and Leaders, follow similar imitation strategies. Moreover, they both identify each other as sources of valuable information, and imitate each other's trades, while at the same time both groups tend to veer away from imitating trades of the central group, which provides inferior information.

We explore this idea further in Table 7, by analyzing the industry concentration of stocks in each copycat quantile and imitation group. Specifically, we sort all stocks held

**Table 7** Imitation and industry concentration

| CopyQ | Industry concentration | | | Mean | | Industry | |
|---|---|---|---|---|---|---|---|
| | Following | Neither | Leading | Following | Neither | Leading | Delta Ind |
| 5 | 5.89 | 4.76 | 4.45 | 6.56 | 6.67 | 6.50 | − 0.063*** |
| 4 | 4.65 | 4.38 | 4.31 | 6.45 | 6.55 | 6.44 | − 0.032*** |
| 3 | 4.43 | 4.16 | 4.28 | 6.40 | 6.53 | 6.39 | − 0.030*** |
| 2 | 4.47 | 3.72 | 4.42 | 6.37 | 6.51 | 6.36 | − 0.014** |
| 1 | 4.47 | 3.41 | 4.48 | 6.31 | 6.51 | 6.31 | − 0.005 |
| 0 | 4.26 | 6.99 | 4.26 | 6.21 | 6.47 | 6.21 | − 0.000 |
| − 1 | 4.48 | 3.37 | 4.51 | 6.31 | 6.51 | 6.31 | 0.003 |
| − 2 | 4.32 | 3.65 | 4.39 | 6.34 | 6.52 | 6.35 | 0.022*** |
| − 3 | 4.31 | 4.00 | 4.51 | 6.41 | 6.57 | 6.42 | 0.029*** |
| − 4 | 4.46 | 4.13 | 4.84 | 6.45 | 6.60 | 6.48 | 0.040*** |
| − 5 | 4.49 | 4.71 | 5.91 | 6.52 | 6.68 | 6.57 | 0.049*** |

Stocks in the portfolios of all funds in the sample are classified into 10 industry groups, as tabulated in Kacperczyk et al. (2005), and then further grouped into those in which the fund manager is following others trades ('Following'), leading others trades ('Leading'), or doing neither ('Neither'). Within each of these three groups, portfolio weights are aggregated by industry. Industry Concentration is calculated as the standard deviation of aggregate portfolio weights, and are displayed in table columns 2, 3 and 4. Mean Industry is calculated as the average industry code (from 1 to 10) for all stocks in each group (Following, Leading and Neither), and tabulated in columns 5, 6 and 7. 'Delta Ind' depicts the difference between the mean industry of stocks in which a fund Leads versus those in which it Follows. Standard t-tests are used to establish whether these differences are significant. Statistical significance is denoted by ∗∗∗, ∗∗ and ∗ for significance at the 1%, 5% and 10% levels, respectively

[9] These test include the Kolmogorov–Smirnov, Kruskal–Wallis and Mann–Whitney tests to compare distributions.

by the funds in our sample into groups, first by the quantile into which the fund that holds them is classified, as we did before, and then into three groups determined by whether the fund manager imitates another manager ('Following'), is in turn imitated ('Leader'), or neither is the case ('Neither'). In addition, we also classify stocks into 10 industry groups, as tabulated in Kacperczyk et al. (2005), by labeling each with a number representing the industry groups to which it belongs (i.e.: 1 to 10). In Table 7 we present this information aggregated into two measures. First, industry concentration expressed as the standard deviation of the aggregate portfolio weights for each industry. The logic behind this measure is that if a fund is highly concentrated in one or a few industries the portfolio weights will be high for these industries, while they will be low for all others, leading to a high standard deviation of weights. The contrary will be true if a fund is more diversified, with similar weights placed on all industries. In addition, we calculate the mean of the portfolio industry weights, to show the general industry dominance in each group. While this last measure will naturally tend towards the middle of the 1 to 10 scale, we look for the deviations from this mean, and differences between groups.

In the first half of Table 7 we observe that industry concentration varies across Copycat Score quantile groups, as well as through Leading, Following and Neither groups. However, a pattern is clearly discernible. In Table 3 we showed that Zero funds (those in the middle quantile) obtain the highest performance in stocks in which they neither lead nor follow. This is echoed in Table 7, as it is in these same stocks in which they are more concentrated, with an Industry Concentration measure of 6.99, versus their concentrations in stocks in which they lead and imitate, which are 4.26 for both. As we move away from the central group, we do not observe such high levels of industry concentration for other quantiles, until we reach the extremes. Followers, quantile group 5, are highly concentrated in the stocks in which they follow, with an Industry Concentration measure of 5.98, whereas Leaders are more concentrated in the stocks in which they lead, with a similar measure of 5.91. Kacperczyk et al. (2005) argue that industry concentration is evidence of superior skill. What we see is funds that have higher industry concentrations precisely in the stocks with which they obtain their highest average returns. Moreover, the next portion of the table shows in which industry, on average, funds tend to cluster for stocks in which they lead, follow and do neither. As we can see, the industries where fund managers concentrate in tend to be significantly different for stocks in which they lead and those in which they follow, except for funds in the middle groups. For these, the difference are small and statistically insignificant. Finally, we observe that, while the extreme quantiles (Leaders and Followers) show the largest differences between industries in which they follow and those in which they lead, there is an interesting cross-group similarity: the average industry measure for stocks in which Leaders lead is 6.57, almost identical to that of stocks in which Followers follow, which is 6.56. Conversely, the stocks in which Followers lead have an average measure of 6.50, which again is very close to that of stocks in which Leaders tend to follow, 6.52. These results suggest that one group benefits from the information obtained by imitating the other's stock picks, in terms of complementing their skills in industries where they have an advantage.

The evidence presented above allows us to propose a definition of 'smart' copycatting, based on two characteristics. First, the use of a partial imitation strategy. A fund manager uses her own superior private information to trade some stocks, and imitates trades

of other managers who are better at identifying opportunities in other stocks. Second, the ability to identify the best fund managers and trades to imitate, in order to exploit their superior information. Taken together, this evidence supports the view of an imitation ecosystem, in which some fund managers participate. In this environment some managers outperform using their own information when advantageous and successfully imitating when necessary. Managers who are not part of this ecosystem, for example those in the Zero group, underperform not just due to their own inferior stock picking skills, but also because when they attempt imitation they fail to identify good managers and trades, and so follow other poor performers.

#### Determinants of the Copycat Score

In this section we look for the determinants that can help explain the observed cross-sectional variation in the Copycat Score.

First, we look at the decision maker(s) behind the fund's strategy. A fund's management structure has been shown to have a strong influence on investment decisions.[10] Csaszar (2012) examines data of mutual funds with single manager versus committee management and, within funds managed by committees, looks at the impact of different levels of consensus required to make a trading decision (buy or sell a stock). Csaszar finds that higher consensus requirements lead to higher errors of omission (failure to buy a stock that subsequently has high performance), but also lower errors of commission (buying a stock that then underperforms), and lower action decisions in general. Csaszar uses a proprietary dataset that codes different management structures in a large number of mutual funds. Since we do not have access to that dataset, we test instead the effects that changes in management have on the Copycat Score. The best setting for a clean test is one where a fund shows a single change in its manager throughout the period studied. This results in a sample of 464 individual funds. In over 70% these funds the difference in the value of the Copycat Score before and after the manager change is statistically significant. Thus, a manager's strategy is a key factor that determines the Copycat Score. In what follows, we present evidence that the manager's actions are, in turn, strongly affected by her level of skill, as well as other factors.

Next, we search for relationships between the Copycat Score and variables of interest. We begin by estimating pairwise correlations of the absolute value of the Copycat Score and a number of performance and/or skill measures that have been previously used in the literature (and also used in Table 4), as well as characteristics of the mutual funds in the sample. Since we observe a strong U-shaped pattern in the characteristics of funds when sorted into quantiles, we use the absolute value of the Copycat Score in our main specifications (see detailed motivation for this in Sect. 2). The measures of skill include Return Gap (Kacperczyk, Sialm Zheng 2008), Active Share and Tracking Error (Cremers and Petajisto 2009), $R^2$ (Amihud and Goyenko 2013), past fund alpha obtained from a four-factor model, and the fund's Industry Concentration, estimated as the standard deviation of the percentages of assets allocated by each fund to 10 industry groups as tabulated in Kacperczyk et al. 2005. Fund characteristics include Total Net Assets, the

[10] We are grateful for an anonymous referee for pointing this out.

percentages of fund assets invested in common equity and cash, Turnover Ratio, and the fund's Expense Ratio.

With the exception of Return Gap (which is not considered to be a measure of fund manager skill but rather the difference between the performance of observed and unobserved fund manager decisions), the Copycat Score has a statistically significant correlation with all measures presented. Moreover, these associations also have the correct sign for each measure of skill. This means that a fund with a high absolute value of the Copycat Score will also have values of various measures which are consistent with fund manager skill.[11]

In Table 8 we regress the Copycat Score and its components on a set of explanatory variables similar to those listed above. There are two differences between the independent variables used in this table and the those used to obtain the pairwise correlations described above. First, given it's nonexistent correlation with the Copycat Score, we remove Return Gap from the set of regressors. Instead, we add the Hoberg et al. (2017) measure of competition ('Peers'). Hoberg et al. show that mutual funds that face more competition tend to underperform, compared to those that compete in less crowded environments (in terms of buy-side competition). We speculate that the same is true whether funds compete to buy stocks based on the manager's own information, or imitation-based trading. Second, in some specifications we add variables that have been shown in past research to predict future fund performance (see, for example, Bali et al. 2011). These include return reversal and momentum, which consist of the fund's return in quarter $t-1$, and the accumulated return from quarter $t-4$ to $t-2$, respectively, and the preceding quarter's fund flows. Finally, in some models we add an indicator variable which takes the value of 1 if the time period corresponds to a recession, as informed by NBER, and 0 otherwise.[12]

As we can see in models (1) and (2) of Table 8, reversals, momentum and fund flows have insignificant coefficients and therefore do not explain the variation of the Copycat score. Funds with higher (absolute value) Copycat scores tend to have higher expense ratios, somewhat higher size (TNA) and percentage of assets kept as cash, and slightly lower turnover ratios, age, and percentage of assets invested in common equity. These coefficients are significant though small (except for the coefficient for the expense ratio), and are mostly consistent with the information provided by summary statistics in Table 1. One potential puzzle posed by these results is the higher expense ratio of funds at both ends of the Copycat score spectrum. The literature on trade imitation hints that the motivation for engaging in this strategy might be twofold: not only can managers make potentially profitable trades by simply imitating others, in doing so they can also reduce the cost related to doing their own research. Thus, some authors speculate that copycat funds would have lower overall expenses. However, this conjecture is based on the assumption of a pure imitation strategy, that leaves no room for managers who also develop and use their own private information. Instead, we show that skilled imitators

[11] These results are not shown for brevity, but are available upon request.

[12] The time spans of the data available vary for these measures, which is why the number of observations vary depending on the variables included. Data on fund Industry Concentration, alpha and $R^2$ is available for the full duration of our sample, spanning the period 2000–2016. Active Share and Tracking Error are obtained from Anti Petajisto's web page, and ends in 2008. Finally, the Hoberg et al. (2017) Peers data is available up to 2012.

**Table 8** Determinants of the Copycat Score

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| IC | | | 0.035*** | 0.065*** | 0.074*** | 0.068** | 0.054** |
| Alpha | | | 0.419*** | 0.360*** | 0.375*** | 0.380*** | −0.340** |
| $R^2$ | | | −0.055*** | −0.066*** | −0.035** | −0.032** | 0.018 |
| Active | | | | | 0.038*** | 0.031*** | 0.036*** |
| Tracking | | | | | 0.027 | 0.020 | 0.020 |
| Peers | | | | −0.055*** | | −0.032*** | −0.040*** |
| REV | 0.005 | −0.004 | | | | | 0.002 |
| MOM | 0.004 | −0.003 | | | | | 0.010 |
| Flow | 0.002 | 0.002 | | | | | 0.003 |
| Exp Ratio | 0.713*** | 0.704*** | | | | | 0.177 |
| Turn Ratio | −0.002*** | −0.002*** | | | | | −0.005*** |
| logTNA | 0.001*** | 0.001*** | | | | | 0.001*** |
| Fund Age | −0.0002*** | −0.0002*** | | | | | −0.0001*** |
| PerCom | −0.0002*** | −0.0002*** | | | | | −0.0003*** |
| PerCash | 0.0002*** | 0.0002*** | | | | | 0.0002 |
| Recession | | −0.008*** | | | | | −0.009*** |
| Observations | 69,903 | 69,903 | 77,516 | 53,965 | 22,884 | 22,249 | 16,763 |
| Adjusted $R^2$ | 0.024 | 0.029 | 0.057 | 0.081 | 0.085 | 0.092 | 0.147 |

The absolute value of the quarterly Copycat measure, obtained from 2000 to 2016, is regressed on measures of fund outperformance or manager skill, and lagged fund characteristics. Measures of skill include the fund's Industry Concentration, estimated as the standard deviation of the percentages of assets allocated by each fund to 10 industry groups, as tabulated in Kacperczyk et al. (2005). Also included are past $R^2$ and fund Alpha obtained from a four-factor model following Amihud and Goyenko (2013), Active Share and Tracking Error (Cremers and Petajisto 2009), and the number of Peers or competing funds (Hoberg et al. 2017) as a percentage of all mutual funds in each period of time. The data on the Copycat score, alpha and $R^2$ is from 2000 to 2016. Data for Active Share and Tracking Error ends in 2009. Data on buy-side competing peer funds runs through 2012. Fund characteristics include measures of return reversal ('REV') and momentum ('MOM'), which consist of the fund's return in quarter *t-1*, and the accumulated return from quarter *t-4* to *t-2*. In addition we use the preceding quarter's fund flows, Expense Ratio, Turnover Ratio, the log of Total Net Assets ('logTNA'), the fund's age, and the percentages of fund assets invested in common equity ('PerCom') and cash ('PerCash'). Some models include a dummy variable that takes the value of 1 if the time period lies within an NBER-identified recession. The data for these variables spans 2000–2016. Standard errors are double clustered at the fund and quarter level, and a HAC covariance matrix is used. Statistical significance is denoted by ***, ** and * for significance at the 1%, 5% and 10% levels, respectively

use partial imitation strategies which encompass both, imitation and original research to outperform their peers who are not successful at either. Thus, it is no surprise that these funds, which offer higher overall returns, might have higher expense ratios. Finally, at the bottom of model (2), we see that the 'recession' coefficient is negative and significant. This result implies that fund managers at the extremes of the Copycat Score scale adjust their approach to imitation, resulting in a reduced absolute value of the Copycat score during recessions. This is consistent with managers actively adjusting their strategy as a reaction to market forces.

As we have seen in Table 2, funds with higher (absolute value) Copycat Scores outperform their competition. Thus, we are also interested in the relationship between the Copycat Score and other measures of fund manager skill.

Kacperczyk et al. (2005) show that 'focused' managers, whose funds have a higher level of concentration in specific industries, make better stock picks. Both, Amihud and Goyenko (2013) and Cremers and Petajisto (2009), argue that 'active' managers are the ones likeliest to ourperform, where active is interpreted as deviation from the fund's relevant passive benchmark. Thus, active funds are those with higher Active Share measures,

higher Tracking Error, and lower $R^2$, as standard risk factors are less able to explain these funds' performance. Hoberg et. al. (2017) show that funds that face fewer competitors tend to outperform those that trade in more crowded segments. Finally, Amihud et al. (2013) also show evidence consistent with the persistence of past alpha in subsequent results. Following this intuition, a measure that encompasses these aspects of skill and performance should have a positive correlation with industry concentration, past alpha, Active Share and Tracking Error, and be negatively correlated with $R^2$ and Peers. As we can see in models (3) to (6) of Table 8, the predicted coefficient signs are indeed the ones observed, with all but the Tracking Error coefficients being statistically significant.

Finally, in model (7) Table 8 we include all independent variables. We confirm that most results remain unchanged, with two exceptions. The coefficients for $R^2$ and the percentage of capital invested in cash become statistically insignificant. In addition, the coefficient for alpha remains significant, but now has a negative sign. This change could be brought on by a myriad of reasons unrelated to fund performance, from multicollinearity issues to the reduced size of the dataset (which goes from over 77 thousand observations in model (3) to less than 17 thousand in model (7)), and thus is of little concern.

In addition to the analysis described above, we replicate Table 8 but instead of the Copycat Score we use the measure's main components, wLead (the aggregate portfolio weight of stocks in which the fund leads trades) and wFoll (the aggregate portfolio weight of stocks in which the fund imitates trades). This allows us to contrast these results with those of the full Copycat Score, and with evidence from previous research in which the main measure is dependent on imitation only. We find that both turnover ratio and size (TNA) have similar coefficients to those obtained with the Copycat Score. This is probably due to the similarity in these characteristics between the extreme quantile funds (Leaders and Followers), and those in the middle (Zeros). Thus, these variables do not help explain the variation observed in the Copycat Score. On the other hand, funds with higher wFoll or wLead have lower expenses, and insignificant coefficients for age and percentage investment in stocks. Moreover, the 'recession' variable is insignificant for wFoll and wLead, and the coefficients for the skill-related variables are statistically significant, but have the wrong sign in all cases except for IC and alpha.[13]

The evidence presented here shows that focusing on imitation only as a single strategy, as the literature has done so far, fails to capture the potential skill and outperformance of a more nuanced, partial imitation approach that combines leading and following. The results in Table 8 are consistent with the notion that although imitation is pervasive in the industry, it is by no means a guarantee of outperformance. In particular, this is not the case for the less skilled fund managers who do not show outperformance in their own stock picks. Rather, it is the combination of these components, leading and following, and their imbalance towards a marked strategy dominated by smart imitation or clear leadership, that propels funds towards a strong and persistent advantage. Moreover, the results depicted above show that while the Copycat Score is related to other measures of skill and performance, the information it provides is not subsumed by any of these. We show that, in effect, fund management skill is a multifaceted concept, with many abilities which can combine to aid the managers who possess them outperform

[13] These tests are not included for brevity, but are available upon request.

their peers. 'Smart' imitation, as evinced by the Copycat Score, is one of these skills. Fund managers who posses this skill tend to also have higher than average levels of other skills, and thus also tend to outperform the average mutual fund.

Finally, we briefly address the concern raised in the recent literature over mandated portfolio disclosure (for example, Verbeek and Wang 2013). The argument is that increased disclosure is detrimental to skillful money managers, in that it forces them to share information that other, less skilled managers can observe and imitate. If there is any value in this information, then the less skilled fund managers can use it to improve their performance at the expense of the skillful. Although we commit the results of our tests to the Additional file 1: online appendix for brevity, these do not support the hypothesis that increased portfolio disclosure hurts skillful fund managers. Specifically, we use the 2004 regulation change that increased mandated disclosure frequency from semiannual to quarterly as a natural experiment. We show that while imitation itself does increase post-2004, it is simply part of the trend identified before, and that increases in imitation measure pre- and post-2004 are similar to those observed for other years. That is, the increase in imitation cannot be attributed to the change in regulation. Moreover, the average value of the complete copycat measure, that is, imitating minus leading, actually decreases after this regulation change. More compelling evidence is produced by the relative performance of net Followers versus that of net Leaders. If an increase in the availability of information were to benefit imitators, then we would expect the difference in performance between groups to increase after 2004. However, depending on the specification used, we either find no significant effect, or a small change in the opposite direction. That is, the difference in performance actually diminishes.

## Conclusions

Skillful mutual fund managers are assumed to be those able to identify the best stock picks and thus successfully navigate market uncertainty. We find that some fund managers exhibit a different type of skill: that of identifying peers better able to pick some stocks, in order to imitate their trades. We use a VAR-Granger methodology to test each fund's trades in each of its constituent stocks for imitation. Using this data we identify stocks in which the fund manager follows others' trades, as well as stocks in which the manager is imitated by others. We contribute to the existing literature on trade imitation by aggregating this information into a novel "Copycat Score" for each fund. Using this measure, we then study the funds' performance, as well as the implications revealed by this new measure in terms of the fund manager's strategy.

We find that funds labeled as either Followers and Leaders (those with the highest and lowest Copycat Scores, respectively), consistently outperform other funds. While the percentage of fund assets devoted to these strategies may change, we find that overall Leading and Following are strategies that persist in time, as does the benefit accrued to those who engage in them. The Copycat Score is shown to be a strong predictor of fund performance, even after controlling for various known measures of fund manager skill. However, it is also part and parcel with other skills, as net Followers also excel at picking stocks independently, and net Leaders attain higher than average returns in stocks in which they imitate others.

Partial imitation strategies have been shown to be successful in other industries. We present evidence that these strategy are not only employed by mutual fund managers as well,

but that they can be profitable. This, in turn, indicates that there is value in the mandated disclosures of mutual fund portfolios, and that some fund managers are able to capitalize on that value. Moreover, our results show a more nuanced picture of imitation than has been previously presented in the literature. Imitation is pervasive in the mutual fund industry, but not all copycats are the same. Indiscriminate trade imitation does not help fund managers improve performance. However, our Copycat Score captures 'smart' imitation, which does predict persistent outperformance.

Our findings have various implications. First, in the search for fund manager skill, as we introduce a new measure that sheds light on a hitherto unexplored facet of it. The Copycat Score can be used to identify fund managers that successfully implement partial imitation strategies and outperform their peers because of them. Second, for regulators, as we show that mandated portfolio disclosures have value and are being actively exploited by some traders. Finally, the synchronized trading evinced by imitation has implications for asset pricing in that copycatting might affect the price discovery process for securities. That is, a security could remain undervalued until 'discovered' by a fund manager who then invests in it. If this manager is imitated by others, then these copycats will also invest in the security in subsequent periods, attracting further attention to it and causing its price to rise and its expected return to diminish.

**Abbreviations**

| | |
|---|---|
| VAR | Vector Auto Regressive |
| CRSP | Center for Research in Security Prices |
| SEC | Securities Exchange Commission |
| REV | Reversal |
| MOM | Momentum |
| TNA | Total Net Assets |
| IC | Industry Concentration |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40854-022-00398-7.

**Additional file 1**. Appendix A: Further Tests (online appendix).

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**Availability of data and materials**
The datasets analyzed in this study include: 'NPeers' data, provided by the authors, and CRSP (Center for Research in Security Prices) and Thompson Financial CDA/Spectrum data available through the WRDS (Wharton Research Data Services) portal with subscription.

## Declarations

**Competing interests**
The author declares that they have no competing interests.

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## Publisher's Note