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Does style-shifting activity predict performance? Evidence from equity mutual funds☆

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A B S T R A C T

This study introduces an innovative approach to measuring the "style-shifting activity" (*SSA*) of mutual funds using daily returns. Applying our new measure to a comprehensive sample of 2631 active US equity mutual funds, we show (i) that *SSA* predicts future performance, especially for current outperformers, and (ii) that *SSA* adds new information previously not captured by alternative return-based activity measures such as tracking error or *R*-squared. Comparing the three measures, we show that *SSA* captures activity very selectively, which makes it a stable and reliable predictor of future performance. Tracking error and *R*-squared, however, seem to additionally capture some unobserved fund characteristics, as the direction and power of their predictions depend heavily on the consideration of time- and fund-fixed effects. Moreover, investment strategies based on past *SSA* and past performance earn up to 2.4% (3.6%) p.a. risk-adjusted net (gross) returns which is economically and statistically significant.

JEL classification:
G11
G20
G23

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1. Introduction and literature

One of the most frequently asked questions in mutual fund research is whether active fund management creates value for investors. We contribute to this debate by introducing an innovative approach to measuring the style-shifting activity of funds and by systematically testing its predictive power regarding future performance. Most studies document that, on average, actively managed funds underperform their passive benchmarks. Still, there might be substantial differences in the ability of fund managers to create value (see, e.g., Kosowski, Timmermann, Wermers, & White, 2006). In this context, recent research focuses on analyzing the impact of activity on performance. Among others, Cremers and Petajisto (2009) as well as Amihud and Goyenko (2013) show that higher management activity is related to higher future performance. The reasoning behind these studies is that a fund can only beat its benchmark if it deviates from it. Also, more activity might signal new investment ideas and therefore be proxy for skill. To measure activity, such studies apply both return-based and holdings-based approaches.

Holdings-based activity measures like "industry concentration index" (Kacperczyk, Sialm, & Zheng, 2005) or "active share" (Cremers & Petajisto, 2009), among others, define activity as a fund's deviation from the market portfolio or its benchmark index. Similar studies following this idea are Brands, Brown, and Gallagher (2005) and Kaplan and Sensoy (2005). Other holdings-based approaches determine a fund's activity as drift in its investment styles (see, e.g., Ainsworth, Fong, & Gallagher, 2008; Brown, Van Harlow, & Zhang, 2009; Brown, Van Harlow, & Zhang, 2012; Meier &

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Rombouts, 2009; Wermers, 2012), as deviation from its peer group (see, e.g., Gupta-Mukherjee, 2013), or as change in its total risk (see, e.g., Huang, Sialm, & Zhang, 2011). Nevertheless, implementing holdings-based approaches has several disadvantages.[2] First, a timely determination of fund activity can be difficult, because fund managers typically disclose portfolio holdings at the latest possible date, otherwise so-called copycat funds could steal a substantial portion of the copied fund's return (see, e.g., Frank, Poterba, Shackelford, & Shoven, 2004; Phillips, Pukthuanthong, & Rau, 2014). For this reason, current legal regulation allows funds to disclose quarterly portfolio holdings with a considerable lag of 60 days (U.S. Securities and Exchange Commission, 2004). Second, due to window dressing there may be substantial discrepancies between actual fund portfolio characteristics during a specific time period and the holdings reported at the beginning or at the end of that period (see, e.g., Agarwal, Gay, & Ling, 2014; Carhart, Kaniel, Musto, & Reed, 2002; Elton, Gruber, Blake, Krasny, & Ozelge, 2010; He, Ng, & Wang, 2004; Morey & O'Neal, 2006; Musto, 1999; Sias, 2007). Third, holding-based approaches often have to deal with incompleteness and therefore considerably smaller data samples caused by irregular and infrequent portfolio disclosure.[3]

Return-based activity measures like "tracking error" (e.g., Idzorek & Bertsch, 2004; Müller & Weber, 2014; Roll, 1992; Wermers, 2003) or "*R*-squared" (e.g., Amihud & Goyenko, 2013; Brown et al., 2009; Müller & Weber, 2014) usually measure activity as a fund's idiosyncratic return variance, either absolute or relative to its total return variance. We contribute to the existing research on mutual fund management activity by introducing an innovative measure that uses the fund's returns to measure its "style-shifting activity" (*SSA*), a specific type of activity previously analyzed based on holdings information only.

Originally, return-based style-shifting was introduced by Herrmann and Scholz (2013) in the context of hybrid mutual funds to measure the performance created by actively shifting between different fixed income and equity styles.[4] As this information has not been used to measure management activity before, we define *SSA* as the difference between multifactor regression betas from two consecutive quarters where the factors represent different investment styles. This way, the measure is capable of providing style-shifting information of the same frequency as approaches that measure style-changes or style-drift with quarterly holdings data (see, e.g., Ainsworth et al., 2008; Brown et al., 2009, 2012; Meier & Rombouts, 2009; Wermers, 2012). To get reliable estimates for quarterly style betas we use daily returns in our main analysis. In Section 5, we will comment on the robustness of this approach using monthly return data.

We argue that *SSA* is a useful measure for three main reasons. First, as *SSA* is a return-based measure, it provides information about the fund activity level without a sizable delay, without the caveats imposed by window dressing and suffers less from incomplete data than holdings-based approaches. Moreover, the return-based approach is superior to holdings-based measurement of style-shifting as it allows calculations of *SSA* at each point in time, while holdings-based style-shifting is limited to the exact timing of quarterly holdings reports.

Second, in contrast to other popular return-based activity measures such as tracking error and *R*-squared, *SSA* in particular captures dynamic management activity and is not biased by constant style bets passively taking the fund away from its benchmark. For example, consider a fund which states the S&P 500 index as its benchmark. In addition, the fund deviates from the index to place a 20% factor bet on the S&P 600 Small Cap Index and afterwards stops actively managing the fund but simply keeps these style exposures constant. *SSA* will be low because style betas will not change considerably over time. However, tracking error, *R*-squared and even holdings-based measures such as active share (Cremers & Petajisto, 2009; Petajisto, 2013) will be quite high, despite the fund being in fact passive over time.

Third, there are different approaches to active management as well as the measurement thereof. On the one hand, stock picking might be measured using active share (Cremers & Petajisto, 2009) or *R*-squared (Amihud & Goyenko, 2013). On the other hand, market, sector or factor timing might be measured using the industry concentration index (Kacperczyk et al., 2005) or tracking error. Still, all such measures are rather unspecific and measure different aspects of activity in a relatively broad sense. Therefore, Petajisto (2013) combines active share and tracking error to define more distinctive activity types like the "diversified stock picker", the "concentrated stock picker" and the "factor better". With the "active style-shifter" we add another very specific type of activity which could be combined with these classifications to get an even more detailed and comprehensive picture of active fund management.

In our empirical analysis we examine two specific research questions. The first concerns the relationship between current fund activity and future performance. On the downside, more active funds may produce inferior risk-adjusted returns on average as more intensive research and higher trading costs might increase fund expenses to the point of diminishing relative performance.[5] Moreover, higher activity could also stem from noise trading or overconfidence. On the upside, many studies report a positive activity-performance relation arguing that a higher degree of activity signals skill and superior information (e.g., Amihud & Goyenko, 2013; Cremers & Petajisto, 2009). Thus, current high activity, mainly in the form of stock selection, market timing, or style-shifting activities, should be positively related to future performance.

Hypothesis One. Currently more active funds yield on average higher risk-adjusted returns going forward than less active funds.

With our second research question, we analyze the relation between *SSA* and other return-based activity measures. Specifically, we use the tracking error ("*TE*") and *R*-squared ("R^2") in combination with *SSA* to predict future performance. We argue that the three measures capture different aspects of management activity and that a combination should provide more information about future fund performance than single measures.

Hypothesis Two. Combining popular activity measures with *SSA* improves predictions of future risk-adjusted fund returns.

To test these hypotheses, we employ *SSA* to a large cross-section of active US domestic equity mutual funds. Following Herrmann and Scholz (2013), we use daily return data over two consecutive

[2] See also Amihud and Goyenko (2013) for a comprehensive discussion regarding the potential disadvantages of holdings data.

[3] For example, using monthly holdings data Elton, Gruber, Blake (2012) are only able to use 318 funds of their original fund sample of 2582 due to data issues.

[4] For example, in the hybrid fund performance models used by Comer (2007), Comer, Larrymore, and Rodriguez (2009a, 2009b), and Herrmann and Scholz (2013), the factors represent different fixed income asset classes (government, corporate, MBS, high yield) and maturities (long-term, mid-term) as well as different equity styles (high vs. low market beta, value vs. growth, large cap vs. small cap, momentum vs. contrarian).

[5] Among others, Carhart (1997) and Bogle (1998) document this negative relation between fund expenses and performance.

quarters to determine SSA.[6] Hence, even if the relation between activity and performance is relatively short-lived, this allows us to obtain reliable results. Analogously, we determine all other variables of interest such as performance and fund characteristics as well as the alternative activity measures TE and R^2 over the combined semi-annual measurement period. This approach closely follows a methodology used by Amihud and Goyenko (2013).[7] Regarding our first research question we report a positive relation between high current SSA and future performance, which is stable for different panel regression approaches.[8] Moreover, we additionally show that this positive relation is non-linear as current outperformers do exceptionally well with more activity while underperformers do not. This confirms our first hypothesis, that higher activity leads to better performance. On the other hand, our results using TE and R^2 are mixed and depend on the respective regression approach used. The results suggest that, besides activity, TE and R^2 are more related to other unobserved fund characteristics, as regressions are heavily affected by including time- and fund-fixed effects. In contrast, SSA captures activity very selectively and is thus less affected by considering these time- and fund-fixed effects.

Regarding our second research question, we find that the different measures capture different aspects of activity as they are jointly significant in predicting performance. This finding even holds when SSA is orthogonalized against TE and R^2 to isolate the impact of SSA which goes beyond the other measures. Specifically, the SSA-performance relation remains positive and significant, especially for current outperformers, while TE and R^2 show mixed results depending on the regression approach. This confirms our second hypothesis that SSA adds new information previously not captured by the other two measures.

In addition, using a similar double-sorting procedure like Amihud and Goyenko (2013), we analyze the economic value of predicting performance based on activity. Thus, we conditionally sort funds into portfolios along the two dimensions of activity and then performance, and quantify the respective post-ranking performance. An investment strategy based on high past SSA and high past performance earns up to 2.4% (3.6%) p.a. risk-adjusted net (gross) returns which is economically remarkable as well as statistically significant. Finally, we disclose that another investment strategy based on high activity according to two combined measures outperforms all strategies based on single-measure high activity. These findings confirm both our hypotheses.

The remainder of this paper is organized as follows. Section 2 describes performance models and activity measures. Section 3 introduces the data, reports relations between activity measures and presents summary statistics. Section 4 provides more details on our methodology and reports the results of our empirical study. Section 5 comments on robustness with respect to alternative performance models and monthly return data. Section 6 concludes.

[6] Other studies using daily data and quarterly periods to measure fund performance are, e.g., Bollen and Busse (2001, 2005) and Comer et al. (2009a).

[7] Amihud and Goyenko (2013) use daily data over semi-annual measurement periods as a robustness test to their main analysis which is done using monthly data. Results are described as being similar to the main results. As we use daily returns in our main analysis, we do it the other way around and present our robustness results based on monthly returns in Section 5.

[8] Amihud and Goyenko (2013) present similar analyses using cross-sectional Fama and MacBeth (1973) regressions. In addition, they comment on robustness checks applying panel regressions. We present panel regressions as our main results. Our cross-sectional Fama and MacBeth (1973) results are qualitatively the same but less significant, presumably because our sample period is only half as long. For brevity, these panels are not reported in the paper but available upon request.

2. Performance models and measures of active management

To determine semi-annual performance and activity measures, we employ a methodology similar to that used by Amihud and Goyenko (2013) and extract alpha, tracking error TE and the coefficient of determination R^2 from the multifactor regression expressed in Eq. (1):

$$r_{i,d,t} = \alpha_{i,t} + \sum\nolimits_{k=1}^{N} b_{i,t}^{k} f_{d,t}^{k} + e_{i,d,t} \tag{1}$$

where $r_{i,d,t}$ represents the excess return of fund i on day d and $\alpha_{i,t}$ the performance of fund i in the semi-annual period t. Alpha is usually interpreted as the daily abnormal performance earned by active management.[9] Due to its immense popularity in the literature on fund performance, we use alpha as the relevant performance measure to examine the relation between activity and fund performance. $b_{i,t}^{k}$ is the factor loading to daily factor returns $f_{d,t}^{k}$ during period t. As $k = 1, \ldots, N$ factors, we use the daily returns of the four Carhart (1997) factors to represent different equity investment styles. $e_{i,d,t}$ is the error term of which the standard deviation is the TE and higher values signal more activity.

$$TE_{i,t} = Stdev(e_{i,d,t}) \tag{2}$$

This definition differs from another common calculation of TE, which is the standard deviation of return differences between the fund and its benchmark index. In comparison, the TE we use here is more immune to the bias from constant factor bets.[10]

As R^2 is negatively skewed, with the majority of values being close to one, we follow Amihud and Goyenko (2013) and apply a logistic transformation first suggested by Cox (1970).[11] The logistic transformed measure TR^2 is defined by:

$$TR_{i,t}^2 = \log\left(\left(\sqrt{R_{i,t}^2} + 0.5/D\right) / \left(1 - \sqrt{R_{i,t}^2} + 0.5/D\right)\right) \tag{3}$$

with D being the number of days in the specific semi-annual period t. The resulting distribution of TR^2 is more symmetric. Higher values of TR^2 signal less activity, so to make it conveniently comparable to those of SSA and TE, we additionally change the sign so that our final measure is "$-TR^2$".

To determine SSA within semi-annual period t, we refer to Herrmann and Scholz (2013), who define style-shifting as the change in factor loadings from one quarter to the next. To estimate the factor loadings, we use the multifactor regression:

$$r_{i,d,q,t} = \alpha_{i,q,t} + \sum\nolimits_{k=1}^{N} b_{i,q,t}^{k} f_{d,q,t}^{k} + e_{i,d,q,t}, \tag{4}$$

where $r_{i,d,q,t}$ represents the excess return of fund i on day d of quarter q in the semi-annual period t, $\alpha_{i,q,t}$ is the performance of fund i in quarter q, $b_{i,q,t}^{k}$ is the factor loading to daily factor returns $f_{d,q,t}^{k}$ during quarter q, and $e_{i,d,q,t}$ is the error term. SSA of fund i in semi-annual period t is defined as the sum of absolute differences

[9] Grinblatt and Titman (1989), Coles, Daniel, and Nardari (2006) and Krimm, Rohleder, Scholz, and Wilkens (2015) show that a positive alpha may capture superior stock selection as well as superior timing.

[10] In contrast to Cremers and Petajisto (2009), we determine tracking error based on the daily error terms of a multifactor model instead of a one-factor model. Idzorek and Bertsch (2004) use a similar definition of tracking error, employing a multifactor model in combination with restricted style exposures following Sharpe (1992).

[11] The mean R-squared of the pooled non-overlapping semi-annual periods is 0.9189.

between style betas in $q-1,t$ and q,t as presented in Eq. (5).[12] Higher values of *SSA* indicate more activity.

$$SSA_{i,t} = \sum_{k=1}^{N} |b^k_{i,q,t} - b^k_{i,q-1,t}| \quad (5)$$

This definition corresponds to Wermers (2012), among others, and equally regards increases and decreases in style exposures as being activity, because both may signal a fund's potential to beat its benchmark in the future.[13] *SSA* measures a fund's active style-shifts as well as passive style-changes resulting from a buy-and-hold strategy. In the latter case, portfolio weights and, accordingly, a fund's style exposures change over time due to the different performance of style factors. Here, we define passive management as keeping style exposures constant. Consequently, we see both a fund's active style-shifts and its reluctance to adjust to changing style exposures resulting from a buy-and-hold strategy as equal sources of activity.

3. Data and summary statistics

3.1. Data sources and screening

The fund sample we use in our empirical analysis stems from the Center of Research in Security Prices (CRSP) Survivor Bias Free Mutual Fund Database and includes all active US domestic equity funds which have complete daily returns over at least two consecutive semi-annual measurement periods between October 1, 1998 and December 31, 2009. Different share classes are aggregated on fund level using CRSP portfolio codes and by manual name matching (see, e.g., Bessler, Blake, Lückoff, & Tonks, 2014). Moreover, we follow, e.g., Comer et al. (2009a), Benos and Jochec (2011), Amihud and Goyenko (2013), and Busse, Goyal, and Wahal (2014) and screen for certain keywords in a fund's name, such as "retirement", "solution", "target", "index", "ETF", "global", "international", or "world", to ensure that our fund sample does not include funds with an undesired investment category. As we use fund characteristics as control variables, we exclude funds that do not provide any information on fund size (monthly total net assets), fees (annual total expense ratios) and turnover (annual turnover ratio). The final sample consists of 2631 funds. For these funds we calculate the fund age as the time difference in years since the first occurrence in the CRSP database. Further, we use the funds' main investment objective (CRSP objective codes) to control for style effects.

The factor returns used in the performance models are from Kenneth R. French's online data library and include the value-weighted CRSP market return (Jensen, 1968), the Fama and French (1993) size factor SML and the value factor HML, and the Carhart (1997) momentum factor MOM. These factors represent distinctive equity investment styles, and changes in factor loadings can thus be interpreted as style-shifting.

3.2. Relations between activity measures

Table 1 presents pairwise and multivariate relations between the three activity measures *SSA*, *TE* and $-TR^2$ calculated for pooled observations from non-overlapping semi-annual windows in the period from 1998 to 2009. "Correlation" represents the pairwise standard correlations, which are around 60% for all three combinations. The highest correlation is reported for *SSA* and *TE* (63.40%) whereas the lowest correlation is reported for *SSA* and $-TR^2$ (57.67%). This means that although management activity along the various dimensions is positively related, there is still considerable variation between them giving confidence to our second hypothesis that *SSA* provides very specific additional information previously not captured by the other less-specific activity measures.

To control for multivariate relations, the table also shows "$\sqrt{R^2}$", which is the square root of the coefficient of determination derived from regressing one activity measure with the other two, and can be interpreted as the correlation of one measure with a linear combination of the other measures. It is below 70% for all combinations and lowest for *SSA*, thus further encouraging the expectation that our new measure adds information previously not captured by *TE* and $-TR^2$. Variance inflation factors derived from the respective R^2 statistics are around 2, which indicates that multicollinearity should not severely bias our results.

Table 1
Relations between activity measures.

	Correlation			$\sqrt{R^2}$
	SSA	*TE*	$-TR^2$	
SSA	100.00			63.95
TE	63.40	100.00		69.51
$-TR^2$	57.67	60.97	100.00	64.19

This table shows relations between the three activity measures *SSA*, *TE* and $-TR^2$ for pooled observations from non-overlapping 6-month periods from 1998 to 2009. "Correlation" is the pairwise standard correlation. "$\sqrt{R^2}$" is the square root of the coefficient of determination from a pooled regression of one activity measure by the other two. It represents the correlation of one activity measure with a linear combination of the other two.

3.3. Summary statistics along different dimensions of activity

In the following we illustrate the distributions of funds, of different fund characteristics and of management activity along the different activity dimensions. For the univariate distributions, we sort funds semi-annually into quintiles based on *SSA*, *TE* and $-TR^2$. Then, we employ an unconditional double-sorting procedure based on *SSA* and then either *TE* or $-TR^2$, which results in twenty-five different fund portfolios for each of the bivariate distributions. For these portfolios, we report average *SSA* as well as the average number of funds per period and the mean (expense ratio and turnover ratio) or the median (total net assets and fund age) fund characteristics. Funds sorted into the high (low) quintile are most (least) active according to the respective activity measure. The results for *TE* and $-TR^2$ are quite similar, so we comment mainly on *TE*.

Panel A of Table 2 reports the time-series average of *SSA*. An average fund shows an *SSA* of 54.43% per period, which seems reasonable considering we are considering four different equity styles. The univariate sorting shows that the most active funds in the High-*SSA* quintile have a clearly higher *SSA* of 111.45%. The *SSA* of the least active funds in the low quintile is only 17.08%. The univariate sorting also shows that *SSA* decreases monotonically also in the *TE* and $-TR^2$ quintiles, which is consistent with the positive and substantial correlations documented in Table 1. Therefore, also the double-sorted portfolios show the expected pattern of decreasing activity from High/High to Low/Low.

Panel B reports the average number of funds per period sorted into different fund portfolios. The overall average number of funds per half-year is 1604.36, which are evenly distributed into the univariate quintiles. Unconditionally double-sorted funds show

[12] *SSA* may also be defined as the sum of squared inter-quarterly changes in style exposures. However, both alternative definitions are highly correlated with a standard correlation of 87% and a Spearman (1904) rank correlation of 99%, so we concentrate on only one definition.

[13] We define *SSA* in terms of absolute instead of relative style-shifts to prevent small absolute changes based on a near-zero factor loading being interpreted as high relative activity.

Table 2
Fund characteristics along different dimensions of activity.

SSA quintile	*TE* quintile						$-TR^2$ quintile					
	High	2	3	4	Low	All	High	2	3	4	Low	All
Panel A: *SSA* (in %)												
Low	20.61	20.00	19.63	19.38	15.59	17.08	21.52	20.43	19.27	18.98	15.44	17.08
4	32.70	32.42	32.75	32.54	31.45	32.30	34.13	33.27	32.18	31.97	31.54	32.30
3	47.06	47.19	46.28	45.62	45.15	46.28	48.57	46.96	45.44	45.69	45.16	46.28
2	67.40	65.57	64.42	62.59	61.59	65.16	66.70	64.32	65.01	65.42	61.39	65.16
High	121.72	100.37	93.79	88.41	74.44	111.45	115.31	109.30	109.08	100.84	93.59	111.45
All	93.74	64.40	50.66	39.80	23.66	54.43	82.39	66.31	55.30	42.97	25.26	54.43
Panel B: Number of funds												
Low	4.77	16.32	33.32	65.68	201.14	321.23	11.27	19.09	34.59	65.55	190.73	321.23
4	17.00	43.95	72.68	106.36	80.82	320.82	29.64	48.45	68.64	95.91	78.18	320.82
3	35.77	72.32	91.68	90.50	30.73	321.00	48.77	69.68	82.32	83.32	36.91	321.00
2	79.18	97.59	87.91	48.27	7.86	320.82	78.82	90.45	82.55	56.45	12.55	320.82
High	183.77	90.64	35.41	10.00	0.68	320.50	152.00	93.14	52.91	19.59	2.86	320.50
All	320.50	320.82	321.00	320.82	321.23	1604.36	320.50	320.82	321.00	320.82	321.23	1604.36
Panel C: Expense ratio (means in %)												
Low	1.48	1.37	1.29	1.13	0.84	0.98	1.45	1.31	1.22	1.13	0.83	0.98
4	1.42	1.38	1.29	1.15	1.02	1.19	1.39	1.34	1.26	1.15	1.03	1.19
3	1.47	1.38	1.29	1.14	1.03	1.26	1.42	1.37	1.27	1.17	1.05	1.26
2	1.46	1.35	1.25	1.17	1.01	1.31	1.44	1.33	1.27	1.23	1.08	1.31
High	1.50	1.36	1.30	1.18	1.09	1.43	1.50	1.40	1.35	1.26	1.16	1.43
All	1.48	1.37	1.28	1.15	0.91	1.24	1.46	1.36	1.28	1.17	0.92	1.24
Panel D: Turnover ratio (means in %)												
Low	105.28	102.00	94.46	74.01	58.46	68.28	79.15	84.71	84.76	76.39	60.22	68.28
4	131.42	100.57	102.64	76.68	70.43	87.12	82.86	97.79	95.80	80.89	82.15	87.12
3	110.81	109.05	94.64	75.05	71.29	91.92	87.30	101.76	97.29	81.96	89.85	91.92
2	125.64	104.44	106.33	80.76	64.47	105.65	98.55	102.36	117.63	102.41	109.41	105.65
High	139.25	117.97	95.94	89.31	105.41	126.84	122.06	125.41	132.97	130.60	286.19	126.84
All	131.81	108.64	99.78	76.68	62.95	95.93	105.87	107.18	106.74	87.07	72.91	95.93
Panel E: Total net assets (medians in Mio. $)												
Low	108.39	188.09	225.10	272.11	453.96	349.73	110.94	225.48	228.41	260.92	478.64	349.73
4	148.91	168.82	219.40	247.00	348.67	235.85	138.49	203.35	211.32	247.64	354.33	235.85
3	159.53	188.24	199.42	259.69	339.27	213.28	131.37	177.00	223.08	239.24	364.91	213.28
2	135.61	179.57	222.14	257.06	273.80	190.69	123.37	181.66	215.15	253.24	316.16	190.69
High	124.83	167.37	241.82	237.53	631.36	149.03	109.83	160.72	205.31	272.59	317.76	149.03
All	131.44	176.45	216.21	256.72	403.79	216.26	119.24	179.38	217.25	250.17	419.25	216.26
Panel F: Fund age (medians in years)												
Low	6.54	8.12	7.95	8.04	8.13	8.12	6.38	8.00	8.13	8.12	8.20	8.12
4	7.83	7.46	7.70	7.79	7.87	7.71	7.50	7.46	8.12	7.63	7.87	7.71
3	7.62	7.62	7.87	7.96	8.29	7.79	7.13	7.71	8.12	7.79	8.29	7.79
2	7.21	7.63	7.63	7.71	7.79	7.62	7.21	7.79	7.58	7.46	8.21	7.62
High	7.20	7.71	7.70	7.58	7.21	7.45	7.46	7.38	7.13	7.79	7.62	7.45
All	7.29	7.63	7.71	7.88	8.12	7.71	7.29	7.63	7.79	7.79	8.12	7.71

This table presents univariate and bivariate distributions of funds and fund characteristics along the different dimensions of fund manager activity. Data for expense ratios, turnover ratios, and total net assets represent year-end (expense ratio, turnover ratio) or month-end (total net assets) values. Fund age is calculated as the difference in years between the date of a fund's last reported return and the date of its first return. We rank funds at the end of each semi-annual period *t* based on the activity measures style-shifting activity (*SSA*), tracking error (*TE*), and negative logistic transformed *R*-squared ($-TR^2$). We then sort them into quintile portfolios according to their activity. In addition, we employ an unconditional double-sorting procedure using a combined ranking based on style-shifting activity (*SSA*) and either tracking error (*TE*) or negative logistic transformed *R*-squared ($-TR^2$). Next, we calculate the average number of funds and the cross-sectional average (expense and turnover ratio) or median (total net assets and fund age) of fund characteristics for the respective quintile portfolios and the twenty-five portfolios resulting from the double-sorting procedure. Finally, we report the time-series averages of the semi-annually determined number of funds and fund characteristics for each portfolio.

the highest concentration on the upward diagonal axis between High/High (183.77 funds) and Low/Low (201.14) which means that active style-shifters are generally also very active according to *TE* and $-TR^2$. Moreover, it is very uncommon that active style-shifters at the same time have a low *TE* or $-TR^2$, and vice versa, which is documented by only 0.68 funds per period in the High-*SSA*/Low-*TE* portfolio and only 4.77 funds per period in the High-*TE*/Low-*SSA* portfolio. However, there are still enough funds away from the diagonal axis to support our expectation that *SSA* delivers specific new information.

Panels C, D, E and F report statistics on different fund characteristics. We find a positive relation between fund activity and expenses. Funds sorted into the High-activity quintile charge an average expense ratio of 1.43% (based on *SSA*), 1.48% (*TE*), and 1.46% ($-TR^2$) compared to an average expense ratio of 1.24% for all funds. Conversely, the least active funds exhibit lower expense ratios of 0.98% (*SSA*), 0.91% (*TE*), and 0.92% ($-TR^2$). Additionally, we find a positive relation between style-shifting activity and turnover ratios. Average absolute differences are considerable between the most active (turnover ratio of 126.84%) and the least active (68.28%) style-shifters. A similar activity-turnover relation holds for *TE* and a somewhat weaker one for $-TR^2$. Our results also reveal that smaller funds are more active style-shifters. On average, the median fund size varies from $149.03 million for the most active to $349.73 million for the least active style-shifters, which is consistent with previous findings in the activity literature such as, e.g., Cremers and Petajisto (2009). Similar patterns are observable for *TE* and $-TR^2$. Regarding fund age, there is no relevant relation with activity. On average, age is 7.71 years.

4. Empirical analysis

4.1. Predicting performance with activity

In this section we test our main research hypothesis, that higher fund activity, especially *SSA*, predicts higher performance. Methodically, we use different panel regressions on observations from non-overlapping semi-annual windows. Specifically, we regress performance in period $t+1$ estimated by Eq. (1), $\alpha_{i,t+1}$, on activity in the previous period t, $Activity_{i,t}$, which is either $SSA_{i,t}$, $TE_{i,t}$, or $-TR_{i,t}{}^2$. Similar to, e.g., Cremers and Petajisto (2009), Du, Huang, and Blanchfield (2009), and Amihud and Goyenko (2013), we add lagged fund characteristics and alpha, $\alpha_{i,t}$, as control variables to our model, given that they potentially affect fund performance. We include style dummies to control for style-fixed effects. Standard errors are clustered by fund to account for heteroskedasticity and serial correlation. The model is represented by Eq. (6), where a positive (negative) beta coefficient $b_{1,t+1}$ indicates a positive (negative) relation between current management activity and future fund performance.

$$\begin{aligned}\alpha_{i,t+1} = {} & b_{0,t+1} + b_{1,t+1} Activity_{i,t} + b_{2,t+1} Expenses_{i,t} \\ & + b_{3,t+1} Turnover_{i,t} + b_{4,t+1} \log(TNA)_{i,t} \\ & + b_{5,t+1} \log(TNA)^2_{i,t} + b_{6,t+1} Fund\,Age_{i,t}/100 + b_{7,t+1}\alpha_{i,t} \\ & + \sum_{s=1}^{S} b^s_{i,t+1} Style_{i,t} + e_{i,t+1} \end{aligned} \tag{6}$$

To find whether there is a non-linear relation between activity and future performance with regard to current performance, we further include interaction terms between activity measures and dummy variables representing outperformers (upper third) and underperformers (lower third) with respect to $\alpha_{i,t}$. A positive $b_{2,t+1}$ coefficient from Eq. (7) indicates that the activity-performance relation is even stronger for current outperformers.

$$\begin{aligned}\alpha_{i,t+1} = {} & b_{0,t+1} + b_{1,t+1} Activity_{i,t} + b_{2,t+1} D^{Out}_{i,t} Activity_{i,t} \\ & + b_{3,q+1} D^{Under}_{i,t} Activity_{i,t} + b_{4,t+1} Expenses_{i,t} \\ & + b_{5,t+1} Turnover_{i,t} + b_{6,t+1} \log(TNA)_{i,t} \\ & + b_{7,t+1} \log(TNA)^2_{i,t} + b_{8,t+1} Fund\,Age_{i,t}/100 + b_{9,t+1}\alpha_{i,t} \\ & + \sum_{s=1}^{S} b^s_{i,t+1} Style_{i,t} + e_{i,t+1} \end{aligned} \tag{7}$$

Panel A of Table 3 presents the results of pooled panel regressions for all three activity measures with style-fixed effects. The control variable results are as expected in that higher expenses and higher turnover are negatively related to future performance. Larger funds and older funds are also related to lower future performance, which is in line with findings by Berk and Green (2004) and Pastor, Stambaugh, and Taylor (2015). Current alpha is positively related to future performance. Models (1), (2), and (3) are estimated using Eq. (6). Consistent with Cremers and Petajisto (2009), Amihud and Goyenko (2013) and Müller and Weber (2014) the results indicate that higher activity as measured by *SSA* and $-TR^2$ significantly predict better performance. The coefficient on *TE* is also positive but insignificant. Models (4), (5) and (6) are estimated using Eq. (7). The results on the overall effect of activity are as before, however the non-linear effects are different in that current outperformance has additional positive effects with higher $-TR^2$ but additional negative effects with higher *SSA* and *TE*. Underperformers show the opposite signs. We are the first to document such a non-linear relation, which could be interpreted as higher activity being worthwhile for skilled managers but as evidence of overconfidence in unskilled ones (e.g., Pütz & Rünzi, 2011).

Panel B reports results from within-panel regressions, adding time-fixed effects and fund-fixed effects. Still, the positive and significant overall effect of *SSA* on future performance remains intact and is even significantly pronounced for current outperformers. On the other hand, the effect of $-TR^2$ on performance turns significantly negative and the interaction terms are insignificant. This may indicate that $-TR^2$ also captures some unobserved fund effects in addition to activity. Also, some of the control variables lose statistical significance.[14]

Overall, the results in Table 3 confirm our first research hypothesis, that higher activity, especially *SSA*, significantly predicts superior future performance. We find a similar positive prediction using $-TR^2$ in Panel A, but the prediction becomes significantly negative in Panel B, indicating that $-TR^2$ might be correlated with unobserved time- and fund-fixed effects. For *TE*, most results indicate a positive but insignificant effect on future performance.

4.2. Combined performance prediction

Findings in Table 3 show that the three activity measures are related to future performance but also that all of them predict performance differently. Thus, in pursuit of our second research hypothesis, we ask whether *SSA* adds new information previously not contained in *TE* and $-TR^2$. To do this, we include different combinations of activity measures in Eqs. (6) and (7) and perform similar regressions as in Section 4.1. Again, models (1), (2) and (3) contain only the overall effects, while models (4), (5) and (6) additionally include the non-linear effects with respect to current performance. The results are reported in Table 4.[15]

Panel A reports results for a pooled panel regression with style-fixed effects. Model (1) combines *SSA* with *TE* and indicates that the effect of *SSA* on performance remains positive and significant while *TE* now shows a significantly negative relation to performance. Model (2) combines *SSA* and $-TR^2$ and shows that their effects on performance are jointly positive and significant. Model (3) combines all three activity measures and all three are jointly significant with the same signs as in the previous models. This confirms our hypothesis that *SSA* adds information not contained in the other measures, which makes it worthwhile to consider. The non-linear effects are partly insignificant and of mixed signs. The only consistent result is that outperformers with a high $-TR^2$ show exceptionally high future performance on average.

Panel B reports results from within-panel regressions, adding time-fixed effects and fund-fixed effects. Again this does not change the overall effect of *SSA* on performance as the coefficients remain positive and significant. However, the influence of *TE* becomes insignificant and, as in Table 3, the overall effect of $-TR^2$ turns significantly negative. The non-linear relations are such that an outperformer can further improve performance with higher *SSA* and $-TR^2$ activity.[16]

Overall the results shown in Table 4 confirm both our first hypothesis, that activity, especially *SSA*, is able to predict performance, and our second hypothesis, that *SSA* adds new and more

[14] Additional results using cross-sectional Fama and MacBeth (1973) regressions are available upon request. These results are largely in line with the findings of our panel regressions without being statistically significant.

[15] The coefficients of the control variables are qualitatively the same as in Table 3. For simplicity and to save space, we do not report them in detail.

[16] Additional results using cross-sectional Fama and MacBeth (1973) regressions are available upon request. These results are economically consistent with the panel results but not statistically significant.

Table 3
Predicting performance based on activity.

Panel A: Pooled panel regression with style-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000096***			0.000104***		
	(10.27)			(8.08)		
TE		0.001727			0.000809	
		(0.86)			(0.32)	
$-TR^2$			0.000053***			0.000051***
			(13.98)			(13.40)
SSA outperformer				−0.000029**		
				(−2.00)		
SSA underperformer				0.000009		
				(0.63)		
TE outperformer					−0.008014***	
					(−3.07)	
TE underperformer					0.009664***	
					(3.61)	
$-TR^2$ outperformer						0.00001***
						(6.40)
$-TR^2$ underperformer						−0.000004***
						(−2.58)
Expenses	−0.002898***	−0.001684***	−0.004279***	−0.002918***	−0.001737***	−0.004309***
	(−5.80)	(−3.41)	(−8.33)	(−5.83)	(−3.49)	(−8.38)
Turnover	−0.000012***	−0.000011***	−0.00001***	−0.000012***	−0.000011***	−0.00001***
	(−4.46)	(−4.38)	(−3.82)	(−4.44)	(−4.33)	(−3.86)
log(TNA)	−0.000018***	−0.000021***	−0.000016***	−0.000018***	−0.000021***	−0.000017***
	(−4.15)	(−4.56)	(−3.72)	(−4.13)	(−4.46)	(−3.78)
$(\log(\text{TNA}))^2$	0.000001***	0.000001***	0.000001***	0.000001***	0.000001***	0.000001***
	(3.04)	(3.42)	(2.79)	(3.01)	(3.28)	(2.79)
Fund Age/100	−0.000005**	−0.000006***	−0.000005**	−0.000005**	−0.000005***	−0.000005**
	(−2.46)	(−2.80)	(−2.47)	(−2.39)	(−2.59)	(−2.22)
Alpha	0.181797***	0.189868***	0.177271***	0.202402***	0.252892***	0.207165***
	(19.68)	(20.25)	(18.80)	(14.35)	(15.70)	(15.31)
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.05	0.04	0.05	0.05	0.05	0.06
Observations	32,818	32,818	32,818	32,818	32,818	32,818

Panel B: Panel regression with fund-fixed effects (within) and style and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000058***			0.000047***		
	(5.64)			(3.47)		
TE		0.004777			0.003074	
		(1.31)			(0.77)	
$-TR^2$			−0.000047***			−0.000046***
			(−6.61)			(−6.60)
SSA outperformer				0.000029**		
				(2.11)		
SSA underperformer				−0.000002		
				(−0.11)		
TE outperformer					0.000424	
					(0.17)	
TE underperformer					0.003103	
					(1.18)	
$-TR^2$ outperformer						0.000002
						(1.23)
$-TR^2$ underperformer						−0.000003
						(−1.53)
Expenses	0.001826	0.001834	0.001888	0.001849	0.001822	0.001826
	(0.91)	(0.91)	(0.93)	(0.92)	(0.90)	(0.90)
Turnover	−0.000002	−0.000002	−0.000002	−0.000002	−0.000002	−0.000002
	(−0.85)	(−0.81)	(−0.59)	(−0.87)	(−0.82)	(−0.61)
log(TNA)	−0.000037***	−0.000037***	−0.00004***	−0.000037***	−0.000037***	−0.00004***
	(−3.44)	(−3.44)	(−3.64)	(−3.44)	(−3.45)	(−3.64)
$(\log(\text{TNA}))^2$	−0.000005***	−0.000005***	−0.000005***	−0.000005***	−0.000005***	−0.000005***
	(−4.86)	(−4.87)	(−4.97)	(−4.87)	(−4.85)	(−4.98)
Fund Age/100	−0.000179*	−0.000172*	−0.000169**	−0.000181*	−0.000172*	−0.000168**
	(−1.93)	(−1.91)	(−1.97)	(−1.93)	(−1.92)	(−1.97)
Alpha	0.040975***	0.041606***	0.039664***	0.022831	0.051871***	0.050814***
	(4.23)	(4.26)	(4.07)	(1.53)	(2.85)	(3.40)
Fund-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.02	0.02	0.02	0.02	0.02	0.02
Observations	32,818	32,818	32,818	32,818	32818	32,818

This table presents coefficients of panel regressions of fund performance in the 6-month post-ranking period $t+1$ on fund activity in the semi-annual ranking period t. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from quarter $q-1$ to quarter q within t. For Models (4), (5) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in the semi-annual ranking period t with respect to performance. We control for lagged fund characteristics (expense ratio, turnover ratio, total net assets, and age) and performance (alpha) as possible predictors of performance. Further, in Panel A we control for style-fixed effects and in Panel B for fund-, style- and time-fixed effects. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

Table 4
Combined performance prediction.

Panel A: Pooled panel regression with style-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000136***	0.00006***	0.000105***	0.000143***	0.000064***	0.000106***
	(13.10)	(5.40)	(9.13)	(7.32)	(3.65)	(5.14)
TE	−0.013861***		−0.021293***	−0.015148***		−0.022825***
	(−6.31)		(−8.61)	(−4.26)		(−5.90)
$-TR^2$		0.000037***	0.000055***		0.000035***	0.000051***
		(8.36)	(11.49)		(7.77)	(10.12)
SSA outperformer				0.000004	−0.000006	0.000016
				(0.16)	(−0.27)	(0.59)
SSA underperformer				−0.000028	−0.000005	−0.000022
				(−1.09)	(−0.25)	(−0.84)
TE outperformer				−0.008531*		−0.003238
				(−1.75)		(−0.63)
TE underperformer				0.012049***		0.00782
				(2.64)		(1.51)
$-TR^2$ outperformer					0.000009***	0.000009***
					(3.43)	(3.25)
$-TR^2$ underperformer					−0.000005*	−0.000002
					(−1.87)	(−0.80)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.06	0.06	0.06	0.06	0.06	0.07
Observations	32,818	32,818	32,818	32,818	32,818	32,818

Panel B: Panel regression with fund-fixed effects (within) and style and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000063***	0.00008***	0.000073***	0.000044**	0.000056***	0.000051**
	(5.65)	(7.38)	(6.51)	(2.23)	(3.18)	(2.54)
TE	−0.003565		0.006373	−0.002617		0.00581
	(−0.91)		(1.50)	(−0.52)		(1.04)
$-TR^2$		−0.000065***	−0.000071***		−0.000067***	−0.000074***
		(−8.80)	(−8.43)		(−9.07)	(−8.60)
SSA outperformer				0.000063**	0.000052***	0.000072***
				(2.52)	(2.60)	(2.84)
SSA underperformer				−0.000015	0.000004	−0.000016
				(−0.63)	(0.21)	(−0.66)
TE outperformer				−0.009228**		−0.007869
				(−2.06)		(−1.62)
TE underperformer				0.005677		0.007096
				(1.28)		(1.43)
$-TR^2$ outperformer					0.000007***	0.000005*
					(2.65)	(1.85)
$-TR^2$ underperformer					−0.000001	0.000000
					(−0.35)	(0.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.02	0.02	0.02	0.02	0.02	0.02
Observations	32,818	32,818	32,818	32,818	32,818	32,818

This table presents coefficients of panel regressions of fund performance in the 6-month post-ranking period $t+1$ on different combinations of fund activity measures in the semi-annual ranking period t. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from quarter $q-1$ to quarter q within t. For Models (4), (5) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in the semi-annual ranking period t with respect to alpha. As in Table 3, we control for lagged fund characteristics (expense ratio, turnover ratio, total net assets, and age) and performance (alpha) as possible predictors of performance. Further, in Panel A we control for style-fixed effects and in Panel B for fund-, style- and time-fixed effects. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

specific information on management activity not captured previously by either *TE* or $-TR^2$. Also *SSA* is a stable measure, while *TE* and $-TR^2$ seem to capture unobserved fund characteristics related to future performance, as the coefficients change clearly when we add time- and fund-fixed effects. To further strengthen these findings, we re-estimate the models with *SSA* orthogonalized with respect to *TE* and $-TR^2$ and vice versa. The results are similar to those in Table 4 and, for brevity, available upon request.

4.3. *Economic value of predicting performance based on activity*

We analyze the economic value of predicting performance using activity by examining a trading strategy based upon fund activity. Specifically, we loosely follow Amihud and Goyenko (2013) and rank funds at the end of each month into quintile portfolios based on their activity in the last 6 months ($Activity_{t-1}$). In addition, we employ a conditional double-sorting procedure, and rank funds within the activity quintiles into further quintile portfolios

Table 5
Economic value of predicting net performance based on activity.

Panel A: *SSA* and *Alpha*

$Alpha_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All	High-Low
Low	−3.5650*	−3.5850***	−2.5705**	−2.2623***	−2.5828***	−2.9348**	−0.9823
	(−1.79)	(−2.97)	(−2.51)	(−2.86)	(−5.14)	(−2.50)	(−0.58)
4	−1.1523	−1.4548	−1.1295	−1.4555***	−1.4710***	−1.4648**	0.3185
	(−0.78)	(−1.50)	(−1.64)	(−2.63)	(−4.58)	(−2.20)	(0.23)
3	−0.4223	−1.0270	−1.0910**	−0.7455	−0.9213***	−0.8573	0.4993
	(−0.31)	(−1.13)	(−2.04)	(−1.41)	(−3.06)	(−1.44)	(0.35)
2	0.2890	−0.0262	0.0419	−0.6158	−0.8095**	−0.0358	1.0983
	(0.21)	(−0.03)	(0.05)	(−1.14)	(−2.42)	(−0.05)	(0.77)
High	2.3583*	1.7403	0.9303	0.7810	0.5388	1.2705	1.8198
	(1.69)	(1.45)	(1.00)	(1.07)	(1.03)	(1.34)	(1.54)
All	−0.4918	−0.8645	−0.7605	−0.8553	−1.0458***	−0.8025	0.5540
	(−0.35)	(−0.91)	(−1.08)	(−1.57)	(−3.74)	(−1.10)	(0.43)
High-Low	5.9233***	5.3253***	3.5008***	3.0433***	3.1213***	4.2053***	
	(3.61)	(4.71)	(3.52)	(3.84)	(5.35)	(4.40)	

Panel B: *TE* and *Alpha*

$Alpha_{t-1}$	TE_{t-1}						
	High	2	3	4	Low	All	High-Low
Low	−4.4208**	−2.7510**	−2.4043***	−2.0573***	−2.3843***	−2.9348**	−2.0365
	(−2.17)	(−2.20)	(−2.83)	(−2.93)	(−5.25)	(−2.50)	(−1.10)
4	−0.6655	−1.2443	−1.1475	−1.5583***	−1.3833***	−1.4648**	0.7178
	(−0.36)	(−1.19)	(−1.52)	(−3.10)	(−4.32)	(−2.20)	(0.39)
3	−0.4193	−0.8705	−0.1747	−1.3810***	−0.8430***	−0.8573	0.4238
	(−0.26)	(−0.81)	(−0.23)	(−2.77)	(−2.66)	(−1.44)	(0.24)
2	0.3153	0.2319	−0.1454	−0.9878**	−0.7808**	−0.0358	1.0960
	(0.22)	(0.23)	(−0.18)	(−2.19)	(−2.42)	(−0.05)	(0.71)
High	3.2253*	1.4023	0.8343	−0.1229	−0.4593	1.2705	3.6845*
	(1.79)	(1.35)	(0.90)	(−0.20)	(−1.14)	(1.34)	(1.96)
All	−0.3840	−0.6405	−0.6048	−1.2193**	−1.1688***	−0.8025	0.7848
	(−0.24)	(−0.64)	(−0.82)	(−2.58)	(−3.97)	(−1.10)	(0.48)
High-Low	7.6460***	4.1533***	3.2385***	1.9345***	1.9250***	4.2053***	
	(4.12)	(3.77)	(3.70)	(2.65)	(4.02)	(4.40)	

Panel C: $-TR^2$ and *Alpha*

$Alpha_{t-1}$	$-TR^2_{t-1}$						
	High	2	3	4	Low	All	High-Low
Low	−4.6268**	−2.5785*	−1.8035	−2.1108***	−2.6905***	−2.9348**	−1.9365
	(−2.60)	(−1.82)	(−1.50)	(−2.64)	(−4.84)	(−2.50)	(−1.18)
4	−1.4875	−1.0650	−1.1725	−1.3860**	−1.4073***	−1.4648**	−0.0803
	(−1.17)	(−0.94)	(−1.41)	(−2.31)	(−3.62)	(−2.20)	(−0.06)
3	−0.6398	−0.2268	−1.0108	−1.2363**	−1.1165***	−0.8573	0.4765
	(−0.58)	(−0.20)	(−1.29)	(−2.01)	(−3.47)	(−1.44)	(0.38)
2	0.5450	−0.2262	0.2162	−0.3623	−1.0288***	−0.0358	1.5738
	(0.43)	(−0.25)	(0.22)	(−0.53)	(−2.67)	(−0.05)	(1.18)
High	3.5400**	0.8958	1.1360	0.2930	−0.6430	1.2705	4.1830**
	(2.09)	(0.83)	(1.08)	(0.33)	(−1.20)	(1.34)	(2.23)
All	−0.5230	−0.6360	−0.5240	−0.9570	−1.3763***	−0.8025	0.8533
	(−0.42)	(−0.61)	(−0.59)	(−1.47)	(−4.02)	(−1.10)	(0.65)
High-Low	8.1670***	3.4743***	2.9395***	2.4038***	2.0475***	4.2053***	
	(4.13)	(3.13)	(3.19)	(4.17)	(3.66)	(4.40)	

Panel D: *SSA* and *TE*

TE_{t-1}	SSA_{t-1}						
	High	2	3	4	Low	All	High-Low
Low	−0.8218	−0.9480*	−1.3083**	−1.3225***	−0.7875**	−1.1688***	−0.0341
	(−0.86)	(−1.79)	(−2.57)	(−3.94)	(−2.37)	(−3.97)	(−0.03)
4	−0.6150	−0.9935	−1.3630***	−1.2848**	−1.3228***	−1.2193**	0.7078
	(−0.46)	(−1.27)	(−2.64)	(−2.57)	(−4.57)	(−2.58)	(0.52)
3	−0.2558	−0.9433	−0.4368	−0.7638	−1.1320***	−0.6048	0.8763
	(−0.17)	(−0.99)	(−0.54)	(−1.30)	(−3.00)	(−0.82)	(0.59)
2	−0.8893	−0.5610	−0.8755	−0.3215	−1.5878***	−0.6405	0.6985
	(−0.56)	(−0.45)	(−0.99)	(−0.42)	(−3.99)	(−0.64)	(0.48)
High	0.1208	−0.8728	0.1696	−0.5855	−0.4053	−0.3840	0.5260
	(0.06)	(−0.55)	(0.13)	(−0.61)	(−0.55)	(−0.24)	(0.35)

Table 5 (*Continued*)

Panel A: *SSA* and *Alpha*

$Alpha_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All	High-Low
All	−0.4918	−0.8645	−0.7605	−0.8553	−1.0458***	−0.8025	0.5540
	(−0.35)	(−0.91)	(−1.08)	(−1.57)	(−3.74)	(−1.10)	(0.43)
High-Low	0.9425	0.0753	1.4778	0.7370	0.3823	0.7848	
	(0.63)	(0.05)	(1.24)	(0.78)	(0.40)	(0.48)	

Panel E: *SSA* and $-TR^2$

$-TR^2_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All	High-Low
Low	−0.7368	−0.8615	−1.5950***	−1.3048***	−0.8313**	−1.3763***	0.0945
	(−0.58)	(−1.01)	(−2.85)	(−2.72)	(−2.41)	(−4.02)	(0.06)
4	−0.6578	−0.8403	−0.8873	−1.3410**	−1.2543***	−0.9570	0.5965
	(−0.49)	(−0.75)	(−1.23)	(−2.50)	(−3.78)	(−1.47)	(0.42)
3	−0.7365	−1.1253	−0.9705	−0.8583	−1.6748***	−0.5240	0.9383
	(−0.46)	(−1.11)	(−1.26)	(−1.32)	(−4.26)	(−0.59)	(0.59)
2	−0.9233	−0.7338	−0.2010	−0.3640	−1.1235**	−0.6360	0.2003
	(−0.53)	(−0.62)	(−0.20)	(−0.53)	(−2.33)	(−0.61)	(0.14)
High	0.5830	−0.7665	−0.1664	−0.4223	−0.3525	−0.5230	0.9355
	(0.35)	(−0.69)	(−0.19)	(−0.52)	(−0.55)	(−0.42)	(0.75)
All	−0.4918	−0.8645	−0.7605	−0.8553	−1.0458***	−0.8025	0.5540
	(−0.35)	(−0.91)	(−1.08)	(−1.57)	(−3.74)	(−1.10)	(0.43)
High-Low	1.3198	0.0950	1.4285*	0.8825	0.4788	0.8533	
	(0.92)	(0.09)	(1.72)	(1.10)	(0.57)	(0.65)	

This table shows average risk-adjusted net performance (in % p. a.) for fund portfolios in the 1-month post-ranking period m. To construct the portfolios, we rank funds into quintile portfolios according to their activity in semi-annual ranking period $t-1$ (Panel A: SSA_{t-1}, Panel B: TE_{t-1}, Panel C: $-TR^2_{t-1}$) and according to their alpha in period $t-1$ ($Alpha_{t-1}$). In addition, we use a conditional double-sorting procedure where we first rank funds in quintiles according to their level of activity and within the activity quintiles according to alpha. Moreover, we also use the conditional double-sorting procedure to create portfolios along different dimensions of activity. Therefore, we first rank funds in quintiles according to SSA_{t-1} in $t-1$ and then within the quintiles according to TE_{t-1} (Panel D) and according to $-TR^2_{t-1}$ (Panel E), respectively. Funds are equal weighted within the portfolios. Portfolio performance is measured in each month as multifactor alpha. The numbers represent time series averages of these alphas. Standard errors are HAC-consistent using Newey and West (1987). *T*-statistics are reported in parentheses.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

according to their performance in the last 6 months ($Alpha_{t-1}$), creating 25 double-sorted portfolios. Then, we determine the performance of these portfolios over the next month m by estimating post-ranking alphas ($Alpha_m$) based on daily data. Table 5 reports the time series averages of $Alpha_m$ in % p.a.

In Panel A we use *SSA* to rank funds monthly on past activity. The results using the single-sorted portfolios (row "All") show that the most active funds have higher performance (−0.4918% p.a.) and the least active show the lowest performance (−1.0458% p.a.). However, the difference (0.5540% p.a.) is not statistically significant.[17] The double-sorted portfolios show clearer differences. This is mainly due to the fact that $Alpha_{t-1}$ proves to be a strong predictor of future performance because the single sorting on alpha (column "All") generates a High-Low portfolio alpha of 4.2053% p.a., which is also highly significant. Therefore, of the conditionally double-sorted portfolios, the High/High portfolio shows the highest average performance of 2.3583% p.a., which is statistically significant as well as economically relevant. The worst performance is reported for the portfolios in the upper left corner (e.g., High-*SSA*/Low-*Alpha*: −3.5650% p.a.) leading to an average High-Low portfolio alpha for funds with high SSA activity of 5.9233% p.a. (lower left corner) which is also statistically significant.

Similar patterns are observable in Panels B and C using *TE* and $-TR^2$ to rank activity. The results for single-sorting activity (row "All") generate High-Low portfolio alphas of 0.7848% p.a. (*TE*) and 0.8533% ($-TR^2$), which is somewhat higher than for *SSA* but still statistically insignificant. The double sorting therefore also shows a bit stronger results, with a High-Low portfolio alpha of 7.6460% p.a. for funds with high TE activity and of 8.1670% p.a. for funds with high $-TR^2$ activity (lower left corner) – which are both statistically significant. These findings are overall consistent with those by Amihud and Goyenko (2013). They also show that *TE* and $-TR^2$ discriminate slightly better between future outperformers and underperformers. However, we know from Tables 3 and 4 that this might be due to unobserved fund characteristics and not to management activity per se. Overall, these results confirm our expectation that the information in the more specific activity measure *SSA* adds value for investors.

To go a bit deeper into our second hypothesis, that *SSA* adds information previously not captured in the other measures, Panels D and E examine the joint performance prediction of combined activity measures. Therefore, after single-sorting funds into quintiles based on SSA_{t-1}, we conditionally double-sort funds into quintiles using *TE* (Panel D) and $-TR^2$ (Panel E). Although less significant, the results clearly indicate that the combined rankings are superior to the single rankings. Specifically, the double-sorted High/High portfolios using *SSA*/*TE* (0.1208% p.a.) and *SSA*/$-TR^2$ (0.5830% p.a.) outperform all three single High portfolios (row "All", High) using *SSA* (−0.4918% p.a.), TE (−0.3840% p.a.) and $-TR^2$ (−0.5230% p.a.). High/High also outperforms the unsorted overall average ("All/All") portfolio which shows a performance of −0.8025% p.a. Moreover, the poorest double-sorted portfolio performance results are concentrated in the upper right corners of both panels with the least active funds. Overall, we see our second

[17] Results are annualized by multiplying daily figures with 250 trading days.

Table 6
Economic value of predicting gross performance based on activity.

Panel A: *SSA* and *Alpha*

$Alpha_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All *Alpha*	*SSA* H-L
Low	−2.2288	−2.0885*	−1.2913	−1.0643	−1.4790***	−1.5860	−0.7498
	(−1.13)	(−1.72)	(−1.29)	(−1.36)	(−2.87)	(−1.36)	(−0.45)
4	0.3020	−0.3440	0.2242	−0.1636	−0.3918	−0.1977	0.6938
	(0.20)	(−0.36)	(0.32)	(−0.31)	(−1.28)	(−0.31)	(0.48)
3	1.0073	0.3818	0.0629	0.2580	−0.0814	0.2395	1.0888
	(0.74)	(0.41)	(0.11)	(0.49)	(−0.25)	(0.41)	(0.76)
2	1.8910	1.3505	1.2003	0.6563	−0.0228	1.1318	1.9140
	(1.37)	(1.35)	(1.63)	(1.13)	(−0.07)	(1.65)	(1.37)
High	3.6035**	3.0948***	2.3328**	2.0233***	1.7238***	2.6240***	1.8798
	(2.56)	(2.62)	(2.45)	(2.76)	(3.24)	(2.73)	(1.60)
All *SSA*	0.9225	0.4858	0.5090	0.3463	−0.0482	0.4445	0.9708
	(0.66)	(0.51)	(0.73)	(0.64)	(−0.17)	(0.61)	(0.75)
Alpha H-L	5.8325***	5.1835***	3.6240***	3.0875***	3.2028***	4.2100***	
	(3.55)	(4.70)	(3.67)	(3.91)	(5.30)	(4.41)	

Panel B: *TE* and *Alpha*

$Alpha_{t-1}$	TE_{t-1}						
	High	2	3	4	Low	All *Alpha*	*TE* H-L
Low	−2.6735	−1.4945	−1.0435	−0.8993	−1.3908***	−1.5860	−1.2828
	(−1.30)	(−1.21)	(−1.22)	(−1.24)	(−3.16)	(−1.36)	(−0.69)
4	0.6803	0.1780	0.1215	−0.4865	−0.3475	−0.1977	1.0275
	(0.37)	(0.17)	(0.17)	(−1.04)	(−1.11)	(−0.31)	(0.56)
3	1.1150	0.4995	1.0248	−0.0857	−0.0915	0.2395	1.2065
	(0.68)	(0.47)	(1.31)	(−0.17)	(−0.29)	(0.41)	(0.69)
2	1.6588	1.6163	1.1390	0.0439	0.0337	1.1318	1.6253
	(1.16)	(1.59)	(1.46)	(0.10)	(0.10)	(1.65)	(1.03)
High	4.7940***	2.7845***	2.2025**	1.0443	0.5335	2.6240***	4.2605**
	(2.65)	(2.71)	(2.34)	(1.63)	(1.40)	(2.73)	(2.30)
All *TE*	1.1258	0.7223	0.6920	−0.0746	−0.2510	0.4445	1.3768
	(0.70)	(0.72)	(0.94)	(−0.16)	(−0.88)	(0.61)	(0.84)
Alpha H-L	7.4675***	4.2788***	3.2460***	1.9435**	1.9243***	4.2100***	
	(4.00)	(3.85)	(3.78)	(2.57)	(4.19)	(4.41)	

Panel C: $-TR^2$ and *Alpha*

$Alpha_{t-1}$	$-TR^2_{t-1}$						
	High	2	3	4	Low	All *Alpha*	$-TR^2$ H-L
Low	-3.1783*	−1.3238	−0.3705	−0.9943	−1.6140***	−1.5860	−1.5643
	(−1.78)	(−0.95)	(−0.30)	(−1.25)	(−2.90)	(−1.36)	(−0.96)
4	0.0357	0.3030	−0.0569	−0.0889	−0.4378	−0.1977	0.4735
	(0.03)	(0.27)	(−0.07)	(−0.15)	(−1.26)	(−0.31)	(0.37)
3	0.7705	1.1898	0.4595	−0.0945	−0.2925	0.2395	1.0628
	(0.69)	(1.02)	(0.57)	(−0.15)	(−0.87)	(0.41)	(0.84)
2	2.0333	1.2028	1.3033	0.7710	−0.1976	1.1318	2.2310*
	(1.61)	(1.39)	(1.38)	(1.10)	(−0.51)	(1.65)	(1.67)
High	5.0120***	2.2333**	2.5500**	1.4973*	0.2643	2.6240***	4.7475**
	(3.02)	(2.03)	(2.38)	(1.66)	(0.51)	(2.73)	(2.61)
All $-TR^2$	0.9458	0.7253	0.7790	0.2207	−0.4543	0.4445	1.4000
	(0.77)	(0.70)	(0.89)	(0.34)	(−1.35)	(0.61)	(1.08)
Alpha H-L	8.1903***	3.5570***	2.9205***	2.4915***	1.8783***	4.2100***	
	(4.19)	(3.19)	(3.03)	(4.45)	(3.43)	(4.41)	

Panel D: *SSA* and *TE*

TE_{t-1}	SSA_{t-1}						
	High	2	3	4	Low	All *TE*	*SSA* H-L
Low	0.3880	0.2503	−0.2538	−0.2725	−0.3108	−0.2510	0.6988
	(0.42)	(0.47)	(−0.50)	(−0.84)	(−0.94)	(−0.88)	(0.62)
4	0.8543	0.2828	−0.1845	−0.1815	−0.3833	−0.0746	1.2375
	(0.64)	(0.37)	(−0.36)	(−0.37)	(−1.37)	(−0.16)	(0.89)
3	1.1918	0.3840	0.8518	0.4205	−0.0488	0.6920	1.2408
	(0.79)	(0.40)	(1.04)	(0.72)	(−0.13)	(0.94)	(0.85)
2	0.4538	0.7823	0.4558	0.9198	−0.3933	0.7223	0.8470
	(0.29)	(0.64)	(0.51)	(1.18)	(−0.98)	(0.72)	(0.59)
High	1.7260	0.7193	1.6615	0.8455	0.8938	1.1258	0.8323
	(0.85)	(0.45)	(1.29)	(0.87)	(1.20)	(0.70)	(0.55)

Table 6 (*Continued*)

Panel A: *SSA* and *Alpha*

$Alpha_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All *Alpha*	*SSA* H-L
All *SSA*	0.9225	0.4858	0.5090	0.3463	−0.0482	0.4445	0.9708
	(0.66)	(0.51)	(0.73)	(0.64)	(−0.17)	(0.61)	(0.75)
TE H-L	1.3380	0.4693	1.9153	1.1180	1.2045	1.3768	
	(0.88)	(0.33)	(1.62)	(1.16)	(1.26)	(0.84)	

Panel E: *SSA* and $-TR^2$

$-TR^2_{t-1}$	SSA_{t-1}						
	High	2	3	4	Low	All$-TR^2$	*SSA* H-L
Low	0.5955	0.2406	−0.5503	−0.2633	−0.3490	−0.4543	0.9448
	(0.47)	(0.29)	(−0.99)	(−0.57)	(−1.02)	(−1.35)	(0.64)
4	0.7208	0.5883	0.3575	−0.2063	−0.3048	0.2207	1.0255
	(0.53)	(0.52)	(0.50)	(−0.38)	(−0.94)	(0.34)	(0.71)
3	0.6438	0.2482	0.3213	0.3223	−0.5583	0.7790	1.2020
	(0.41)	(0.24)	(0.42)	(0.50)	(−1.41)	(0.89)	(0.77)
2	0.6088	0.6238	1.1335	0.9058	−0.0084	0.7253	0.6170
	(0.35)	(0.53)	(1.14)	(1.32)	(−0.02)	(0.70)	(0.43)
High	2.0325	0.7255	1.2633	0.9675	0.9715	0.9458	1.0613
	(1.20)	(0.65)	(1.46)	(1.17)	(1.49)	(0.77)	(0.85)
All *SSA*	0.9225	0.4858	0.5090	0.3463	−0.0482	0.4445	0.9708
	(0.66)	(0.51)	(0.73)	(0.64)	(−0.17)	(0.61)	(0.75)
$-TR^2$ H-L	1.4370	0.4848	1.8135**	1.2308	1.3205	1.4000	
	(0.98)	(0.46)	(2.21)	(1.53)	(1.57)	(1.08)	

This table shows average risk-adjusted gross performance (in % p. a.) for fund portfolios in the 1-month post-ranking period *m*. To construct the portfolios, we rank funds into quintile portfolios according to their activity in semi-annual ranking period $t-1$ (Panel A: SSA_{t-1}, Panel B: TE_{t-1}, Panel C: $-TR^2_{t-1}$) and according to their alpha in period $t-1$ ($Alpha_{t-1}$). In addition, we use a conditional double-sorting procedure where we first rank funds in quintiles according to their level of activity and within the activity quintiles according to alpha. Moreover, we also use the conditional double-sorting procedure to create portfolios along different dimensions of activity. Therefore, we first rank funds in quintiles according to SSA_{t-1} in $t-1$ and then within the quintiles according to TE_{t-1} (Panel D), and according to $-TR^2_{t-1}$ (Panel E), respectively. Funds are equal weighted within the portfolios. Portfolio performance is measured in each month as multifactor alpha. The numbers represent time series averages of these alphas. Standard errors are HAC-consistent using Newey and West (1987). *T*-statistics are reported in parentheses.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

research hypothesis confirmed, that *SSA* together with the other measures adds significant value for investors.[18]

To give even further depth to our results, we re-estimate Table 5 using gross returns instead of net returns. The reason is that if superior and active fund management goes hand-in-hand with higher fund fees, studying net performance might dilute our results. Thus, employing gross returns instead of net returns can provide additional insights. Moreover, gross return is more informative about skill, as it represents the performance created by the manager's activity as opposed to the return paid to the investors (e.g., Fama & French, 2010; Pastor et al., 2015).

The results presented in Table 6 indicate that the economic relations do not differ by much between net and gross returns. However, activity seems to become a bit more discriminative, as the average High-Low performance of the single-sorted quintile portfolios (row "All") is now larger than before, with 0.9708% p.a. for *SSA*, 1.3768% p.a. for *TE* and 1.4000% p.a. for $-TR^2$. This is consistent with the results in Table 2 where higher activity is shown to be related to higher expense ratios. Double-sorted portfolio performance is more or less the same as before but with an upward shift of 1.2% p.a., which is equal to the overall average expense ratio reported in Table 2. Regarding skill, the most actively managed funds (High/High in panels D and E) created average risk-adjusted returns of 1.7260% p.a. (*TE*) and 2.0325% p.a. ($-TR^2$) which is economically remarkable but statistically insignificant. Overall the gross return results further strengthen our previous findings and present additional evidence in favor of our research hypotheses.

4.4. Determinants of activity

In the previous sections, we have proved that activity in general, but especially *SSA*, can significantly predict performance, in that more active funds have higher performance. To go further into the economic relations determining activity, Table 7 shows results for pooled regressions of activity on lagged characteristics with style and time-fixed effects as presented by Eqs. (8) and (9):

$$\begin{aligned} Activity_{i,t} = {} & b_{0,t} + b_{1,t}Expenses_{i,t-1} + b_{2,t}Turnover_{i,t-1} \\ & + b_{3,t}\log(TNA)_{i,t-1} + b_{4,t}\log(TNA)^2_{i,t-1} \\ & + b_{5,t}Fund\,Age_{i,t-1}/100 + \sum_{s=1}^{S} b^s_{i,t}Style_{i,t-1} \\ & + \sum_{x=1}^{X} b^x_{i,t}Time_{i,t-1} + e_{i,t} \end{aligned} \tag{8}$$

$$\begin{aligned} Activity_{i,t} = {} & b_{0,t} + b_{1,t}Expenses_{i,t-1} + b_{2,t}Turnover_{i,t-1} \\ & + b_{3,t}\log(TNA)_{i,t-1} + b_{4,t}\log(TNA)^2_{i,t-1} \\ & + b_{5,t}Fund\,Age_{i,t-1}/100 + b_{6,t}D^{Out}_{i,t-1} + b_{7,q}D^{Under}_{i,t-1} \\ & + \sum_{s=1}^{S} b^s_{i,t}Style_{i,t-1} + \sum_{x=1}^{X} b^x_{i,t}Time_{i,t-1} + e_{i,t} \end{aligned} \tag{9}$$

[18] Bandarchuk and Hilscher (2013) show that results from double-sorting analyses can be spurious if the characteristics are correlated. Such a double-sorting might in fact simply produce a more extreme single sorting. To make sure that our result in Panels D and E are not a result from the correlations between *SSA*, *TE* and $-TR^2$, we additionally double sort on *SSA* and *SSA*. The result is inferior to those in Panels D and E. For brevity, this additional panel is available upon request.

Table 7
Determinants of activity.

	SSA		*TE*		$-TR^2$	
	(1)	(2)	(3)	(4)	(5)	(6)
Expenses	13.6832***	13.1520***	0.0838***	0.0805***	46.7200***	45.1393***
	(14.73)	(14.37)	(15.86)	(15.52)	(17.64)	(17.52)
Turnover	0.0116***	0.0112***	0.0001**	0.0001**	−0.0173**	−0.0184**
	(2.67)	(2.63)	(2.43)	(2.39)	(−2.01)	(−2.23)
log(TNA)	−0.0181***	−0.0177***	−0.0001***	−0.0001***	−0.0780***	−0.0768***
	(−3.03)	(−3.02)	(−3.57)	(−3.58)	(−4.63)	(−4.68)
$(\log(\text{TNA}))^2$	0.0011*	0.0012**	0.0000**	0.0000**	0.0037**	0.0038**
	(1.89)	(1.98)	(2.26)	(2.36)	(2.15)	(2.25)
Fund Age/100	0.0045	0.0040	0.0000	0.0000	0.0274**	0.0257**
	(0.89)	(0.81)	(1.09)	(1.01)	(2.02)	(1.97)
Outperformer		0.0818***		0.0005***		0.2423***
		(13.47)		(16.50)		(19.06)
Underperformer		0.0681***		0.0004***		0.2028***
		(13.21)		(17.11)		(16.94)
Style Dummies						
Micro Cap	0.1711**	0.1624*	0.0014***	0.0014**	0.4927	0.4670
	(2.06)	(1.93)	(2.64)	(2.56)	(1.52)	(1.45)
Small Cap	0.0567	0.0513	0.0004	0.0004	−0.1737	−0.1895
	(0.76)	(0.68)	(0.92)	(0.86)	(−0.57)	(−0.62)
Mid Cap	0.0896	0.0856	0.0008	0.0008	0.0529	0.0410
	(1.20)	(1.13)	(1.63)	(1.59)	(0.17)	(0.13)
Large Cap	−0.2883***	−0.2714***	−0.0016***	−0.0015***	−1.4788***	−1.4285***
	(−3.81)	(−3.54)	(−3.39)	(−3.19)	(−4.82)	(−4.66)
Growth & Income	−0.1347*	−0.1276*	−0.0006	−0.0006	−0.4178	−0.3967
	(−1.79)	(−1.68)	(−1.29)	(−1.20)	(−1.36)	(−1.30)
Growth	−0.014	−0.0112	0.0001	0.0001	−0.2337	−0.2252
	(−0.19)	(−0.15)	(0.18)	(0.22)	(−0.77)	(−0.74)
Income	−0.1106	−0.1075	−0.0005	−0.0005	−0.2253	−0.2160
	(−1.46)	(−1.40)	(−1.07)	(−1.04)	(−0.73)	(−0.70)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.18	0.19	0.46	0.47	0.36	0.37
Observations	32818	32818	32818	32818	32818	32818

This table presents coefficients of a panel regression of activity in the 6-month post-ranking period t (SSA_t, TE_t, $-TR_t^2$) on lagged fund characteristics. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from quarter $q-1$ to quarter q within t. For Models (2), (4) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in $t-1$ with respect to alpha. We control for style- and time-fixed effects using dummy variables. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

where $Activity_{i,t}$ is either $SSA_{i,t}$, $TE_{i,t}$ or $-TR^2_{i,t}$ and the fund characteristic variables are defined as in Table 3. Additionally, Eq. (9) contains dummy variables indicating whether a fund was an outperformer (upper third) or an underperformer (lower third) in period $t-1$ with respect to alpha. The observations are pooled over non-overlapping semi-annual measurement periods. Standard errors are clustered by fund to control for heteroskedasticity and serial correlation.

The first striking observation is that the adjusted R^2 statistic to the *SSA* regression is only about 19% whereas *TE* and $-TR^2$ show adjusted R^2 statistics of about 47% and 37%, respectively.[19] This could be related to our previous findings that *TE* and $-TR^2$ capture some unobserved fund effects in addition to activity, which makes the activity-performance relation disappear or change when time- and fund-fixed effects are considered. The result also strengthens our belief that *SSA* delivers valuable stand-alone information about activity that is more independent of other fund characteristics, which explains the stable results in Tables 3 and 4.

The results on fund characteristics are largely in line with findings by Amihud and Goyenko (2013) and indicate that higher expenses are related to higher activity, which is consistent with intuition and with results from the previous tables. We document a positive and significant relation between turnover and *SSA* and *TE* which also in line with economic intuition, however we observe a negative and significant one with $-TR^2$. Larger funds are significantly less active which is consistent with findings in Cremers and Petajisto (2009). Older funds, on the other hand, are more active, however significantly so only for $-TR^2$.

Both previous outperformance and underperformance are linked to significantly higher activity. The former can be explained

Table 8
SSA summary statistics from alternative models.

	Mean	Standard deviation	Min	Max
Semi-annual *SSA*				
Carhart	54.43	41.65	0.22	613.13
Fama and French	42.21	34.73	0.46	632.25
Ferson and Schadt	629.73	768.66	4.12	22,494.16
Quarterly (constant) market beta				
Carhart	98.99	18.23	−137.36	311.39
Fama and French	100.68	19.30	−149.27	364.77
Ferson and Schadt	93.39	780.03	−12,283.51	17,419.38

This table shows pooled summary statistics for semi-annual *SSA* and (the constant part of) quarterly market beta calculated over non-overlapping semi-annual periods by alternative performance models. Figures are denoted in %.

[19] Amihud and Goyenko (2013) report an R^2 of 39% in a similar regression of TR^2 with fund characteristics, style dummies and time dummies.

Table 9
Predicting performance based on activity (Fama & French, 1993).

Panel A: Pooled panel regression with style-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000014			0.000014		
	(1.18)			(0.80)		
TE		0.000337			−0.000676	
		(0.18)			(−0.26)	
$-TR^2$			0.000038***			0.000037***
			(11.16)			(10.96)
SSA outperformer				−0.000038*		
				(−1.91)		
SSA underperformer				0.000042**		
				(2.03)		
TE outperformer					−0.006074**	
					(−2.18)	
TE underperformer					0.00743***	
					(2.59)	
$-TR^2$ outperformer						0.000008***
						(4.92)
$-TR^2$ underperformer						−0.000004**
						(−2.03)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.03	0.04	0.03	0.03	0.04
Observations	32818	32818	32818	32818	32818	32818

Panel B: Panel regression with fund-fixed effects (within) and style and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	−0.000003			−0.000017		
	(−0.22)			(−0.95)		
TE		0.001831			−0.00072	
		(0.49)			(−0.16)	
$-TR^2$			−0.000032***			−0.000032***
			(−4.70)			(−4.64)
SSA outperformer				0.000003		
				(0.14)		
SSA underperformer				0.000035*		
				(1.69)		
TE outperformer					0.001537	
					(0.56)	
TE underperformer					0.003699	
					(1.24)	
$-TR^2$ outperformer						0.000004**
						(2.06)
$-TR^2$ underperformer						−0.000003
						(−1.56)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.02	0.02	0.02	0.02	0.02	0.02
Observations	32,818	32,818	32,818	32,818	32,818	32,818

This table presents coefficients of panel regressions of fund performance in the 6-month post-ranking period $t+1$ on fund activity in the semi-annual ranking period t. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from quarter $q-1$ to quarter q within t. For Models (4), (5) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in the semi-annual ranking period t with respect to performance. We control for lagged fund characteristics (expense ratio, turnover ratio, total net assets, and age) and performance (alpha) as possible predictors of performance. Further, in Panel A we control for style-fixed effects and in Panel B for fund-, style- and time-fixed effects. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

by "tournament behavior" in outperformers, who increase activity to preserve their winner status (e.g., Brown, Van Harlow, & Zhang, 1996; Busse, 2001). The latter can be explained by the urge in underperformers who increase their activity to shake off their loser status. Finally, the results on the style dummies indicate that micro-cap funds have a significant tendency to above-average activity, whereas large cap funds and, to some extent, growth & income funds have a significant tendency to below average activity. Otherwise the styles seem to have only minor impact on the activity level of most mutual funds.

5. Robustness tests

5.1. Alternative performance models

To test if our results are stable across different alternative models, we replicate our main empirical analysis using net returns with two alternative models. The first is the Fama and French (1993) three-factor model. Table 8 shows pooled summary statistics for *SSA* from our non-overlapping semi-annual measurement periods. The statistics for the Carhart (1997) and the Fama and

Table 10
Predicting performance based on activity (Ferson & Schadt, 1996).

Panel A: Pooled panel regression with style-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000006***			0.000012***		
	(2.87)			(3.00)		
TE		−0.075631***			−0.067596***	
		(−6.64)			(−4.78)	
$-TR^2$			−0.000162***			−0.000164***
			(−7.69)			(−7.80)
SSA outperformer				0.000002		
				(0.33)		
SSA underperformer				−0.000014***		
				(−3.04)		
TE outperformer					0.015456	
					(1.00)	
TE underperformer					−0.03834**	
					(−2.53)	
$-TR^2$ outperformer						−0.000003
						(−0.43)
$-TR^2$ underperformer						0.000022***
						(2.72)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.01	0.01	0.01	0.01	0.01	0.01
Observations	32,818	32,818	32,818	32,818	32,818	32,818

Panel B: Panel regression with fund-fixed effects (within) and style and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.00001***			0.000011**		
	(3.29)			(2.40)		
TE		−0.095103***			−0.095734***	
		(−4.02)			(−3.67)	
$-TR^2$			−0.000368***			−0.000373***
			(−8.93)			(−9.07)
SSA outperformer				0.000008		
				(1.63)		
SSA underperformer				−0.000009*		
				(−1.95)		
TE outperformer					0.011787	
					(0.76)	
TE underperformer					−0.013678	
					(−0.90)	
$-TR^2$ outperformer						0.000025***
						(3.14)
$-TR^2$ underperformer						−0.000001
						(−0.12)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.04	0.05	0.05	0.04	0.05	0.05
Observations	32,818	32,818	32,818	32,818	32,818	32,818

This table presents coefficients of panel regressions of fund performance in the 6-month post-ranking period $t+1$ on fund activity in the semi-annual ranking period t. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from quarter $q-1$ to quarter q within t. For Models (4), (5) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in the semi-annual ranking period t with respect to performance. We control for lagged fund characteristics (expense ratio, turnover ratio, total net assets, and age) and performance (alpha) as possible predictors of performance. Further, in Panel A we control for style-fixed effects and in Panel B for fund-, style- and time-fixed effects. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.
** Statistical significance at the 5% level.
*** Statistical significance at the 1% level.

French (1993) models are within a reasonable range, with mean *SSA* from one quarter to the next of 54.43% and 42.21%, respectively. Standard deviation as well as extreme values are also acceptable. However, given the difference of roughly 12% between the means, "momentum shifting" seems to be a considerable part of *SSA* which is not covered by the Fama and French (1993) model.

Therefore, we expect less significant results compared to our main analysis, which is exactly what we find. Overall, the results are quite similar, so in Table 9 we present only the single-measure performance prediction analysis (similar to Table 3) to demonstrate the difference between the models.[20] Panel A shows pooled panel regression results with style-fixed effects. *SSA* is positively related to future performance, however this time not significantly. *TE* and $-TR^2$ results are as in our main analysis. Panel B shows a within-panel regression with additional time- and fund-fixed effects. *SSA*

[20] For brevity, the additional tables of our analysis using Fama and French (1993), show similar results to Tables 1, 2, 4, 5 and 7 and are available upon request.

results are now negative but insignificant, while $-TR^2$ turns significantly negative as in our main analysis. Thus, momentum seems to be an important style which must be considered when measuring *SSA*. This is consistent with very recent findings by Barroso and Santa-Clara (2015), that momentum profitability fluctuates notably over time so that momentum-shifting can be a reasonable management strategy.

As the second alternative model, we use a Carhart (1997) four-factor model with conditional market beta following Ferson and Schadt (1996). Daily conditioning variables are from the Federal Reserve Bank of St. Louis homepage and from Thomson Reuters Datastream. Specifically, we use the daily S&P 500 dividend yield, the term spread (yield spread between 10-year U.S. government bond and a 3-month T-bill), the default spread (yield spread between BAA and AAA bonds) and a liquidity premium represented by the 3-month T-bill yield (e.g., Coggins, Beaulieu, & Gendron, 2009). All lagged conditioning variables are demeaned. As we are interested in actual changes of style and not in the elusive reactions to daily macroeconomic signals, we use the constant component of the fund's conditional market beta when calculating style-shifting activity.

The *SSA* statistics from the Ferson and Schadt (1996) conditional model shown in Table 8 are distinctively higher than those from the other models, with a mean *SSA* from quarter to quarter of 629.73% and a maximum of 22,494.16%. We suspect the reason for these figures to be related to very short measurement periods, which are as low as three months. This might lead to the conditioning macroeconomic variables dominating the market return. In this context, the lower part of Table 8 shows statistics for the quarterly market betas used to calculate *SSA*. While the Carhart (1997) and Fama and French (1993) market betas are in very reasonable range, the Ferson and Schadt (1996) constant market betas have a huge standard deviation of 780% as well as extreme values of −12,284% and +17,419%, which makes us rather suspicious as to the reliability of *SSA*. Moreover, correlations between *SSA* and the other measures are much lower with 30.92% (TE) and 40.32% ($-TR^2$) compared to the values around 60% reported in Table 1.[21]

In Table 10 we present results for performance predictions using single-activity measures (similar to Table 3). Despite the noisiness of the *SSA* measure, we find many of our results to be quite similar to our main analysis.[22] Panel A shows the results for pooled panel regressions with style-fixed effects. The results are such that *SSA* has a significant and positive effect on future performance while *TE* and $-TR^2$ show significant and negative impact on performance. In Panel B showing within-panel results with additional time- and fund-fixed effects, these relations remain robust, while control variables are now insignificant. These results overall strengthen the findings from our main analysis, that *SSA* is a reliable predictor of future performance.

5.2. Monthly return data

One major advantage of *SSA* is that it is capable of measuring a very specific type of activity: Style-shifting from one quarter to the next. In doing so, it also captures short-lived relations between the level of current activity and future performance. However Amihud and Goyenko (2013), from whom we borrow much of the methodology for convenient comparability, work mainly with monthly return-data over bi-annual measurement periods. Therefore, we replicate our main analysis using monthly net returns. Data for this robustness test is also taken from the CRSP database using similar screening criteria as described in Section 3.1. Our final sample of 4662 active US domestic equity mutual funds covers the same period as our daily data from 1998 to 2009.[23] To calculate *SSA*, we split the bi-annual measurement periods in half to measure style-shifts from one year to the next, thereby sacrificing the measure's short-term properties. The one-month performance $alpha_{i,m}$ used for performance prediction and double-sorting analysis is calculated as out-of-sample alpha following Eq. (11):

$$alpha_{i,m} = r_{i,m} - \sum_{k=1}^{N} b_{i,t-1}^{k} f_{m}^{k} \tag{11}$$

where $r_{i,m}$ is the excess return of fund i in month m, $b_{i,t-1}^{k}$ is the factor loading of fund i to factor k in bi-annual period $t-1$ and f_m^k, $k = 1, \ldots, N$, are the returns of the Carhart (1997) equity style factors in month m.

Panel A of Table 11 reports comparable correlations between the three activity measures using monthly data parallel to those in Table 1 using daily data. In addition, Panel B reports correlations between similar activity measures calculated from monthly and daily data. "Cross-sectional" reports correlations between the average activity measures of the funds. Values above 90% prove that monthly and daily data measure average relative activity very consistently. "Pooled" additionally integrates the time dimension. The relatively low values, especially for *SSA*, show that changes in activity over time within a fund cannot be measured very consistently due to the difference between semi-annual (daily) and bi-annual (monthly) measurement periods. This might also be due to the short measurement periods of twelve months used for estimating the annual betas.

Table 11
Relations between activity measures (monthly vs. daily, 1998–2009).

Panel A. Monthly data

	Correlation			$\sqrt{R^2}$
	SSA	*TE*	$-TR^2$	
SSA	100.00			67.10
TE	64.20	100.00		70.34
$-TR^2$	53.43	58.59	100.00	62.11

Panel B. Monthly vs. daily data

	Correlation *SSA*	*TE*	$-TR^2$
Cross-section	90.78	95.16	92.68
Pooled	33.48	52.56	49.24

This table shows relations between the three activity measures *SSA*, *TE* and $-TR^2$ for pooled semi-annual observations from 24-month measurement periods from 1998 to 2009. In Panel A, "Correlation" is the pairwise standard correlation. "$\sqrt{R^2}$" is the square root of the coefficient of determination from a pooled regression of one activity measure by the other two. It represents the correlation of one activity measure with a linear combination of the other two. In Panel B, "Cross-section" is the correlation between average activity of funds measured using monthly data and average activity of funds using daily data. "Pooled" is the correlation between activity measured for each fund and each semi-annual period using monthly data and activity measured using daily data.

[21] For brevity, these correlations (similar to Table 1) and further tables based on the additional analysis using Ferson and Schadt (1996) show similar results to Tables 2, 4, 5 and 7, and are available upon request.

[22] In fact, only the double-sorting results (similar to Table 5), where future performance is measured over very short one-month periods, are negatively affected by the noisiness of *SSA*.

[23] In even further robustness checks, we use monthly returns of 4935 funds over the period from 1990 to 2009 which is only one year shorter than in Amihud and Goyenko (2013). The results are qualitatively the same and available upon request.

Table 12
Predicting performance based on activity (monthly data, 1998–2009).

Panel A: Pooled panel regression with style-fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000561**			0.000514		
	(2.14)			(1.63)		
TE		0.013192			−0.00717	
		(0.56)			(−0.27)	
$-TR^2$			0.001702***			0.001564***
			(7.24)			(6.73)
SSA outperformer				−0.00109***		
				(−3.59)		
SSA underperformer				0.001103***		
				(3.51)		
TE outperformer					−0.14734***	
					(−5.42)	
TE underperformer					0.150882***	
					(5.95)	
$-TR^2$ outperformer						0.000807***
						(9.80)
$-TR^2$ underperformer						−0.000687***
						(−7.41)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.03	0.03	0.04	0.04	0.04	0.04
Observations	36,986	36,986	36,986	36,986	36,986	36,986

Panel B: Panel regression with fund-fixed effects (within) and style and time dummies

	(1)	(2)	(3)	(4)	(5)	(6)
SSA	0.000268			−0.000006		
	(1.00)			(−0.02)		
TE		−0.029717			−0.052853	
		(−0.93)			(−1.48)	
$-TR^2$			0.001081***			0.001152***
			(2.76)			(2.93)
SSA outperformer				0.000263		
				(0.84)		
SSA underperformer				0.000454		
				(1.38)		
TE outperformer					−0.02452	
					(−0.86)	
TE underperformer					0.077825***	
					(2.85)	
$-TR^2$ outperformer						0.000396***
						(4.06)
$-TR^2$ underperformer						−0.000435***
						(−4.15)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Overall R^2	0.08	0.08	0.08	0.08	0.08	0.09
Observations	36.986	36.986	36.986	36.986	36.986	36.986

This table presents coefficients of panel regressions of fund performance in the 1-month post-ranking period m on fund activity in the bi-annual ranking period $t-1$. Style-shifting activity (*SSA*) is calculated as the absolute difference in factor loadings from the first to the second year within $t-1$. For Models (4), (5) and (6) we include dummy variables indicating if a fund was an outperformer (upper third) or an underperformer (lower third) in the bi-annual ranking period $t-1$ with respect to performance. We control for lagged fund characteristics (expense ratio, turnover ratio, total net assets, and age) and performance (alpha) as possible predictors of performance. Further, in Panel A we control for style-fixed effects and in Panel B for fund-, style- and time-fixed effects. Standard errors are clustered by fund. *T*-values are reported in parentheses.

* Statistical significance at the 10% level.

** Statistical significance at the 5% level.

*** Statistical significance at the 1% level.

To display our findings based on monthly data, we present single-measure performance prediction results in Table 12 (similar to Table 3).[24] Panel A shows pooled panel results with style-fixed effects from overlapping semi-annual periods. The results indicate that all three performance measures are positively related to performance, *SSA* and $-TR^2$ significantly. Thus, we confirm the results documented above in our main analysis and those by Amihud and Goyenko (2013). Panel B shows within-panel regression results with additional time- and fund-fixed effects. $-TR^2$ remains a significant and positive predictor of future performance. *SSA* is positively related to future performance in the linear regressions and positively related to out- and underperformance in the non-linear regression, though not significantly, which might be due to the higher noisiness of beta estimates and *SSA* measures when using monthly returns. *TE* becomes negative but insignificant. Overall, the results of the robustness test strengthen our belief in *SSA* as a consistent and valuable addition to the mutual fund activity literature.

[24] For brevity, further tables based on the additional analysis using monthly data show similar results to Tables 2, 4, 5 and 7 and are available upon request.

6. Summary and conclusion

This study introduces an innovative approach to measuring the "style-shifting activity" of mutual funds. By using conveniently available return-data to calculate a type of activity usually measured based on detailed portfolio holdings, we combine the two dominant streams of the mutual fund activity literature. Applying our new measure on a comprehensive sample of 2631 active US equity mutual funds, we are able to confirm our two main research hypotheses, that (i) *SSA* predicts future performance, especially for current outperformers, and (ii) that *SSA* adds new information previously not captured by the popular return-based activity measures tracking error and *R*-squared.

Moreover, comparing the three measures, we show that *SSA* captures activity very selectively. This makes it a stable and reliable predictor of future performance, as this finding is consistent for a wide range of different regression approaches. Tracking error and *R*-squared, on the other hand, seem to capture some unobserved fund characteristics besides management activity, as their predictions regarding future performance depend heavily in sign and power on the consideration of time- and fund-fixed effects.

Finally, in using a double-sorting portfolio approach we show that investment strategies based on past *SSA* and past performance earn up to 2.4% (3.6%) p.a. risk-adjusted net (gross) returns, which is economically and statistically significant. In a further test, we document that risk-adjusted portfolio returns from double-sorting on combinations of past activity is superior to sorting on single measures. Overall, our results provide convincing evidence in favor of style-shifting activity as a valuable activity measure both in its own right and as an addition to other popular measures such as tracking error and *R*-squared.

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