9-2021

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Turan G. Bali
Georgetown University

Stephen J. Brown
New York University

Mustafa O. Caglayan
Florida International University

Umut Celiker
Cleveland State University, u.celiker@csuohio.edu

JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 56, No. 6, Sept. 2021, pp. 2136–2169

doi:10.1017/S0022109020000794

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Turan G. Bali
Georgetown University McDonough School of Business
turan.bali@georgetown.edu

Stephen J. Brown
Monash Business School and NYU Stern School of Business
stephen.brown@monash.edu

Mustafa O. Caglayan
Florida International University College of Business
mustafa.caglayan@fiu.edu (corresponding author)

Umut Celiker
Cleveland State University Monte Ahuja College of Business
u.celiker@csuohio.edu

Abstract

This paper investigates hedge funds' ability to time industry-specific returns and shows that funds' timing ability in the manufacturing industry improves their future performance, probability of survival, and ability to attract more capital. The results indicate that the best industry-timing hedge funds in the manufacturing sector have the highest return exposure to earnings surprises. This, together with persistently sticky earnings surprises, transparent information environment in regards to earnings releases, and large post-earnings-announcement drift in the manufacturing industry, explain to a great extent why best-timing hedge funds can generate significantly larger future returns compared to worst-timing hedge funds.

I. Introduction

In this paper we investigate if hedge funds can time industry-specific returns and whether timing ability within specific industries pays off in terms of superior future performance, higher probability of survival, and larger fund flows. Standard & Poor's (S&P) Global Market Intelligence Hedge Fund Tracker report provides information on changes in hedge funds' industry allocations on a quarterly basis. Motivated by such reports, we test whether hedge funds change their allocations in industries in a timely manner ahead of positive and negative industry-specific news, and whether

We thank an anonymous referee, Vikas Agarwal, George Aragon, Yong Chen, Jarrad Harford (the editor), Bing Liang, and Tim Simin (a referee) for their constructive comments and suggestions. We also benefited from discussions with Michael Gallmeyer, Shahid Hamid, Qiping Huang, Qiang Kang, Edward Lawrance, Ozde Oztekin, Gokhan Sonaer, Quan Wen, and seminar participants at Florida International University and Georgetown University. We thank Kenneth French and David Hsieh for making a large amount of data publicly available in their online data library. We thank Vikas Agarwal for sharing data on options factors. All errors remain our responsibility.

such behavior results in superior future performance. Specifically, we ask the following questions: Can hedge funds time industry-specific returns by strategically adjusting their betas to industry news based on their forecasts of future economic conditions in those industries? If so, does industry-timing ability improve future fund performance and how much economic value does it bring to hedge fund investors? We believe the answers to these questions are important for hedge fund managers and investors, and contribute to a growing academic literature on learning by investors.

While this is the first paper to analyze hedge funds' timing ability in industries, it follows an extensive literature that has studied various aspects of the timing ability of professional fund managers. Following the pioneering work by Treynor and Mazuy (1966), a large number of studies have investigated the market-timing, volatility-timing, liquidity-timing, and macro-timing abilities of mutual funds and hedge funds.[1] By analyzing hedge funds' ability to time industry-specific returns, this paper contributes significantly to the growing literature on the timing ability of professional fund managers by providing a new aspect of timing ability. More importantly, the results indicate that hedge funds' industry-timing ability, particularly in the manufacturing sector, predicts the cross-sectional variation in future hedge fund returns. From this perspective, the findings also contribute to the literature on the cross-sectional determinants and predictors of hedge fund performance.[2]

In testing the industry-timing ability of hedge funds, we use the market-orthogonalized industry returns in order to differentiate industry-timing ability of hedge funds from their market-timing ability, as industry raw returns are strongly correlated with market returns. For this, we first regress the industry excess returns on the market excess return on a 24-month rolling window basis and obtain industry residual returns each month going back 24 months. Then, by employing the Treynor–Mazuy (1966) timing model, we regress the individual hedge fund excess returns on the industry residual returns and the squared industry residual returns again on a 24-month rolling window basis to obtain the industry-timing coefficients of hedge funds. Lastly, we test the predictive power of these industry-timing coefficients over future hedge fund returns via both Fama and MacBeth (1973) cross-sectional regressions and portfolio-level analyses.

Among the 12 Fama and French (1997) industries tested, we find that hedge funds with stronger ability to time manufacturing-industry-specific news generate significantly higher returns in future months. Specifically, hedge funds in the highest manufacturing industry-timing decile generate a 0.64% per month higher and statistically significant average return in the next month compared to funds in the lowest manufacturing industry-timing decile. This significant return spread between the best- and worst-timing hedge funds is not explained by Fama and

[1]A partial list analyzing fund managers' different aspects of timing ability includes Henriksson and Merton (1981), Jagannathan and Korajczyk (1986), Grinblatt and Titman (1989), Ferson and Schadt (1996), Busse (1999), Jiang, Yao, and Yu (2007), Chen and Liang (2007), Cao, Chen, Liang, and Lo (2013), and Bali, Brown, and Caglayan (2014).

[2]See Fung and Hsieh (1997), (2000), (2001), (2004), Agarwal and Naik (2000), (2004), Liang and Park (2007), Fung, Hsieh, Naik, and Ramadorai (2008), Jagannathan, Malakhov, and Novikov (2010), Sadka (2010), Titman and Tiu (2011), Bali, Brown, and Caglayan (2011), (2012), (2014), Agarwal, Arisoy, and Naik (2017), and Agarwal, Ruenzi, and Weigert (2017) for other cross-sectional determinants of future hedge fund performance.

French (1993), Carhart (1997), and Fung and Hsieh (2001), (2004) hedge fund risk factors either. The results from the multivariate Fama–MacBeth cross-sectional regressions also show that the positive relation between hedge funds' manufacturing industry-timing coefficients and their future returns persists after controlling for individual fund characteristics and funds' market-timing, liquidity-timing, and volatility-timing abilities simultaneously. Also, the long-term predictability tests indicate that the positive relation between manufacturing industry-timing betas and hedge fund returns lasts up to 6 months. Our results show that the funds with better timing ability in the manufacturing industry attract more capital and have higher probability of survival in the following 6- to 12-month period. Timing the other 11 industries does not yield such results in terms of future performance, flows, and survival.

In an attempt to explain why industry-timing coefficients predict future hedge fund returns, specifically in the manufacturing industry but not in other industries, we explore the relationship between hedge funds' industry-timing betas and their exposures to earnings surprises. We believe that earnings news could be an important component of industry-specific returns, and hedge funds with stronger ability to time industry-specific returns could have higher return exposures to the earnings news. Specifically, if a hedge fund is good at timing industry-specific returns and those returns are related to earnings surprises, then we should expect to see higher returns for that fund when earnings significantly deviate from their expected values in either direction. In line with this hypothesis, we find that the average beta for the absolute value of the standardized unexpected earnings (SUEs) increases monotonically from the worst industry-timing decile to the best industry-timing decile, and the difference in SUE betas is positive and highly significant in a meaningful way only in the manufacturing industry. On the other hand, we find no such relation between industry-timing coefficients and hedge funds' SUE betas in other industries. This suggests that hedge fund managers that time manufacturing industry-specific returns pay particular attention to earnings news in the manufacturing industry.

We also find that manufacturing industry's earnings surprises exhibit the highest persistence among all of the 12 Fama–French industries studied. The persistently high autocorrelation in manufacturing SUE suggests that firms in the manufacturing industry are more likely to generate same-direction earnings surprises as their peers in the following months. In addition, we analyze the degree of information uncertainty (transparency vs. opaqueness) in firms' earnings releases and investigate if there is a connection between the transparency of the industry, the magnitude of the post-earnings-announcement drift, and the industry-timing ability that is unique to the manufacturing industry. We find that the information environment in the manufacturing industry, in regards to earnings releases, is one of the most transparent among all industries considered. In relation to this, we also find that the manufacturing industry experiences the largest combined post-earnings-announcement drift on positive and negative earnings surprises. We believe all these findings together explain to a great extent why best-timing hedge funds can generate significantly larger returns in future months compared to worst-timing hedge funds in the manufacturing industry.

In our analysis, we also control for the use of public information in testing the timing ability. A fund manager may give the illusion that she can time manufacturing industry-specific returns by reacting solely to lagged earnings surprises which are public information. Following Ferson and Schadt (1996), we generate manufacturing industry-timing coefficients controlling for the effect of reacting to past earnings surprises, and find that manufacturing industry-timing coefficients continue to predict future hedge fund returns. This suggests that the predictive power of manufacturing industry-timing coefficients is not confined to the use of past SUEs only.

Lastly, in an effort to provide a more direct, corroborating evidence on hedge funds' industry-timing skill in the manufacturing sector, we analyze hedge funds' 13F stock holdings. We find that compared to the worst manufacturing industry-timing funds, the best manufacturing industry-timing funds hold significantly more (less) dollar amount of manufacturing industry stocks in the quarter heading up to the materialization of the best (worst) manufacturing industry-specific returns.

The rest of the paper is organized as follows: Section II describes the hedge fund data and industry returns. Section III presents the empirical results on the industry-timing ability of hedge funds. Section IV investigates the source of hedge funds' industry-timing ability particularly in the manufacturing sector. Section V uses hedge funds' 13F holdings data to provide evidence on the industry-timing ability of hedge funds in the manufacturing sector. Section VI concludes the paper.

II. Data

In this section, we first describe the hedge fund database, provide summary statistics on the number of hedge funds, hedge fund returns, and fund characteristics. We then present descriptive statistics on industry returns obtained from Kenneth French's online data library.

A. Hedge Fund Sample

This paper uses monthly hedge fund returns and fund characteristics data of 11,987 individual hedge funds from the Lipper Trading Advisor Selection System (TASS) database. Even though hedge fund returns go back as far as 1974, the TASS database does not include defunct funds prior to 1994. Thus, in an effort to mitigate potential survivorship bias in the data, we select 1994 as the start of our sample period. The TASS database, in addition to reporting monthly returns (net of fees) and assets under management (AUM), provides information on certain fund characteristics, including management fees, incentive fees, redemption periods, minimum investment amounts, and lockup and leverage provisions. The summary statistics on fund returns, AUM, and fund characteristics are provided in Section 1 of the Supplementary Material. Panel A of Table I in the Supplementary Material provides statistics on the numbers, returns, and AUM of hedge funds on a yearly basis for the sample of 11,987 hedge funds. Panel B of Table I in the Supplementary Material reports the cross-sectional mean, median, standard deviation, minimum, and maximum values for certain hedge fund characteristics for the period Jan. 1994–Sept. 2018. Moreover, in Section 2 of the Supplementary Material, we provide a detailed discussion on how we handle potential data bias issues, such as survivorship bias, backfill bias, and multi-period sampling bias (look-ahead bias) in our paper (see Fung and Hsieh (2000), Liang (2000), Aggarwal and Jorion

(2010), and Agarwal, Fos, and Jiang (2013) for discussions on data biases in hedge fund studies). After addressing all potential data bias issues, the total number of hedge funds in our sample reduces to 7,902 from 11,987 funds.[3]

B. Industries

This paper uses Fama–French 12-industry classification. Panel A of Table II in the Supplementary Material lists the names, abbreviations, and details of the 12-industry classifications. While industry #12 (others) includes some sectors unrelated to each other, we keep it in our analysis for the sake of completeness. Generated on a 24-month rolling window basis, in Panel B of Table II in the Supplementary Material, we report average values for the mean, standard deviation, minimum, and maximum statistics of the value-weighted monthly industry returns for each of the 12 industries. The mean of the 24-month rolling window average industry returns ranges between 0.71% (telecom industry) and 1.13% (business equipment, tech industry) per month across different industries over the sample period Jan. 1994–Sept. 2018. Similarly, the average of the 24-month rolling window standard deviation of returns ranges from 3.43% (nondurables industry) to 6.53% (business equipment industry) across different industries during the same time period. On the other hand, the same rolling-window average return and standard deviation figures for the (Center for Research in Security Prices) CRSP market value-weighted index are 0.86% and 4.07%, respectively, suggesting that industries can show significant deviation from the market in terms of both returns and risk.

Lastly, in Panel C of Table II in the Supplementary Material, the average correlations between the value-weighted monthly industry returns (generated on a 24-month rolling window basis) are reported to the left of the diagonal of the correlation matrix, and the average correlations between the industry residual returns (generated again on a 24-month rolling window basis) are reported to the right of the diagonal of the correlation matrix. The correlation matrix shows that the correlations among industries generated from the industry residual returns are significantly lower compared to the correlations generated from value-weighted industry returns. In fact, while the average cross-correlation between the 12 industries using the value-weighted returns is 57.6%, the average cross-correlation using the industry residual returns is only -2.6%. The correlation matrix also shows that the value-weighted industry returns are strongly and positively correlated with the market return. These high correlations of the industries with the market validate our use of market-orthogonalized industry returns in testing hedge funds' timing abilities in industries.

[3]After taking care of all potential data bias issues, we also winsorize hedge fund returns each month cross-sectionally at 0.125% and 99.875% percentiles to eliminate the effect of erroneously entered excessively high positive and negative returns by the database vendor. It came to our attention that a few hedge funds had monthly returns over 1,000% in random months and a few other funds had monthly returns less than -300% again in some other random months. We believe these returns are mistakenly inputted into the TASS database and winsorizing hedge fund returns at small 0.125% and 99.875% percentiles helps us to get rid of those erroneously inserted excessively high and low returns while preserving the structure and dynamics of hedge fund returns at tail ends.

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

III. Empirical Results

In this section, we first examine whether hedge funds' industry-timing ability generates superior returns via both parametric cross-sectional Fama–MacBeth regressions and nonparametric portfolio tests. We then study the predictive power of hedge funds' industry-timing betas over future hedge fund returns across different hedge fund investment styles. Next, we analyze the long-term predictive power of industry-timing coefficients and investigate the persistence in manufacturing industry-timing betas. Lastly, we evaluate the link between hedge funds' industry-timing ability and future fund flows and future fund survival.

A. Fama–MacBeth Regressions of Future Hedge Fund Returns on Industry-timing Coefficients

We analyze the relationship between hedge funds' industry-timing ability and their next-month returns first with cross-sectional Fama–MacBeth regressions. Since our focus is on the industry-timing ability of hedge funds, and because industry returns are highly correlated with market returns, we start our analysis by orthogonalizing industry returns with respect to the market. For this, we regress the industry excess returns on the market excess return on a 24-month rolling window basis using the following equation:

$$R_t^j = \theta_0^j + \theta_1^j \cdot \mathrm{MKT}_t + \varepsilon_t^j, \tag{1}$$

where R_t^j is the Fama and French (1997) value-weighted industry excess return for industry j in month t, MKT_t is the excess return on the CRSP value-weighted market index in month t,θ_1^j is the industry beta for industry j, and ε_t^j is the residual error term, which corresponds to the industry-specific return for industry j in month t, denoted by $\mathrm{RES\_IND}_{j,t}$. By running equation (1) for the first time during the period Jan. 1994–Dec. 1995 and on a 24-month rolling window basis afterward for each of the 12 industries separately, we obtain industry residual returns (i.e., industry-specific returns) for each industry for each month going back 24 months. We then employ the Treynor and Mazuy (1966) timing model and regress the individual hedge fund excess returns on the industry and squared industry residual returns (for each of the 12 industries separately) on a 24-month rolling window basis using the following equation:

$$R_{i,t} = \beta_{0,i}^j + \beta_{1,i}^j \cdot \mathrm{RES\_IND}_{j,t} + \beta_{2,i}^j \cdot \mathrm{RES\_IND}^2_{j,t} + e_{i,t}, \tag{2}$$

where $R_{i,t}$ is the excess return on fund i in month t, $\mathrm{RES\_IND}_{j,t}$ is the industry-specific return for industry j in month t, and $\mathrm{RES\_IND}^2_{j,t}$ is the squared industry residual return for industry j in month t. In equation (2), $\beta_{2,i}^j$ represents the industry-timing coefficient for fund i in industry j. By running regression equation (2) for the first time for the period Jan. 1994–Dec. 1995 and on a 24-month rolling window basis afterward, we obtain time-series of industry-timing coefficients for each fund and industry. Our estimation of $\beta_{2,i}^j$ is feasible in that it only uses past information available to investors, so there is no look-ahead bias. Also, estimating regressions

(1) and (2) in this order enable us to differentiate hedge funds' industry-timing ability from their market-timing ability.

1. Univariate Fama–MacBeth Regressions

In order to examine the predictive power of the industry-timing coefficients on future hedge fund returns, at each month starting from Jan. 1996, we run univariate Fama–MacBeth cross-sectional regressions for each industry by regressing the one-month-ahead hedge fund excess returns on the industry-timing coefficients obtained from equation (2):

$$R_{i,t+1} = \omega_t + \lambda_t \cdot \beta^{j}_{2,i,t} + \varepsilon_{i,t+1}, \tag{3}$$

where $R_{i,t+1}$ is the excess return on fund i in month $t+1$ and $\beta^{j}_{2,i,t}$ is the industry-timing coefficient for fund i and industry j in month t. ω_t and λ_t are, respectively, the monthly intercepts and slope coefficients.[4]

Panel A of Table 1 reports the time-series average slope coefficients from equation (3) over the sample period from Jan. 1996 to Sept. 2018 for each of the 12 Fama–French industries. The corresponding Newey and West (1987) t-statistics are reported in parentheses.[5] Panel A shows a positive and significant relation between hedge funds' industry-timing coefficients and future returns for the manufacturing industry (MNF) only. The average slope coefficient on the manufacturing industry-timing beta is 0.181 with a t-statistic of 2.46. On the other hand, the average slope coefficients for the other 11 industries range from −0.112 (TLC) to 0.109 (DRB), with statistically insignificant t-statistics ranging from −1.50 to 1.47. This initial set of results provides evidence that timing the manufacturing-industry-specific returns predicts the cross-sectional dispersion in future hedge fund returns. However, timing the industry-specific returns in other industries does not lead to higher next-month returns.[6]

2. Multivariate Fama–MacBeth Regressions

We next examine whether individual fund characteristics, funds' risk and return attributes, as well as their market-, liquidity-, and volatility-timing abilities

[4]The industry-timing coefficients utilized in the Fama–MacBeth regressions are in standardized form so that it helps us compare the economic significance and the impact that different industries' timing coefficients have on future hedge fund returns.

[5]We find that the autocorrelation in time-series slope coefficients (estimated from equation (3)) on the industry-timing beta variable dies out quickly after the first lag. Thus, in estimating the Newey–West t-statistics, we follow Newey and West (1994), and set the number of lags equal to the integer part of [4* $(T/100)^{(2/9)}$], where T is the number of observations in the sample period. For T = 273 months in our sample (from Jan. 1996 to Sept. 2018), we use 5 lags in estimating the Newey–West t-statistics in our tables. When we adjust the standard errors (that are estimated using Newey–West) with the methodology proposed by Shanken (1992), we find that the Newey–West t-statistics do not change significantly. This suggests that the generated regressors problem does not significantly alter our main inferences.

[6]We also investigate whether the predictive power of manufacturing industry-timing coefficients persists at the presence of funds' timing ability in other industries by running bivariate Fama–MacBeth cross-sectional regressions of 1-month-ahead hedge fund excess returns on funds' manufacturing industry-timing beta and funds' industry-timing beta in other industries. The results indicate that funds' timing ability in other industries does not eliminate or weaken the significantly positive link between funds' timing ability in the manufacturing industry and their future returns.

TABLE 1

Univariate and Multivariate Fama–MacBeth Regressions of Hedge Fund Excess Returns on Industry-Timing Coefficients

Panel A of Table 1 reports the average slope coefficients from univariate Fama–MacBeth cross-sectional regressions of 1 month-ahead hedge fund excess returns on industry-timing coefficients (separately) over the sample period Jan. 1996–Sept. 2018. The cross-section regressions are run and average slope coefficients are reported separately for each of the 12 Fama–French industries. Panel B reports, for the same sample period Jan. 1996–Sept. 2018, the average slope coefficients from multivariate Fama–MacBeth cross-sectional regressions of 1 month-ahead hedge fund excess returns on manufacturing industry-timing coefficients controlling for fund characteristics, funds' risk and return attributes, as well as their market, liquidity, and volatility timing ability. In both panels, during the sample period, the average number of observations in the cross-section is 1,617 funds. ALPHA is the 9-factor alpha estimated over the past 24 months; STDEV is the standard deviation of monthly hedge fund returns over the past 24 months; SIZE is measured as the natural logarithm of the monthly assets under management (AUM) in millions of dollars; AGE is measured as the natural logarithm of the number of months in existence since inception; MGMTFEE is a fixed percentage fee of assets under management; INCENTFEE is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate; REDEMP is the minimum number of days an investor needs to notify a hedge fund before the investor can redeem the invested amount from the fund; MIN_INVEST is the minimum initial investment amount (measured in millions of dollars in the regression) that the fund requires from its investors to invest in a fund; D_LOCKUP is the dummy variable for lockup provisions (1 if the fund requires investors not to withdraw initial investments for a pre-specified term, and 0 otherwise); D_LEVER is the dummy variable for leverage (1 if the fund uses leverage, and 0 otherwise); MKT_TMG is the fund's market-timing coefficient; LIQ_TMG is the fund's liquidity-timing coefficient; and VOL_TMG is the fund's volatility timing coefficient. In Panel B, all timing coefficients utilized in the regression are generated separately from 24-month rolling window univariate regressions similar to equation (2). For each regression variable, the corresponding Newey–West t-statistics are reported in parentheses. Numbers in bold denote statistical significance.

Panel A. Univariate Fama–MacBeth Regressions

Model	NDRB Tmg Beta	DRB Tmg Beta	MNF Tmg Beta	ENRG Tmg Beta	CHE Tmg Beta	TECH Tmg Beta	TLC Tmg Beta	UTIL Tmg Beta	SHP Tmg Beta	HLTH Tmg Beta	FIN Tmg Beta	OTH Tmg Beta
Univariate	0.093	0.109	**0.181**	0.022	0.081	0.029	−0.112	−0.088	0.026	0.006	−0.024	0.097
	(1.47)	(1.35)	**(2.46)**	(0.30)	(1.04)	(0.40)	(−1.50)	(−1.15)	(0.52)	(0.10)	(−0.29)	(1.46)
R^2 (%)	4.03	5.28	6.34	4.80	5.08	5.09	5.19	5.20	4.59	5.01	5.24	5.25

Panel B. Multivariate Fama MacBeth Regressions

Model	MNF Tmg Beta	ALPHA	STDEV	SIZE	AGE	MGMTFEE	INCENTFEE	REDEMP	MIN_INVEST	D_LOCKUP	D_LEVER	MKT_TMG	LIQ_TMG	VOL_TMG	R^2 (%)
Multi-variate	**0.224**	**0.201**	**0.040**	0.019	−0.006	0.018	**0.004**	**0.002**	**0.005**	**0.062**	0.004	0.003	**0.015**	**−0.022**	18.19
	(2.84)	**(5.76)**	**(1.71)**	(1.44)	(−0.19)	(0.77)	**(2.35)**	**(3.45)**	**(4.24)**	**(2.08)**	(0.21)	(0.24)	**(1.78)**	**(−2.02)**	

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

explain the positive relation between funds' manufacturing industry-timing ability and future returns. If a fund's industry-timing ability in the manufacturing sector was related to its certain fund characteristics, or was linked to that fund's market-, liquidity-, or volatility-timing ability, then controlling for those characteristics and other timing abilities would eliminate the predictive power of the manufacturing industry-timing coefficients. We test this with multivariate Fama–MacBeth regressions by regressing 1-month-ahead hedge fund excess returns on funds' manufacturing industry-timing coefficients, fund characteristics, and other measures of timing ability simultaneously:

$$
\begin{aligned}
(4)\qquad R_{i,t+1} = {} & \omega_t + \lambda_{1,t}\cdot\beta^{\mathrm{MNF}}_{2,i,t} + \lambda_{2,t}\cdot\beta^{\mathrm{MKT}}_{i,t} + \lambda_{3,t}\cdot\beta^{\mathrm{LIQ}}_{i,t} + \lambda_{4,t}\cdot\beta^{\mathrm{VOL}}_{i,t} \\
& + \lambda_{5,t}\cdot \mathrm{ALPHA}_{i,t} + \lambda_{6,t}\cdot \mathrm{STDEV}_{i,t} + \lambda_{7,t}\cdot \mathrm{SIZE}_{i,t} + \lambda_{8,t}\cdot \mathrm{AGE}_{i,t} \\
& + \lambda_{9,t}\cdot \mathrm{MGMTFEE}_i + \lambda_{10,t}\cdot \mathrm{INCENTFEE}_i + \lambda_{11,t}\cdot \mathrm{REDEMP}_i \\
& + \lambda_{12,t}\cdot \mathrm{MIN\_INVEST}_i + \lambda_{13,t}\cdot \mathrm{D\_LOCKUP}_i \\
& + \lambda_{14,t}\cdot \mathrm{D\_LEVER}_i + \varepsilon_{i,t+1},
\end{aligned}
$$

where $R_{i,t+1}$ is the excess return on fund i in month $t+1$, $\beta^{\mathrm{MNF}}_{2,i,t}$ is the manufacturing industry-timing coefficient for fund i in month t obtained from equation (2), $\beta^{\mathrm{MKT}}_{i,t}$ is the market-timing coefficient for fund i in month t estimated following the methodology used in Chen and Liang (2007), $\beta^{\mathrm{LIQ}}_{i,t}$ is the liquidity-timing coefficient for fund i in month t estimated following the methodology used in Cao et al. (2013), and $\beta^{\mathrm{VOL}}_{i,t}$ is the volatility-timing coefficient for fund i in month t estimated following the methodology proposed by Busse (1999). ALPHA, STDEV, SIZE, AGE, MGMTFEE, INCENTFEE, REDEMP, MIN_INVEST, D_LOCKUP, and D_LEVER are fund characteristics: ALPHA is the is the 9-factor alpha estimated over the past 24 months; STDEV is the standard deviation of monthly hedge fund returns over the past 24 months; SIZE is measured as the natural logarithm of the assets under management (AUM) in millions of dollars; AGE is measured as the natural logarithm of the number of months in existence since inception; MGMTFEE is a fixed percentage fee of assets under management, typically ranging from 1% to 2%; INCENTFEE is a fixed percentage fee of the fund's annual net profits above a designated hurdle rate; REDEMP is the minimum number of days an investor needs to notify a hedge fund before the investor can redeem the invested amount from the fund; MIN_INVEST is the minimum initial investment amount (measured in millions of dollars in the regression) that the fund requires from its investors to invest in a fund; D_LOCKUP is the dummy variable for lockup provisions (1 if the fund requires investors not to withdraw initial investments for a prespecified term, and 0 otherwise); and D_LEVER is the dummy variable for leverage (1 if the fund uses leverage, and 0 otherwise).

Panel B of Table 1 reports the time-series average slope coefficients from equation (4) over the period from Jan. 1996 to Sept. 2018. In this regression specification, all timing coefficients utilized in the regression as control variables are generated separately from 24-month rolling window univariate regressions similar to equation (2). The results from Panel B show that the average slope coefficient on $\beta^{MNF}_{2,i,t}$ is 0.224 with a t-statistic of 2.84, suggesting that manufacturing industry-timing coefficients continue to be a strong predictor of next-month hedge fund returns in a multivariate setting controlling for fund characteristics, funds' risk and return attributes, as well as their market-, liquidity-, and volatility-timing abilities.

By analyzing the significance of average slope coefficients on the control variables, we see that the past 9-factor alpha, standard deviation, incentive fee, redemption period, minimum investment amount, and dummy for lockup variables have significant explanatory power over the next-month hedge fund returns.[7] However, controlling for these fund characteristics does not eliminate or weaken the predictive power of manufacturing industry-timing coefficients. Among funds' other timing abilities, consistent with Cao et al. (2013), who show a positive and significant relation between funds' liquidity-timing betas and their future alphas, we also find that the average slope coefficient on the liquidity-timing beta is positive and significant. Similarly, in line with Busse (1999), we find that the average slope coefficient on the volatility-timing beta is negative and significant, suggesting that funds with better volatility-timing ability (i.e., funds with larger negative volatility-timing coefficients) produce superior future returns. Most importantly, these significant links between liquidity/volatility-timing ability and future fund performance do not diminish the significantly positive relation between funds' timing ability in the manufacturing industry and their future returns.

B. Univariate Portfolio Analysis of Manufacturing Industry-Timing Coefficients

Next, we examine the relation between manufacturing industry-timing coefficients and future returns via univariate portfolio tests. Each month, we sort hedge funds in ascending order into deciles according to their manufacturing industry-timing coefficients ($\beta_{2,i,t}^{\mathrm{MNF}}$) obtained from equation (2). The first column in Table 2 presents the funds' average $\beta_{2,i,t}^{\mathrm{MNF}}$ in each timing decile. The second column of Table 2 reports the percentage of hedge funds that have statistically significant manufacturing industry-timing coefficients (at the 10% significance level or better) in each timing decile. We find that the percentage of funds with positive significant timing coefficients in the manufacturing industry increases slowly at first from 0% in decile 1 to 3% in decile 5, but then increases exponentially to 25% in decile 9, and finally to 48% in decile 10. These higher percentages in higher ranked deciles provide evidence of industry-timing ability in the manufacturing sector for a respectable number of hedge funds. The third column in Table 2 reports that the standard deviations of decile 10 and decile 1 portfolio returns (best and worst manufacturing industry-timing funds) are noticeably higher than the other decile portfolios.

The fourth column of Table 2 shows that the next-month returns of hedge funds increase monotonically as we move from decile 1 to decile 10. Hedge funds in the highest manufacturing industry-timing decile generate 0.64% per month higher returns (with a statistically significant Newey–West t-statistic of 2.66) in the next

[7]The positive and significant average coefficients on the redemption period, minimum investment amount, and lockup variables are consistent with Aragon (2007) and Aragon, Martin, and Shi (2019) who find a positive and significant premium for lockup funds vs. nonlockup funds.

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

TABLE 2

Univariate Portfolios of Hedge Funds Sorted on Manufacturing Industry-Timing Coefficients

Table 2 reports decile portfolios formed every month from Jan. 1996 to Sept. 2018 by sorting hedge funds based on their manufacturing industry-timing coefficients. Decile 1 is the portfolio of hedge funds with the lowest industry-timing coefficients (worst-timing funds) and decile 10 is the portfolio of hedge funds with the highest industry-timing coefficients (best-timing funds). The table reports the average magnitude of the manufacturing industry-timing betas, percentage of funds with positive and significant manufacturing industry-timing betas (at 10% significance level or better), standard deviations, as well as the 1-month-ahead average raw returns and 9-factor alphas for each decile. The last 2 rows show the average monthly raw return and 9-factor alpha differences between decile 10 and decile 1, and between decile 10 and the rest (the average of the remaining 9 deciles). Average returns and alphas are defined in monthly percentage terms. Newey--West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the return and alpha differences between decile 10 and decile 1, and between decile 10 and the rest.

	MNF Tmg Beta	% of Funds with Positive Significant MNF Tmg Betas	Std. Dev. (%)	Next-Month Raw Returns (%)	Next-Month 9-Factor Alphas (%)
Low	−0.428	0.00%	3.04	0.32 (1.34)	−0.25 (−1.16)
2	−0.185	0.06%	2.21	0.42 (2.59)	−0.07 (−0.50)
3	−0.112	0.47%	1.78	0.47 (3.60)	0.05 (0.50)
4	−0.069	1.20%	1.57	0.49 (4.26)	0.10 (1.24)
5	−0.038	3.11%	1.58	0.52 (4.78)	0.13 (1.62)
6	−0.011	5.50%	1.63	0.54 (5.24)	0.17 (2.50)
7	0.020	8.81%	1.64	0.56 (5.12)	0.18 (2.55)
8	0.060	15.04%	1.79	0.61 (5.09)	0.23 (3.21)
9	0.126	24.91%	2.42	0.77 (4.80)	0.32 (3.15)
High	0.342	47.55%	3.01	0.96 (4.31)	0.47 (2.69)
High-Low				**0.64** **(2.66)**	**0.72** **(2.52)**
High-Rest (deciles 1 through 9)				**0.44** **(2.94)**	**0.37** **(2.23)**

month compared to funds in the lowest manufacturing industry-timing decile.[8] This corresponds to a 7.68% per annum return difference between the best-timing and worst-timing hedge funds in the manufacturing industry. The significant return spread between the best- and worst-timing hedge funds is not explained by the Fama and French (1993), Carhart (1997), and Fung and Hsieh (2001) standard 9 hedge fund risk factors either.[9] The last column of Table 2 shows that the 9-factor alpha spread between the best- and worst-timing hedge funds is 0.72% per month

[8]We also check the next-month return spread between best- and worst-timing hedge funds in other industries. Consistent with the findings from Fama–MacBeth regressions, we do not find a positive and significant return spread between best- and worst-timing hedge funds in the other 11 industries analyzed.

[9]We obtain risk-adjusted returns (9-factor alphas) for the difference portfolio between decile 10 and decile 1 by regressing the return difference between decile 10 and 1 on the following 9 risk factors: MKT-R_f, SMB, HML, MOM, DEF (Fama and French (1993) default return spread), TERM (Fama and French (1993) term return spread), BDTF (Fung and Hsieh (2001) bond trend-following factor), FXTF (Fung and Hsieh (2001) currency trend-following factor), and CMTF (Fung and Hsieh (2001) commodity trend-following factor). The detailed descriptions of these 9 hedge fund risk factors as well as their data sources are provided in Section 3 of the Supplementary Material.

and highly significant with a t-statistic of 2.52.[10] All the results from our portfolio analysis, combined with the earlier findings from Fama–MacBeth regressions, provide corroborating evidence of an economically and statistically significant positive relation between hedge funds' industry-timing ability in the manufacturing sector and their future raw and risk-adjusted returns.

Table 2 also reports that the positive and significant link between manufacturing industry-timing coefficients and future fund returns is driven by the outperformance of funds with a stronger industry-timing ability, not by the underperformance of funds with a weak industry-timing ability. Both raw returns and 9-factor alphas of funds in decile 10 are positive and highly significant, namely, a 0.96% per month raw return with a t-statistic of 4.31 and a 0.47% per month 9-factor alpha with a t-statistic of 2.69. Whereas, funds in decile 1 have statistically insignificant raw and risk-adjusted returns. As an additional test, when we compare the performance of decile 10 to the performance of the remaining 9 deciles (computed as the average monthly returns of the remaining 9 deciles), we find that the next month return and 9-factor alpha spreads between decile 10 and the rest of the funds are 0.44% (t-stat = 2.94) and 0.37% (t-stat = 2.23) per month, respectively (see the last row in Table 2). These positive and statistically significant return and alpha spreads between decile 10 and the average of the remaining 9 deciles suggest that the best manufacturing industry-timing funds, on average, not only generate superior raw and risk-adjusted returns compared to decile 1, but also compared to the average of the remaining 9 deciles.[11]

C. Robustness Checks on the Predictive Power of Manufacturing Industry-Timing Coefficients

In this section we perform various robustness tests on the predictive power of manufacturing industry-timing coefficients. First, we conduct a subsample analysis to see if the positive and significant relation between manufacturing industry-timing ability and future hedge fund returns exists during both pre- and post-world financial crisis periods. Table IV of the Supplementary Material shows that the positive and significant return and alpha spreads between the best- and worst-timing hedge funds in the manufacturing industry continue in both subsample periods, with stronger t-statistics observed especially in the second half of our sample period covering the years after 2008. These findings provide evidence that

[10]In addition to the standard 9 hedge fund risk factors, we also check if the option-based risk factors of Agarwal and Naik (2004) explain the predictive power of manufacturing industry-timing coefficients over future returns. After controlling for the option-based risk factors, we find that the alpha spread between the best- and worst-timing hedge funds persists at 0.77% per month with a significant t-statistic of 2.31 (for the sample period ending in Oct. 2017), suggesting that the option-based risk factors do not eliminate the predictive power of manufacturing industry-timing betas over future hedge fund returns. We thank Vikas Agarwal for sharing option-based risk factors with us.

[11]We also examine the average fund characteristics within each of the manufacturing industry-timing deciles. Table III of the Supplementary Material shows that both the 9-factor alphas and lagged returns increase monotonically as we move from decile 1 to decile 10. On the other hand, incentive fee, leverage, and standard deviation exhibit a U-shaped relation with the manufacturing industry-timing coefficients, while size (AUM), minimum investment amount, and redemption period display an inverse U-shaped relation with the manufacturing industry-timing coefficients.

hedge fund investors can use manufacturing industry-timing coefficients as a reliable predictor of solid future fund performance in different market conditions.

As another robustness test, we use the methodology utilized by Cao et al. (2013), and generate manufacturing industry-timing coefficients from equation (2) controlling for the 7 risk factors of Fung and Hsieh (2001), (2004). Using the manufacturing industry-timing coefficients estimated from this methodology, Panel A of Table V in the Supplementary Material shows that the best manufacturing industry-timing funds continue to generate superior returns compared to the worst manufacturing industry-timing funds. Specifically, the raw and risk-adjusted return spreads between the best and worst manufacturing industry-timing funds are 0.52% (t-stat = 2.51) and 0.63% (t-stat = 2.63) per month, respectively. When we use these newly generated manufacturing industry-timing coefficients in multivariate Fama–MacBeth regressions together with the other market-, liquidity-, and volatility-timing coefficients generated also by controlling the Fung-Hsieh risk factors, we still obtain a positive and significant average slope coefficient on the manufacturing industry-timing beta (0.178, t-stat = 2.83) in Panel B of Table V of the Supplementary Material. These results suggest that manufacturing industry-timing betas' predictive power over future hedge fund returns prevails after accounting for funds' exposures to standard known hedge fund risk factors, ruling out potential concerns that our main findings are driven by funds' exposures to the Fung-Hsieh risk factors.

In a separate analysis, we also estimate industry-timing coefficients using the Henriksson and Merton (1981) model. Timing ability in the context of Henriksson–Merton implies that hedge funds are able to increase their exposure to the manufacturing industry when the abnormal return on the manufacturing industry is positive (or when the realized return is above the fair rate of return justified by the manufacturing industry's systematic risk). The predictive power of the manufacturing industry-timing coefficients on future hedge fund performance persists when the Henriksson–Merton model is utilized.[12] We report portfolio test results on the manufacturing industry-timing coefficients generated from the Henriksson–Merton model in Panel A of Table VI in the Supplementary Material. Similar to the results from the Treynor–Mazuy (1966) model, we obtain positive and significant return and alpha spreads between the best- and worst-timing hedge funds in the manufacturing industry. In addition, when we rerun the multivariate Fama–MacBeth regressions, Panel B of Table VI in the Supplementary Material shows that the positive and significant relation between manufacturing industry-timing coefficients and future fund returns persists after we control for fund characteristics and funds' other timing-abilities. These results indicate that our main findings are not sensitive to the timing model utilized in estimating the industry-timing betas.[13]

[12]The strong predictive power of manufacturing industry-timing coefficients obtained from the Henriksson–Merton model also rules out a possible interpretation of the manufacturing industry-timing coefficients obtained from the Treynor–Mazuy model as the manufacturing-industry-specific volatility.

[13]As a further robustness check, we follow the methodology proposed by Getmansky, Lo, and Makarov (2004) and estimate unsmoothed hedge fund returns. Then, we form decile portfolios based on the manufacturing industry-timing betas estimated with unsmoothed hedge fund returns. Table VII of the Supplementary Material shows that correcting for smoothed returns of hedge funds does not reduce the significance of the cross-sectional relation between manufacturing industry-timing ability and future hedge fund returns.

D. Bivariate Portfolio Sorts Between Industry-, Market-, Liquidity-, and Volatility-Timing Betas

To validate the findings from multivariate Fama–MacBeth regressions, in this section we conduct independent bivariate portfolio tests between the manufacturing industry-timing ability and funds' other timing abilities. That is, each month during our sample period Jan. 1996–Sept. 2018, hedge funds are independently sorted into quintiles based on their market-timing betas, liquidity-timing betas, volatility-timing betas, and manufacturing industry-timing betas such that 25 bivariate portfolios are created to compare the performance of the best manufacturing industry-timing funds (quintile 5) against the worst-manufacturing industry-timing funds (quintile 1) within each market-, liquidity-, and volatility-timing quintiles.

Panel A of Table 3 reports the return and 9-factor alpha spreads between high and low manufacturing industry-timing funds controlling for funds' market-timing ability. The return and alpha spreads are all positive and significant within each market-timing quintile without exception. Panel B of Table 3 presents results from a similar bivariate portfolio analysis controlling for funds' liquidity-timing ability. The return and alpha spreads are again positive and significant within each liquidity-timing quintile without exception. Lastly, controlling for funds' volatility-timing ability, Panel C of Table 3 shows that all return and alpha spreads are again all positive and highly significant within each volatility-timing quintile without exception. Thus, the results from bivariate portfolio analysis validate our conjecture that the manufacturing industry-timing ability of hedge funds is a timing ability that is distinct from market-, liquidity-, and volatility-timing abilities of hedge funds.

TABLE 3

Bivariate Portfolios of Hedge Funds Sorted on Manufacturing Industry-Timing Betas After Controlling for Market-Timing, Liquidity-Timing, and Volatility-Timing Betas

In Table 3, for each month during our sample period Jan. 1996–Sept. 2018, hedge funds are sorted in an ascending order into quintiles based on their market-timing betas, liquidity-timing betas, volatility-timing betas, and manufacturing industry-timing betas simultaneously (independently) such that 25 portfolios are created to compare the performance of best manufacturing industry-timing funds against worst-manufacturing industry-timing funds within each of the 5 market-timing, 5 liquidity-timing, and 5 volatility-timing quintiles. The table reports the next-month average monthly raw return and 9-factor alpha differences between best and worst manufacturing industry-timing funds within each of the 5 market-timing, 5 liquidity-timing, and 5 volatility-timing quintiles. Average returns and alphas are defined in monthly percentage terms. Newey–West adjusted *t*-statistics are provided in parentheses. Numbers in bold denote statistical significance of the difference portfolio between best and worst manufacturing industry-timing funds.

	Next-Month Raw Returns (%)					Next-Month 9-Factor Alphas (%)				
	1	2	3	4	5	1	2	3	4	5
Panel A. Controlling for Market-Timing Betas										
Best MNF timer-Worst MNF timer	**0.43**	**0.52**	**0.57**	**0.53**	**0.42**	**0.51**	**0.58**	**0.64**	**0.57**	**0.44**
	(2.30)	**(2.96)**	**(2.71)**	**(3.09)**	**(2.13)**	**(2.34)**	**(3.08)**	**(2.76)**	**(2.80)**	**(1.91)**
Panel B. Controlling for Liquidity-Timing Betas										
Best MNF timer-Worst MNF timer	**0.46**	**0.48**	**0.27**	**0.55**	**0.85**	**0.47**	**0.48**	**0.35**	**0.65**	**0.90**
	(2.17)	**(2.39)**	**(1.91)**	**(2.54)**	**(2.79)**	**(2.06)**	**(2.21)**	**(1.87)**	**(2.54)**	**(2.61)**
Panel C. Controlling for Volatility-Timing Betas										
Best MNF Timer-Worst MNF Timer	**0.50**	**0.51**	**0.44**	**0.54**	**0.62**	**0.51**	**0.57**	**0.48**	**0.56**	**0.66**
	(2.33)	**(2.51)**	**(2.35)**	**(2.44)**	**(2.64)**	**(2.12)**	**(2.28)**	**(2.16)**	**(2.36)**	**(2.61)**

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

E. Hedge Fund Style Analysis of the Industry-Timing Ability in the Manufacturing Sector

In this section, we test if the positive and significant relation between industry-timing ability and future returns is specific to a group of hedge fund investment style. The TASS database classifies hedge funds into 10 different styles: convertible arbitrage, fixed income arbitrage, managed futures, equity market-neutral, long-short equity hedge, event driven, multi-strategy, global macro, emerging markets, and fund of funds.[14] We analyze the predictive power of the manufacturing industry-timing coefficients for each of the 10 investment styles separately via portfolio tests. Since the number of hedge funds that belong to a specific style is small for certain investment styles, we conduct univariate portfolio tests by sorting hedge funds into quintiles as opposed to deciles.

Table 4 reports, for each of the investment style separately, the number of hedge funds in that style as well as the next-month returns and 9-factor alphas of the quintile portfolios sorted on manufacturing industry-timing coefficients. Since we test industry-timing ability with equities, we expect to find stronger results for hedge fund investment styles that trade mostly equities. On the other hand, we do not expect to find any significant return and alpha spreads for hedge fund investment styles that do not trade equities. In line with our expectations, for fixed income arbitrage, convertible arbitrage, and managed futures funds (investment styles that primarily trade fixed income, currencies, and commodities), we do not find a positive and significant relation between industry-timing coefficients and future returns. Whereas, in investment styles that heavily trade equities, such as long-short equity hedge, equity market-neutral, event driven, and emerging market funds, the next month return spreads between the best and worst industry-timing funds range between 0.29%–0.55% per month with significant *t*-statistics ranging between 2.02–2.52. Similarly, the 9-factor alpha spreads for these four investment styles are also positive and significant, ranging from 0.36% to 0.71% per month with *t*-statistics in between 1.96–2.41.

Table 4 also shows that our findings do not hold for global macro and multi-strategy funds. This could be due to the fact that global macro fund managers focus on differentiating in between various countries' economies rather than differentiating in between various industries within the U.S.[15] The insignificant alpha spreads for the multi-strategy funds suggest that these funds trade other instruments heavily outside of equities. In short, the results from investment style analysis are consistent with our expectations, and indicate that the positive relation between industry-timing coefficients and future returns is stronger for hedge funds that specialize in equity trading.

[14]Recently TASS took out all managed future funds from its database. Since we had originally downloaded return series of individual hedge funds prior to this change in the database, we have return series of managed futures funds through June 2016, and therefore include them in this analysis as a separate hedge fund investment style even though their returns do not last through the end of our sample period Sept. 2018.

[15]We believe the different results obtained for Global Macro and Emerging Market hedge funds, in terms of the relation between industry-timing ability and future returns, might be due to the wider range of investment products that Global Macro hedge fund managers can trade particularly in developed economies against the limited number of products (primarily equities) that Emerging Market hedge fund managers can trade in emerging market economies.

TABLE 4

Univariate Portfolios of Hedge Funds Sorted on Manufacturing Industry-Timing Coefficients for each Hedge Fund Investment Style

In Table 4, for each hedge fund investment style, quintile portfolios are formed separately every month from Jan. 1996 to Sept. 2018 by sorting hedge funds based on their manufacturing industry-timing coefficients. Quintile 1 is the portfolio of hedge funds with the lowest industry-timing coefficients and quintile 5 is the portfolio of hedge funds with the highest industry-timing coefficients. The table reports the 1-month-ahead average raw returns and 9-factor alphas for each quintile. The last row shows the average monthly raw return and 9-factor alpha differences between quintile 5 (best-timing funds) and quintile 1 (worst-timing funds). Average returns and alphas are defined in monthly percentage terms. Newey–West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the 5-1 difference portfolio.

	Convertible Arbitrage (199)		Fixed Income Arbitrage (224)		Managed Futures (386)		Multi-Strategy (582)		Global Macro (373)	
	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas
1	0.60	0.15	0.46	0.13	0.42	0.06	0.51	0.09	0.54	0.16
	(2.98)	(0.67)	(3.49)	(0.72)	(1.89)	(0.27)	(3.59)	(0.63)	(2.87)	(0.85)
2	0.55	0.23	0.41	0.13	0.29	−0.01	0.55	0.22	0.56	0.19
	(4.96)	(1.92)	(4.81)	(1.27)	(1.42)	(−0.05)	(6.22)	(2.59)	(4.19)	(1.43)
3	0.51	0.19	0.41	0.15	0.37	0.07	0.59	0.28	0.51	0.19
	(5.11)	(1.78)	(7.02)	(2.73)	(2.39)	(0.49)	(7.56)	(4.18)	(4.76)	(1.96)
4	0.55	0.26	0.45	0.19	0.46	0.20	0.69	0.40	0.52	0.17
	(5.63)	(2.50)	(6.46)	(2.71)	(3.11)	(1.37)	(8.53)	(6.15)	(4.30)	(1.54)
5	0.60	0.23	0.61	0.30	0.69	0.41	0.75	0.35	0.45	0.11
	(3.45)	(1.41)	(6.21)	(3.04)	(3.20)	(1.86)	(6.00)	(3.28)	(2.85)	(0.73)
5-1 diff.	−0.01	0.08	0.14	0.17	0.24	0.33	0.24	0.26	−0.10	−0.05
	(−0.04)	(0.30)	(1.00)	(0.96)	(1.02)	(1.31)	(1.62)	(1.55)	(−0.49)	(−0.23)

	Long-Short Equity Hedge (2,209)		Event Driven (576)		Equity Market-Neutral (318)		Emerging Markets (654)		Fund of Funds (2,312)	
	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas	Raw Returns	9-Factor Alphas
1	0.46	−0.010	0.45	−0.01	0.30	0.04	0.48	−0.33	0.22	−0.21
	(2.27)	(−0.68)	(2.90)	(−0.03)	(1.81)	(0.25)	(1.40)	(−0.96)	(1.64)	(−1.71)
2	0.63	0.14	0.52	0.14	0.39	0.14	0.63	−0.05	0.38	0.05
	(4.25)	(1.64)	(5.07)	(1.74)	(5.30)	(1.97)	(2.57)	(−0.20)	(4.21)	(0.63)
3	0.66	0.18	0.60	0.27	0.51	0.30	0.51	−0.11	0.41	0.06
	(4.86)	(2.96)	(7.20)	(4.26)	(6.79)	(4.88)	(2.12)	(−0.51)	(4.52)	(0.81)
4	0.78	0.27	0.69	0.39	0.88	0.61	0.55	−0.05	0.47	0.14
	(4.86)	(3.20)	(8.67)	(6.63)	(1.86)	(1.47)	(2.15)	(−0.23)	(5.28)	(1.96)
5	1.01	0.46	0.74	0.35	0.69	0.44	1.03	0.39	0.50	0.16
	(4.63)	(3.07)	(5.82)	(3.54)	(5.06)	(3.66)	(3.39)	(1.88)	(4.51)	(1.90)
5-1 diff.	**0.55**	**0.56**	**0.29**	**0.36**	**0.39**	**0.40**	**0.55**	**0.71**	**0.28**	**0.37**
	(2.52)	**(2.41)**	**(2.22)**	**(2.21)**	**(2.05)**	**(1.96)**	**(2.02)**	**(2.21)**	**(2.48)**	**(2.76)**

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

TABLE 5

Long-Term Predictive Power of the Manufacturing Industry-Timing Betas

In Table 5, decile portfolios are formed every month from Jan. 1996 to Sept. 2018 by sorting hedge funds based on their manufacturing industry-timing coefficients. Decile 1 is the portfolio of hedge funds with the lowest industry-timing coefficients (worst-timing funds) and decile 10 is the portfolio of hedge funds with the highest industry-timing coefficients (best-timing funds). The table reports the average raw returns and 9-factor alphas of decile portfolios with holding periods of 3-, 6-, and 9-months. The last row shows the average monthly raw return difference and the 9-factor alpha difference between decile 10 (best-timing funds) and decile 1 (worst-timing funds). Average returns and alphas are defined in monthly percentage terms. Newey–West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the return and alpha differences between decile 10 and decile 1.

	3-Month Holding Period		6-Month Holding Period		9-Month Holding Period	
	Raw Returns (%)	9-Factor Alphas (%)	Raw Returns (%)	9-Factor Alphas (%)	Raw Returns (%)	9-Factor Alphas (%)
Low	0.37 (1.64)	−0.11 (−0.71)	0.43 (2.43)	−0.06 (−0.46)	0.51 (2.97)	0.02 (0.15)
2	0.39 (2.43)	−0.04 (−0.39)	0.45 (3.52)	0.02 (0.21)	0.49 (3.91)	0.05 (0.65)
3	0.42 (3.24)	0.02 (0.20)	0.45 (4.44)	0.05 (0.71)	0.48 (4.80)	0.08 (1.14)
4	0.47 (4.12)	0.10 (1.39)	0.47 (5.31)	0.10 (1.64)	0.49 (5.52)	0.11 (1.89)
5	0.47 (4.04)	0.09 (1.19)	0.49 (5.59)	0.11 (1.74)	0.50 (5.71)	0.12 (1.93)
6	0.51 (4.60)	0.15 (1.99)	0.50 (5.97)	0.14 (2.35)	0.50 (5.99)	0.14 (2.35)
7	0.56 (4.69)	0.18 (2.38)	0.53 (5.80)	0.15 (2.43)	0.52 (5.71)	0.14 (2.36)
8	0.66 (4.97)	0.24 (3.02)	0.62 (6.03)	0.22 (3.28)	0.59 (5.77)	0.19 (2.90)
9	0.72 (4.81)	0.26 2.93)	0.69 (5.41)	0.23 (2.78)	0.65 (5.09)	0.19 (2.34)
High	0.97 (4.35)	0.43 (2.61)	0.88 (4.77)	0.35 (2.38)	0.79 (4.25)	0.26 (1.72)
High-Low	**0.59** **(2.44)**	**0.54** **(2.45)**	**0.45** **(2.20)**	**0.41** **(2.13)**	0.28 (1.64)	0.24 (1.24)

F. Long-Run Predictive Power of Manufacturing Industry-Timing Coefficients

In this section, we examine if the positive relation between manufacturing industry-timing betas and future hedge fund returns lasts longer than a month. In our TASS database the average lock-up period for a fund is 3 months. For this reason, it makes sense to examine the predictive power of industry-timing coefficients over a 3 month or longer period. We investigate the long-term predictive power of industry-timing coefficients via portfolios constructed with holding periods of 3, 6, and 9 months.

Table 5 shows that the predictive power of the manufacturing industry-timing coefficients lasts 6 months into the future. For portfolios constructed with 3-month holding periods, we find that the return and 9-factor alpha spreads between best and worst industry-timing funds are 0.59% (*t*-stat = 2.44) and 0.54% (*t*-stat = 2.45) per month respectively. For portfolios constructed with 6-month holding periods, the magnitudes of the return and alpha spreads become smaller, but remain significant; 0.45% (*t*-stat = 2.20) and 0.41% (*t*-stat = 2.13) per month respectively. Lastly, for portfolios constructed with 9-month holding periods, although the best industry-timing funds (decile 10) continue to generate statistically significant returns and

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

9-factor alphas to some extent, the spreads between the best and worst timers get even smaller and become statistically insignificant. These results indicate that the significantly positive link between manufacturing industry-timing coefficients and future returns lasts 6 months into the future, above the 3-month lock-up restrictions, suggesting that investors can actually redeem these returns by investing in those best manufacturing industry-timing funds.

G. Persistence in Manufacturing Industry-Timing Coefficients

Investors will invest in best manufacturing industry-timing funds only if the better timing ability is repeated in the future. We next examine the degree of persistence in manufacturing industry-timing coefficients with a portfolio transition matrix. Table VIII of the Supplementary Material reports the average probability that a hedge fund in decile *i* (defined by the rows) in a given month will be in decile *j* (defined by the columns) in 6, 12, and 24 months after. If the timing ability in the manufacturing industry is completely random, then all the probabilities along each row of Table VIII should be approximately 10%. Instead, in the 6-month (12-month) ahead analysis, for example, all the top-left to bottom-right diagonal elements of the transition matrix exceed 20% (15%), indicating that the manufacturing industry-timing coefficients are highly persistent. This persistence is especially strong for the best manufacturing industry-timing hedge funds; 50% (32%) of the best manufacturing industry-timing funds in decile 10 remain in decile 10 after 6 months (12 months). Even for the 24-month ahead analysis, there is some evidence of persistence in manufacturing industry-timing coefficients as all the top-left to bottom-right diagonal elements of the transition matrix exceed 13%. The percentages reported in the diagonal are the highest percentages in each row, and most importantly, 20% of the best manufacturing industry-timing funds in decile 10 remain in decile 10 after 2 years. These results provide evidence of a strong persistence in manufacturing industry-timing betas.

H. Industry-Timing Betas, Future Fund Flows, and Fund Survival

We next assess whether hedge funds with better industry-timing skills in the manufacturing sector attract more capital and have a higher probability of survival. We measure hedge fund *flow* as the change in a fund's AUM (assets under management) from the previous month to the current month, adjusted with fund returns and scaled with the previous month's AUM.[16] Panel A of Table IX in the Supplementary Material reports the magnitudes of 6- and 12-month-ahead cumulative flows for each decile generated by sorting hedge funds based on their manufacturing industry-timing coefficients. Consistent with our expectation, in the 6-month-ahead cumulative flow analysis, the best industry-timing hedge funds experience statistically significant inflows, while the worst industry-timing hedge funds suffer statistically significant outflows. This translates into a highly statistically significant cumulative flow difference of 2.96% during the next 6-month period (with a *t*-statistic of 6.69) between the best and worst industry-timing hedge funds. In the 12-month-ahead cumulative flow analysis, we also detect a similar

[16]Fund flow is defined as $\{\text{ASSETS}_t - [(1 + \text{RETURN}_t) \cdot \text{ASSETS}_{t-1}]\}/\text{ASSETS}_{t-1}$.

statistically significant cumulative flow difference of 5.76% over the next 1-year period (with a *t*-statistic of 6.89) between the best and worst industry-timing funds.

As an alternative analysis, each month we also run cross-sectional regressions of 6- and 12-month-ahead cumulative fund flows on manufacturing industry-timing coefficients with and without controlling for fund characteristics. Panel B of Table IX in the Supplementary Material reports the average slope coefficients and the corresponding Newey–West *t*-statistics from these univariate and multivariate Fama–MacBeth regressions. For both the 6- and 12-month-ahead flow analyses, we obtain positive and statistically significant average slope coefficients on the manufacturing industry-timing beta in both univariate and multivariate regression settings.

Next, we examine the relationship between fund survival and industry-timing betas using Fama–MacBeth cross-sectional logit regressions. For this, we regress the 6- and 12-month-ahead fund survival (measured as a dummy variable taking the value of 1 if the fund is in existence, and 0 otherwise) on manufacturing industry-timing betas with and without control variables. Panel C of Table IX in the Supplementary Material reports the average slope coefficients and the corresponding *t*-statistics. In both the 6- and 12-month-ahead fund survival logit regressions, we obtain positive and significant average slope coefficients on the manufacturing industry-timing beta in both univariate and multivariate regression settings. In sum, all these results provide evidence that hedge funds that are able to time manufacturing industry-specific returns experience significantly larger inflows and increase their chance of survival significantly in the near-term.

IV. Industry-Timing Ability and Industry Earnings Surprises

In this section, we explore why industry-timing betas predict future hedge fund returns in the manufacturing industry only, but not in other industries. We first study the link between hedge funds' return sensitivities to earnings surprises and funds' ability to time industry-specific returns in each industry. Next, we examine the persistence in earnings surprises in each of the 12 industries. We then test if there is a connection between the information uncertainty in firms' earnings releases, the magnitude of the post-earnings-announcement drift, and the industry-timing ability that could be unique to the manufacturing industry. Lastly, we examine the predictive power of manufacturing industry-timing coefficients after controlling for funds' reaction to past earnings surprises.

A. Link Between Industry-Timing Betas and Hedge Funds' Exposures to Earnings Surprises

In an attempt to explain why timing industry-specific returns pay off in terms of future superior returns in the manufacturing industry, but not in other industries, we investigate the relationship between hedge funds' industry-timing coefficients and hedge funds' exposures to earnings surprises in each industry. We think that earnings surprises (news) could be an important component of industry-specific returns, and hedge funds that better time industry-specific returns could have higher return sensitivities to the magnitude of the earnings surprises in that particular industry. For this, we adapt the methodology proposed by Kim and Kim (2003) to generate a standardized unexpected earnings (SUE) measure for each individual firm for each quarter in our sample. Specifically, for each firm, we define SUE as the difference between the actual current fiscal quarter q earnings minus the forecast for the same quarter q earnings, divided by the standard deviation of the forecast errors over the past 16 quarters:

$$\text{(5)} \qquad \mathrm{SUE}_{i,q} = \frac{Q_{i,q} - E\left(Q_{i,q}\right)}{\sigma\left(Q_{i,q} - E\left(Q_{i,q}\right)\right)},$$

where $Q_{i,q}$ is the quarterly actual earnings of firm i in quarter q, $E(Q_{i,q})$ is the estimated quarterly earnings forecast for firm i in quarter q, and the term in the denominator is the standard deviation of the forecast errors. In estimating $E(Q_{i,q})$, we use the following AR(1) process using the most recent 16 quarter observations where:

$$\text{(6)} \qquad Q_{i,q} - Q_{i,q-4} = \omega_{i0} + \omega_{i1} \cdot \left(Q_{i,q-1} - Q_{i,q-5}\right) + \varepsilon_{i,q}.$$

The estimated earnings forecasts are then calculated using the predicted values from the AR(1) model such that $E(Q_{i,q}) = Q_{i,q-4} + \hat{\omega}_{i1} \cdot (Q_{i,q-1} - Q_{i,q-5}) + \hat{\omega}_{i0}$. After generating a SUE measure for each stock in each quarter, we then assign those SUE measures to those particular months of the quarter in which earnings are made public. Lastly, for each industry, we generate an industry SUE measure on a monthly basis as the average of the standardized unexpected earnings of individual stocks out of those firms that reported earnings in that particular month in that industry.

If a hedge fund is good at timing industry-specific returns and those returns are related to earnings surprises in that industry, then one should expect this particular hedge fund to have higher returns when the earnings surprises are larger in magnitude in that industry, regardless of whether the earnings surprises are positive or negative. Therefore, if the above conjecture is correct, we should expect higher return sensitivity to the absolute value of industry SUEs for those hedge funds that have better timing ability in that particular industry. To test for this conjecture, each month for each fund in each industry-timing decile (formed based on industry-timing coefficients), we regress time-series individual hedge fund excess returns on each industry's absolute value of SUE (separately) on a 24-month rolling window basis. This process generates time-series values of hedge funds' sensitivities to the magnitude of earnings surprises (i.e., SUE betas) for each fund for each industry. We then take the cross-sectional average of the SUE betas across funds within each industry-timing decile each month. Lastly, for each timing decile in each industry, we report in Table 6 the time-series average of the monthly cross-sectional SUE beta averages along with their Newey–West t-statistics. If hedge funds' industry-timing ability is closely related to their exposures to earnings surprises (SUE betas) in that particular industry, then one should expect the magnitude of the average SUE beta in that industry to increase monotonically as we move from the worst- to the best-timing hedge fund group, such that the SUE beta difference between the best- and worst-timing hedge funds is positive and significant in that industry.

TABLE 6

Industry-Timing Beta Deciles' Return Sensitivity to the Absolute Value of SUEs in Each Industry

Table 6 reports hedge funds' average return sensitivities to the absolute value of the standardized earnings surprise (i.e., SUE betas) and the corresponding *t*-statistics for each industry-timing decile (generated by sorting hedge funds according to their industry-timing coefficients) in each industry during the sample period Jan. 1996–Sept. 2018. The last row shows the average SUE beta difference between decile 10 (best-timing funds) and decile 1 (worst-timing funds) in each industry. Newey–West adjusted *t*-statistics are given in parentheses. Numbers in bold denote positive and statistically significant SUE beta differences between decile 10 (best-timing funds) and decile 1 (worst-timing funds).

		NDRB	DRB	MNF	ENRG	CHE	TECH	TLC	UTIL	SHP	HLTH	FIN	OTH
Industry-Timing Beta Deciles	Low	0.728	−1.440	−0.721	0.156	0.030	0.220	0.674	−1.293	−0.167	0.015	0.346	1.486
		(0.76)	(−1.80)	(−1.21)	(0.72)	(0.07)	(0.33)	(1.96)	(−1.68)	(−0.29)	(0.03)	(1.23)	(2.04)
	2	0.156	−0.874	0.084	0.268	0.169	0.004	0.420	−0.718	0.283	−0.102	0.047	0.899
		(0.30)	(−2.02)	(0.25)	(1.21)	(0.78)	(0.01)	(1.99)	(−1.59)	(0.67)	(−0.25)	(0.28)	(1.93)
	3	0.073	−0.754	0.130	0.235	0.108	−0.031	0.277	−0.639	0.247	−0.071	−0.062	0.564
		(0.18)	(−2.35)	(0.53)	(1.29)	(0.53)	(−0.09)	(1.63)	(−1.89)	(0.72)	(−0.21)	(−0.41)	(1.51)
	4	0.025	−0.670	0.250	0.249	0.157	−0.061	0.214	−0.619	0.205	−0.042	−0.139	0.401
		(0.07)	(−2.62)	(1.09)	(1.36)	(0.84)	(−0.21)	(1.45)	(−2.09)	(0.69)	(−0.14)	(−0.97)	(1.21)
	5	0.034	−0.605	0.339	0.250	0.169	−0.070	0.191	−0.615	0.104	−0.021	−0.199	0.262
		(0.11)	(−2.92)	(1.51)	(1.44)	(0.88)	(−0.25)	(1.40)	(−2.35)	(0.41)	(−0.07)	(−1.24)	(0.83)
	6	0.045	−0.507	0.513	0.233	0.215	−0.063	0.191	−0.608	0.122	−0.030	−0.247	0.200
		(0.15)	(−2.71)	(2.02)	(1.47)	(1.06)	(−0.22)	(1.41)	(−2.53)	(0.48)	(−0.10)	(−1.37)	(0.67)
	7	0.107	−0.467	0.692	0.225	0.250	−0.162	0.202	−0.594	0.106	−0.116	−0.328	0.152
		(0.34)	(−2.72)	(2.27)	(1.44)	(1.02)	(−0.52)	(1.42)	(−2.60)	(0.40)	(−0.33)	(−1.58)	(0.49)
	8	0.196	−0.449	0.936	0.265	0.267	−0.195	0.250	−0.569	0.166	−0.236	−0.456	0.024
		(0.51)	(−2.38)	(2.41)	(1.44)	(0.88)	(−0.55)	(1.44)	(−2.50)	(0.55)	(−0.59)	(−1.88)	(0.07)
	9	0.229	−0.499	1.243	0.289	0.294	−0.417	0.380	−0.525	0.219	−0.330	−0.537	−0.130
		(0.45)	(−2.04)	(2.40)	(1.23)	(0.63)	(−0.90)	(1.72)	(−2.08)	(0.56)	(−0.63)	(−1.64)	(−0.31)
	High	−0.519	−0.346	2.143	0.372	0.492	−0.920	0.652	−0.585	−0.185	−0.635	−0.997	−0.647
		(−0.67)	(−0.75)	(2.59)	(0.98)	(0.55)	(−0.96)	(1.92)	(−1.64)	(−0.23)	(−0.81)	(−1.82)	(−1.04)
	High-Low	−1.247	1.094	**2.864**	0.215	0.462	−1.140	−0.023	0.707	−0.019	−0.651	−1.343	−2.133
		(−1.07)	(1.12)	**(3.19)**	(0.54)	(0.46)	(−1.06)	(−0.06)	(0.92)	(−0.02)	(−0.77)	(−2.65)	(−2.78)

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

Table 6 shows that in the manufacturing industry (MNF) the average beta for the absolute value of the earnings surprises (SUE betas) increases monotonically as we move from the worst industry-timing decile to the best industry-timing decile. Also, the spread in SUE betas between the best and worst industry-timing hedge fund deciles is positive (2.86) and highly significant (*t*-stat. = 3.19) only in the manufacturing industry. This positive and significant SUE beta spread is driven primarily by the positive and significant SUE beta of the best timing hedge funds in decile 10; an average SUE beta of 2.14 and a *t*-statistic of 2.59. These results in the manufacturing industry point to a close relationship between industry-timing ability and hedge funds' exposures to earnings surprises, and suggest that hedge fund managers that time the manufacturing industry-specific returns well also pay particular attention to the earnings news in this sector.

We do not, however, find a close relation between industry-timing ability and exposures to earnings surprises (SUE betas) in the other 11 industries. For example, we see a negative and significant SUE beta spread in the finance industry (FIN) due to the negative and significant SUE beta of the best-timing hedge funds (decile 10) in that industry. This does not imply perverse timing, rather it signifies that these funds in decile 10 are paying attention to something other than earnings surprises in the finance industry. In the telecom industry (TLC), even though the SUE beta is positive and marginally significant for the best-timing hedge funds, the SUE beta spread between decile 10 and decile 1 is negative and insignificant, because the SUE beta of the worst-timing hedge funds is larger in magnitude compared to the best-timing funds. The positive and significant SUE beta for decile 1 in the telecom industry signifies that even though these funds are paying attention to earnings surprises, they are not able to time the industry-specific returns well in the telecom industry. These examples show that timing ability in other sectors is not exclusively related to earnings surprises.[17]

All in all, our findings from all these analyses indicate that across all industries analyzed, the relation between industry-timing coefficients and hedge funds' return sensitivities to the absolute value of earnings surprises is the strongest in the manufacturing industry.

B. Persistence in Earnings Surprises Across Industries

We next investigate how persistent the earnings surprises are in each industry. If earnings surprises are particularly persistent in an industry, it would be easier to predict the future earnings surprises of that industry. For this purpose, in Table 7 we report autocorrelations in SUE with lags up to 3 months in each industry over our sample period Jan. 1994–Sept. 2018. Table 7 reveals that for most industries,

[17]We should note that we do not necessarily make an assumption that industry-timing ability stems from paying attention only to earnings surprises. For that reason, we cannot equate industry-timing ability to hedge funds' SUE betas (i.e., return sensitivities to the absolute value of earnings surprises). For other industries, timing industry-specific returns could be due to other factors such as product innovations, industry-specific positive and negative shocks, seasonal factors unique to an industry, and changes in consumer tastes of products in a particular industry. This may explain why in other industries, funds' exposures to the magnitude of earnings surprises are not associated with a better timing ability of industry-specific returns, as there may be other industry-specific factors influencing the industry returns in those industries.

TABLE 7

Autocorrelation in SUEs

Table 7 reports autocorrelations in standardized earnings surprises (SUEs) for different lags up to 3 months in each of the 12 Fama–French industries during the sample period Jan. 1994–Sept. 2018. Numbers in bold denote statistically significant autocorrelation coefficients.

	NDRB	DRB	MNF	ENRG	CHE	TECH	TLC	UTIL	SHP	HLTH	FIN	OTH
Lag 1	**0.312**	**0.313**	**0.630**	**0.405**	**0.202**	**0.403**	**0.121**	**0.099**	**0.263**	0.049	**0.279**	**0.334**
	(5.37)	**(5.40)**	**(10.85)**	**(6.98)**	**(3.49)**	**(6.94)**	**(2.08)**	**(1.71)**	**(4.54)**	(0.84)	**(4.81)**	**(5.76)**
Lag 2	0.086	−0.003	**0.425**	**0.185**	−0.014	**0.307**	0.003	−0.183	−0.168	0.000	0.105	0.093
	(1.35)	(−0.05)	**(5.46)**	**(2.76)**	(−0.23)	**(4.60)**	(0.05)	(−3.12)	(−2.71)	(0.01)	(1.60)	(1.45)
Lag 3	−0.101	−0.081	**0.120**	0.062	−0.050	−0.011	−0.072	−0.202	−0.166	−0.032	−0.011	−0.146
	(−1.58)	(−1.27)	**(2.05)**	(0.90)	(−0.82)	(−0.15)	(−1.23)	(−3.34)	(−2.61)	(−0.56)	(−0.18)	(−2.26)

https://doi.org/10.1017/S0022109020000794 Published online by Cambridge University Press

autocorrelations die out soon after the first lag, suggesting that earnings surprises are not that persistent for most industries. However, we find that the autocorrelation coefficient in SUE is always the highest and most significant in the manufacturing industry for each of the three lags tested. In fact, among the 12 industries, manufacturing industry is the only industry in which the autocorrelation coefficient on the third lag is still positive and significant. All of these findings provide evidence of a much stronger persistence in earnings surprises in the manufacturing industry in terms of intensity and duration compared to other industries.[18] This persistently high autocorrelation in manufacturing SUE suggests that companies in the manufacturing industry are more likely to generate same-direction earnings surprises as their peers in the following months, which makes it easier for hedge fund managers who are aware of this time-series persistence in earnings news in the manufacturing industry to allocate their resources to time the manufacturing industry-specific returns.[19]

C. Earnings-Related Information Uncertainty and Post-Earnings-Announcement Drift

Imhoff and Lobo (1992) show that the return response to unexpected earnings is larger for firms that have more transparent information environment. That is, investors tend to react more strongly to positive and negative news coming from transparent firms that have less information uncertainty, as compared to opaque firms that have more information uncertainty. In other words, investors of firms with more uncertainty in regards to earnings releases will be better prepared for any type of earnings surprises, and therefore they will not react as strongly as the investors of firms with more certainty in their earnings releases. Supporting this link between information uncertainty and the reaction of investors, Kim and Kim (2003) also show that the difference between the average returns on the positive earnings surprise portfolio and the negative earnings surprise portfolio (combined post-earnings-announcement drift on positive and negative earnings surprises) is higher during the next quarter when the earnings information uncertainty is more

[18] It should be noted that there is some evidence of persistence in earnings surprises in the energy (ENRG) and technology (TECH) industries as well. However, the magnitude of the second-order autocorrelation coefficients in these two industries are smaller compared to the manufacturing industry (0.185 (t-stat = 2.76) for ENRG and 0.307 (t-stat = 4.60) for TECH vs. 0.425 (t-stat = 5.46) for MNF). Moreover, the 3rd-order autocorrelation coefficient is positive and insignificant for the energy industry and negative and insignificant for the technology industry, while it is positive and significant for the manufacturing industry (0.120 (t-stat = 2.05)).

[19] In an earlier version of the paper, we replicated our main empirical tests for the mutual fund sample as well. Section 4 and Table X of the Supplementary Material report results from our analysis on mutual funds. We find no evidence of a positive link between mutual funds' manufacturing industry-timing coefficients and their future performance. We believe these results are due to mutual funds' inability to capitalize on the information disseminated by earnings surprises due to the concentration limitations, leverage constraints, and/or short-selling restrictions that they face in their portfolio holdings. In fact, when we analyze portfolio holdings in the 13F database, we find that the magnitudes of the average buy and sell trades of nonhedge funds are half the size of hedge funds' average buy and sell trades (relative to their respective equity portfolio sizes). These significantly smaller concentrated positions of nonhedge funds in the manufacturing industry could perhaps explain why mutual funds are unable to time the manufacturing industry returns.

transparent, and that this post-earnings-announcement drift decreases as the earnings information uncertainty increases.

In this section, to investigate the impact of firms' earnings related information environment on our main findings, we use two alternative measures that quantify the degree of information uncertainty in firms' earnings releases, and investigate if there is a connection between the earnings related transparency of the industry, the magnitude of the post-earnings-announcement drift, and the industry-timing ability that is unique to the manufacturing industry.

To proxy for the degree of information uncertainty in a firm's earnings release, we use the standard deviation of the quarterly forecast errors of the individual stocks over the past 16 quarters. This is the same measure as the standard deviation of the residuals obtained from equation (6) in calculating the estimated earnings with the AR(1) model, $\sigma(\varepsilon)$. As an alternative second measure of the information environment of individual stocks, we use the standard deviation of the quarterly earnings surprises over the past 16 quarters. The earnings surprises for each stock are calculated as the difference between actual earnings per share (EPS) and the median analysts' earnings forecast per share scaled by share price. For both measures, while a low reading would indicate more transparent information environment, a higher reading would imply higher levels of uncertainty in regards to earnings releases.

Panel A of Table 8 reports the time-series average of cross-sectional means of these two measures in each industry for the Jan. 1996–Sept. 2018 period. Comparing the industry averages across the 12 industries shows that the standard deviation of forecast errors is actually the lowest in the manufacturing industry. Similarly, the standard deviation of earnings surprises scaled by share price is the second lowest in the manufacturing industry after the utilities industry. These results suggest that the information environment in the manufacturing industry in regards to earnings releases is one of the most transparent among all industries considered.

Based on the results of Kim and Kim (2003), the manufacturing industry, as one of the most transparent industries, should then experience a stronger post-earnings-announcement drift in returns in the same direction as earnings surprises. We next test whether this conjecture is true. For each industry, we first sort stocks into deciles based on the magnitude of the earnings surprises (SUEs) on a quarterly basis such that decile 1 contains stocks with the largest negative earnings surprises and decile 10 contains stocks with the largest positive earnings surprises. Then, within each industry, we observe the cumulative excess returns (over the market) of individual stocks for the next 30 and 60 trading days after the earnings announcement. In Panel B of Table 8, within each industry, we report for each of the SUE deciles, the cross-sectional average of the 30th and 60th trading day cumulative excess returns of stocks. The last column of Panel B in Table 8 shows the 30th and 60th trading day cumulative excess return differences between decile 10 (the portfolio of stocks with the largest positive earnings surprises) and decile 1 (the portfolio of stocks with the largest negative earnings surprises). Essentially, this last column measures the combined post-earnings-announcement drift on positive and negative earnings surprises 30 and 60 trading days after the earnings announcement in each industry. Consistent with the findings of Imhoff and Lobo (1992) and Kim and Kim, we find the manufacturing industry, as one of the most transparent industries in terms of the degree of uncertainty in earnings releases, also

TABLE 8

Degree of Information Uncertainty and Magnitude of Post-Earnings-Announcement Drift in Industries

Panel A of Table 8 reports the time-series averages of cross-sectional means of the standard deviation of quarterly forecast errors and the standard deviation of quarterly earnings surprises (per share) in each industry for the Jan. 1996–Sept. 2018 period. Panel B reports, for each of the SUE deciles created, the cross-sectional average of the 30th and 60th trading day cumulative excess return performance of individual stocks within each industry. The last column measures the combined post-earnings-announcement drift on positive and negative earnings surprises 30 and 60 trading days after the earnings announcement in each industry. All returns are defined in monthly percentage terms.

Panel A. Degree of Information Uncertainty

Variable	NDRB	DRB	MNF	ENRG	CHE	TECH	TLC	UTIL	SHP	HLTH	FIN	OTH
Std. dev. of forecast errors	0.549	0.839	0.523	1.708	0.635	0.906	1.329	0.711	0.540	0.538	1.887	1.022
Std. dev. of EPS surprises	0.011	0.014	0.008	0.015	0.009	0.011	0.019	0.005	0.009	0.014	0.018	0.013

Panel B. Magnitude of Post-Earnings-Announcement Drift

Industry	Days	SUE P1	SUE P2	SUE P3	SUE P4	SUE P5	SUE P6	SUE P7	SUE P8	SUE P9	SUE P10	P10-P1
NDRB	30	−3.60	−3.69	−1.31	0.82	0.64	0.77	0.72	2.09	2.54	4.89	8.49
	60	−4.47	−4.25	−2.61	0.49	0.47	0.72	0.86	2.36	3.42	4.40	8.87
DRB	30	−5.24	−4.67	−2.10	−0.33	0.26	0.32	0.52	−0.78	−0.08	1.54	6.78
	60	−7.23	−5.86	−2.12	−0.52	1.82	2.20	0.25	−1.41	−1.41	2.30	9.53
MNF	30	−6.80	−5.31	−1.81	−1.02	−0.02	0.52	0.62	1.63	1.52	4.60	11.40
	60	−7.56	−5.48	−2.20	−1.79	−0.48	1.01	0.93	1.99	1.20	4.82	12.38
ENRG	30	−3.15	−2.65	−2.29	−2.46	−0.16	−0.70	0.51	0.67	1.38	3.04	6.19
	60	−3.48	−0.59	−2.61	−0.36	−0.58	−1.74	0.08	1.88	1.20	3.15	6.63
CHE	30	−4.14	−3.29	−1.22	−2.37	1.05	0.44	0.21	2.65	1.96	5.50	9.64
	60	−3.72	−3.10	−1.10	−2.41	1.06	−0.47	−0.23	3.52	1.36	6.50	10.22
TECH	30	−4.31	−3.95	−2.46	−1.35	0.58	1.51	2.38	2.97	4.51	5.53	9.84
	60	−5.38	−5.20	−3.56	−1.93	0.45	1.22	2.37	2.97	5.09	5.91	11.29
TLC	30	−3.42	−1.30	−2.59	−2.73	−0.98	−0.53	1.19	0.62	2.24	3.15	6.57
	60	−2.58	−0.68	−3.18	−2.50	−1.30	0.19	2.12	1.91	1.19	2.10	4.68
UTIL	30	−0.48	−0.70	−0.99	−1.04	0.07	−0.79	−0.29	0.38	0.15	3.00	3.48
	60	−0.35	−0.35	−0.31	−0.66	0.30	−0.94	0.07	0.82	0.71	3.89	4.24
SHP	30	−5.04	−3.19	−3.16	−1.12	0.89	2.00	2.64	3.38	3.69	5.21	10.25
	60	−5.87	−3.03	−3.78	−0.97	0.68	2.51	2.18	3.76	4.20	5.83	11.70
HLTH	30	1.31	−2.22	−1.37	−0.88	0.17	0.78	0.76	1.19	1.94	6.10	4.79
	60	0.11	−2.22	−0.72	−0.78	0.55	1.34	2.48	2.70	2.08	4.78	4.67
FIN	30	−5.46	−2.10	−1.47	−0.23	0.53	1.59	0.75	1.43	0.88	2.07	7.53
	60	−6.68	−3.19	−1.53	−1.12	0.59	1.30	1.20	0.72	0.66	3.39	10.07
OTH	30	−2.85	−3.32	−2.31	−0.06	0.18	0.49	1.09	1.14	2.43	3.31	6.16
	60	−3.08	−3.63	−2.89	−0.32	0.43	0.84	1.23	1.44	2.08	4.82	7.90

experiences the largest combined post-earnings-announcement drift on positive and negative earnings surprises. Specifically, the magnitude of post-earnings-announcement drift 30 trading days (60 trading days) after the earnings announcement is 11.40% (12.38%) in the manufacturing industry.[20]

In sum, among the 12 industries considered, the manufacturing industry is the only industry where the information environment (in regards to earnings releases) is one of the most transparent, the combined post-earnings-announcement drift on positive and negative earnings surprises is the largest, and autocorrelation in SUE is the most persistent. In addition, best-timing hedge funds' exposures to the magnitude of earnings surprises (i.e., SUE betas) is the largest in the manufacturing industry. We believe all these findings combined explain why best-timing hedge funds in the manufacturing industry generate statistically significant larger returns in future months compared to worst-timing hedge funds.

D. Manufacturing Industry Timers vs. Reactors

Highly persistent earnings surprises in the manufacturing industry may make it easier for all funds, not just sophisticated hedge funds, to predict the SUE in the manufacturing industry. That is, by getting in and out of the manufacturing industry by reacting solely to lagged earnings surprises (which is public information), a random hedge fund manager may give the illusion that she can time manufacturing industry-specific returns. Ferson and Schadt (1996) emphasize the separation of the use of public information from measuring timing ability. To address this issue and control for the effect of reacting to past earnings surprises, we add to equation (2) an interaction term between industry residual returns and 1-month-lagged earnings surprises. Specifically, we run the following regression on a 24-month rolling window basis for the manufacturing industry:

$$
\begin{aligned}
(7)\qquad R_{i,t} = {} & \beta_{0,i}^{MNF} + \beta_{1,i}^{MNF} \cdot \text{RES\_MNF}_t + \beta_{2,i}^{MNF} \cdot \text{RES\_MNF}_t^2 \\
& + \beta_{3,i}^{j} \cdot \text{SUE}_{t-1}^{MNF} \cdot \text{RES\_MNF}_t + e_{i,t},
\end{aligned}
$$

where $R_{i,t}$ is the excess return on fund i in month t, RES_MNF_t is the manufacturing industry residual return in month t, RES_MNF_t^2 is the squared manufacturing industry residual return in month t, and $\text{SUE}_{t-1}^{MNF} \cdot \text{RES\_MNF}_t$ is the interaction term between manufacturing industry residual return in month t and standardized unexpected earnings in manufacturing industry in month $t-1$. In equation (7), $\beta_{2,i}^{MNF}$ represents the manufacturing industry-timing coefficient for fund i after controlling for the fund's reaction to past manufacturing industry earnings surprises. After

[20]Technology and shop industries have also large combined post-earnings-announcement drifts on positive and negative earnings surprises. Panel A of Table 8 documents that the shop industry is relatively transparent in regards to earnings releases as well. However, as shown earlier in Table 7, the persistency in SUE in the shop industry is markedly short-lived compared to the manufacturing industry. In the technology sector, compared to the manufacturing industry, the degree of information uncertainty is noticeably higher and the persistency in SUE is relatively more short-lived. We believe these features of these two industries that are significantly different from the manufacturing industry explain why we do not find any evidence for a positive and significant relation between hedge funds' industry-timing coefficients in the technology and shop industries and their future returns.

TABLE 9

Univariate Portfolios of Hedge Funds Sorted on Manufacturing Industry-Timing Coefficients after Controlling for Funds' Reaction to Past Earnings Surprises

In Table 9, decile portfolios are formed every month from Jan. 1996 to Sept. 2018 by sorting hedge funds based on their manufacturing industry timing coefficients generated from equation (7), where we control for hedge funds' reaction to past earnings surprises in the manufacturing sector. Decile 1 is the portfolio of hedge funds with the lowest industry timing coefficients (worst-timing funds) and decile 10 is the portfolio of hedge funds with the highest industry timing coefficients (best-timing funds). The table reports the one-month-ahead average raw returns and 9-factor alphas for each decile. The last row shows the average monthly raw return difference and the 9-factor alpha difference between decile 10 (best-timing funds) and decile 1 (worst-timing funds). Average returns and alphas are defined in monthly percentage terms. Newey–West adjusted *t*-statistics are given in parentheses. Numbers in bold denote statistical significance of the return and alpha differences between decile 10 and decile 1.

	Next-Month Raw Returns (%)	Next-Month 9-Factor Alphas (%)
Low	0.29 (1.23)	−0.27 (−1.36)
2	0.40 (2.39)	−0.08 (−0.63)
3	0.48 (3.63)	0.08 (0.87)
4	0.47 (4.15)	0.11 (1.41)
5	0.53 (4.96)	0.17 (2.35)
6	0.52 (4.85)	0.17 (2.36)
7	0.54 (4.88)	0.18 (2.55)
8	0.62 (5.16)	0.25 (3.39)
9	0.72 (4.87)	0.33 (3.45)
High	0.96 (4.34)	0.50 (2.89)
High-Low	**0.67** **(2.60)**	**0.76** **(2.59)**

obtaining new monthly time-series estimates of manufacturing industry-timing coefficients from equation (7), we examine the predictive power of these timing coefficients using a univariate portfolio test. Table 9 shows that our main manufacturing industry-timing results remain robust after we control for funds' reaction to past earnings surprises in the manufacturing industry. Specifically, the next month return and 9-factor alpha spread between the best- and worst-timing funds remain positive and highly significant; 0.67% (*t*-stat=2.60) and 0.76% (*t*-stat=2.59), respectively. These findings suggest that hedge fund managers' timing ability of the manufacturing industry residual returns is not confined to the use of past SUEs.[21]

V. Testing Manufacturing Industry Timing Ability with 13F Data

In this section, we provide evidence on the timing ability of hedge funds in the manufacturing industry by utilizing Thomson Reuters' 13F stock holdings data.[22]

[21] In Table 9 the return and alpha spreads between the best- and worst-timing funds are slightly larger compared to the original results reported in Table 2. This suggests that after controlling for reactors, the true effect of manufacturing industry-timing ability on future fund returns gets even stronger.

[22] Note that 13F data reported to SEC also includes long positions in derivatives, but these derivatives positions are not reported in commercial databases such as Thomson Reuters. Since we use the

Specifically, we investigate if the long positions of best-timing hedge funds in the manufacturing industry (i.e., funds with the top 10% timing coefficients) differ from worst-timing hedge funds (i.e., funds with the bottom 10% timing coefficients) in accordance with their industry-timing ability.

Although the 13F database has a “typecode” variable to classify different types of institutional investors such as banks, insurance companies, mutual funds, independent advisors, and others, it does not specify which of those institutional investors are actually hedge funds. To detect hedge funds among 13F filers, following Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we manually analyze ADV forms of all institutional investors and identify institutions as hedge funds if the following first and one of the second or third criteria are met: i) the institutional investor charges performance-based fees; ii) more than 50% of assets of an institutional investor are in “other pooled investment vehicles;” and iii) more than 50% of clients of an institutional investor are high-net-worth individuals.[23] This procedure enables us to detect 2,270 of the institutional 13F filers as hedge funds. Next, by matching fund names obtained from our TASS database with the 2,270 hedge fund names obtained from the 13F database, we create a subsample of 998 hedge funds from our original TASS database for which we have now information on their quarterly stock holding levels as well. Clearly, the size of this sample is small compared to our original sample of 7,902 funds. However, this is mainly because an institution with AUM less than $100 million does not have to report its holdings to the SEC. Therefore, our sample of 998 hedge funds out of the 2,270 funds that file for 13F, essentially represents a significant portion of hedge funds that actually report their positions to SEC. Nevertheless, this new sample of hedge funds is biased toward large funds, which may not show good timing ability due to the diseconomies of scale.[24] In addition, 13F reports only the long positions of institutional investors and does not provide information on the short positions of hedge funds. More importantly, we are able to observe the long positions only at the calendar quarter ends, missing intra-quarter trades which may reflect the timing ability of these funds.

Despite these considerable limitations, we use the long only quarterly holdings data of these 998 individual hedge funds to see if we can detect a relationship between funds’ manufacturing industry-timing coefficients and their manufacturing industry stock holdings. Specifically, we first identify the calendar quarters in which the quarterly manufacturing industry residual returns are in their highest and

institutional holdings data from Thomson Reuters’ 13F database, this particular analysis using the holdings data is just based on hedge funds’ stock holdings, not on their derivatives holdings.

[23]We thank Vikas Agarwal for sharing the list of 13F filers detected as hedge funds during the period 1994–2014. For the remaining period 2015–2018, we use ADV files to identify hedge funds among institutions that file for 13F.

[24]We check whether our main finding of a positive and significant relation between manufacturing industry-timing coefficients and superior future performance holds for this small subsample of hedge funds as well. Conducting the univariate portfolio test, we find that funds in the best manufacturing industry-timing decile continue to generate statistically significant higher returns compared to the funds in the worst manufacturing industry-timing decile for this small subsample despite the sample’s bias toward large funds, suggesting that manufacturing industry-timing ability is not unique to small hedge funds only.

lowest 5 percentile of the distribution.[25] We then examine and compare the average manufacturing industry dollar stock holdings of the best and the worst manufacturing industry-timing funds in the prior quarter. Interestingly, at any given quarter during the period 1996–2018, on average, best manufacturing industry-timing funds hold $30.2 million less in manufacturing stocks compared to worst manufacturing industry-timing funds. However, when we analyze the highest and lowest 5 percentile quarterly manufacturing industry residual returns, consistent with the timing ability, the picture looks very different. In the quarter before the highest manufacturing industry residual returns are observed, an average fund in the best manufacturing industry-timing decile holds $70.2 million more in manufacturing stocks compared to an average fund in the worst manufacturing industry-timing decile. This is a $100 million switch in positioning by a best-timing fund from its average holdings in a given quarter. Taking the ratio of the average dollar positions in the manufacturing industry for best timers against worst timers, we find that a best timer holds manufacturing stocks in its portfolio 2.6 times as high as a worst timer before the best manufacturing industry-specific returns occur.

In contrast, in the quarter before the lowest manufacturing industry residual returns are observed, an average fund in the best manufacturing industry-timing decile holds $110.2 million less in manufacturing stocks compared to an average fund in the worst manufacturing industry-timing decile. This is an $80 million reduction in positioning by a best-timing fund from its average holdings in a given quarter. Looking at the ratio of the average dollar positions in the manufacturing industry for best timers against worst timers, this time we see that a best timer's manufacturing industry holdings are only 60% of a worst timer's manufacturing industry holdings.

These findings provide strong evidence of industry-timing ability among a group of hedge funds within the manufacturing industry. When we enlarge the extreme end periods with the highest and lowest quarterly manufacturing industry residual returns such that we pick and analyze the top and bottom 10% or 20% of the sample, we get qualitatively similar results to those obtained from the top and bottom 5% of the sample. Best manufacturing industry-timing funds pile up in the manufacturing industry stocks much more intensely compared to worst manufacturing industry-timing funds in the quarter heading up to the materialization of best manufacturing industry-specific returns. Consistent with their timing ability, best-timing funds also scale down on the holdings of their manufacturing industry stocks significantly compared to worst manufacturing industry-timing funds in the quarter heading up to the realization of worst manufacturing industry-specific returns.[26]

[25]Quarterly manufacturing industry residual returns are obtained by compounding the monthly manufacturing industry residual returns generated from equation (1).

[26]In a separate analysis, we also examine the effect of hedge funds' usage of ETFs on their manufacturing industry-timing ability. In a recent working paper, Huang, O'Hara, and Zhong (2020) reveal that hedge funds use ETFs more as a hedging product by showing that the short interest ratio of industry ETFs positively predicts the industry ETF returns. In line with Huang et al. (2020), we find that short interest ratios of manufacturing ETFs increase before high industry returns are observed. Similarly, short interest ratios decrease before low (extreme negative) industry returns are observed. These results

In a separate but related analysis, using the same 998 hedge fund names matched sample between the 13F and the TASS database, we also investigate whether best-timing hedge funds hold more concentrated positions in the manufacturing industry. For each hedge fund, on a quarterly basis, we first define the average size of the buy (sell) trades as the total value of buys (sells) in the manufacturing industry divided by the number of buy (sell) trades in the manufacturing industry scaled by the total value of the fund's stock holdings in the previous quarter. Analyzing the average size of the buy and sell trades in the manufacturing industry shows that best-timing hedge funds indeed buy and sell noticeably in more concentrated amounts compared to worst-timing hedge funds. Specifically, each buy (sell) trade of best-timing hedge funds in the manufacturing industry constitutes 2.60% (3.05%) of their equity portfolio size, while each buy (sell) trade of worst-timing hedge funds constitutes only 1.97% (2.19%) of their portfolio size. This suggests that a typical buy (sell) trade of a best-timing hedge fund is 32% (39%) larger than the typical buy (sell) trade of a worst-timing hedge fund. These results suggest that better-timing hedge funds' more concentrated positions in the manufacturing industry could play a role in their overall manufacturing industry-timing ability.

VI. Conclusion

Hedge fund managers' processing of information has always been a topic of interest for academics as well as practitioners in the field of finance. The way a hedge fund manager makes use of industry-specific information could show up in the form of better timing ability as well as better security selection resulting in superior returns, higher capital inflows, and endurance. The expansions and contractions that different industries experience due to industry-specific shocks, product innovations, and changes in tastes create an ideal context to investigate hedge funds' timing ability within those industries.

With this paper we investigate whether hedge funds can time industry-specific returns and whether this timing ability predicts the cross-sectional variation in future hedge fund performance. The results indicate that a respectable percentage of funds can time industry-specific returns in the manufacturing sector and those funds with stronger manufacturing industry-timing ability generate significantly higher abnormal returns in the following months. Multivariate Fama–MacBeth cross-sectional regressions also indicate that the predictive power of the manufacturing industry-timing coefficients persists after controlling for various fund characteristics and funds' other timing abilities.

suggest that hedge funds may be using these manufacturing ETFs to hedge their positions in equities of the manufacturing industry. In a different analysis, using the small sample of hedge funds generated by matching the hedge fund names between the 13F and the TASS database, we also do not find a significant difference between best and worst timers in terms of their positions in manufacturing industry ETFs. Concentrating on best timers' manufacturing ETF holdings further, we find that best timers' total positions in ETFs in the months before the best manufacturing industry returns are observed are not economically and statistically different than those of the months before the worst manufacturing industry returns are observed.

The long-term predictability tests also show that the significantly positive link between manufacturing industry-timing coefficients and future returns lasts 6 months into the future, well above the 3-month lock-up restrictions that investors face in the hedge fund industry. In addition to generating higher returns, we find the best manufacturing industry-timing funds experience larger capital inflows and thus have a higher chance of survival in the following 6- to 12-month period.

The results from our analyses on earnings surprises show that, among the 12 industries considered, the manufacturing industry is the only industry where autocorrelation in standardized earnings surprises (SUE) is the most persistent, the information environment in regards to earnings releases is one of the most transparent, and the combined post-earnings-announcement drift on positive and negative earnings surprises is the largest. Furthermore, best-timing hedge funds' exposures to the magnitude of earnings surprises is the largest in the manufacturing industry. All these findings together explain to a great extent why best-timing hedge funds, by paying attention to earnings news in the manufacturing industry, can generate statistically significant larger returns in future months compared to worst-timing hedge funds.

Lastly, our analysis on hedge funds' 13F portfolio holdings provide supporting evidence on the industry-timing ability of hedge funds in the manufacturing sector. In line with their timing ability, best manufacturing industry-timing funds hold significantly more (less) dollar amount of manufacturing industry stocks compared to worst manufacturing industry-timing funds in the quarter heading up to the realization of best (worst) manufacturing industry-specific returns.

Overall, our findings suggest that the industry-timing ability of hedge funds in the manufacturing industry is unique in the sense that its predictive power over future returns persists after controlling for funds' market-, liquidity-, and volatility-timing abilities. Therefore, industry-timing ability should be considered as a new orthogonal component of hedge fund timing ability that is separate from the other previously documented timing abilities in the hedge fund literature.

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S0022109020000794.

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