RATIONAL EXUBERANCE

HEDGE FUND TRADING STRATEGY IN BUBBLES

JACOB GREN

ELIN SÖDERLUND

Bachelor Thesis

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Rational Exuberance: Hedge fund trading strategy in bubbles

Abstract:

This paper examines hedge fund trading strategy in seven bubbles and concludes that hedge funds apply different strategies for different bubbles. We analyze hedge funds' long positions in bubble stocks. Further, we run a regression to account for any short positions. We conclude that, in some bubbles, hedge funds acted in accordance with the efficient market hypothesis by helping bring overvalued stocks back to their fundamentals. However, in other bubbles, hedge funds invested a larger proportion of their portfolio in bubble stocks than the weight the stocks held in the market portfolio, implying that hedge funds were riding these bubbles. This is coherent with studies finding that rational arbitrageurs can benefit from investing in mispriced securities due to limitations to arbitrage. Using a stock-by-stock analysis, we find some evidence that hedge funds anticipated stocks' price peaks and started decreasing their positions before the bubbles burst. However, this trading strategy is not consistent for all bubbles. We contribute to previous research on hedge fund trading strategy by delimiting our scope to solely investigate general trading strategy of hedge funds in bubbles.

Keywords:

Hedge Funds, Stock Bubbles, Positive Feedback Strategy, Mispriced Securities

Authors:

Jacob Gren (24600)

Elin Söderlund (24691)

Tutors:

Riccardo Sabbatucci, Assistant Professor, Department of Finance

Examiner:

Adrien d'Avernas, Assistant Professor, Department of Finance

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I. Introduction

The well-known technology bubble arose in the early 2000s, causing technology stock prices to rise far above their fundamental values. Brunnermeier and Nagel (2004) conclude in their study *Hedge Funds and the Technology Bubble* that instead of acting as a correcting force reverting overvalued stocks back to their fundamentals, hedge funds exacerbated the technology bubble by employing positive feedback trading strategies. That is, continuing to buy bubble stocks when the prices rose. Hence, they disagree with the efficient market hypothesis, which states that riskless arbitrage opportunities and other kinds of mispricings will be eliminated by rational arbitrageurs who are able to perfectly hedge their trades (Fama, 1970). Our study investigates hedge funds' trading strategy in seven different bubbles based on Fama and French (1997) industry classifications to examine whether any general trading strategy among hedge funds exists during bubbles, and whether they exacerbate, rather than correct, potential mispricings. The bubbles we study include the steel and coal bubbles in 2008, and the computer software, computer hardware, electronic equipment, steel, and measurement & control equipment bubbles in 2000. We define our research question as:

Do hedge funds exacerbate bubbles through positive feedback trading strategies rather than acting as rational arbitrageurs and reverting prices back to their fundamentals?

Between 1990-2007, the hedge industry was subject to rapid development, which often is referred to as the hedge fund boom. During this period, the number of hedge funds grew from 530 to 7,634 funds and assets under management from USD 39 billion to USD 1.9 trillion (Stowell, 2012). According to Private Fund Statistics by the SEC (2021), the number of funds amounted to 9,457 in the first quarter of 2021, with more than USD 4.5 trillion of assets managed worldwide (Statista, 2022). Brunnermeier and Nagel (2004) state that hedge funds are presumably closest to the ideal of rational arbitrageurs compared to other investor types. However, not least due to hedge funds' trading strategy during the technology bubble, doubt exists on whether hedge funds act as a correcting force on stock prices when mispricings arise. Some factors they mention that can limit the ability of rational arbitrageurs include noise trader risk and synchronization risks.

While studies based on hedge funds' holdings are unusual due to the limited access to reliable hedge fund data, several previous studies in addition to Brunnermeier and Nagel (2004), exist. Common previous research areas on whether hedge funds correct mispricing include rational arbitrageurs, the efficient market hypothesis, and limits on arbitrage (Akbas, Armstrong, Sorescu and Subrahmanyam, 2015; Fung and Hsieh, 2000; Abreu and Brunnermeier, 2002; DeLong, Shleifer, Summers and Waldmann, 1990). However, previous research on whether hedge funds have a general trading strategy in bubbles is limited, which is why we delimit our scope to solely investigate hedge funds' trading strategy in bubbles.

To answer our research question, we follow Brunnermeier and Nagel's (2004) methodology which they have divided into three parts. First, to study the proportion of hedge funds' long positions invested in bubble stock, we use the SEC 13F filings, where all institutional investment managers with more than USD 100 million in assets under management are required to disclose their quarterly long equity holdings (SEC Form

13F)[1]. We compare this proportion to the weight these stocks held in the market portfolio to examine whether hedge funds, to a more significant extent, invested in bubble stocks and how that proportion changed during the bubble period. Second, we run a regression to test if our findings hold even when including hedge fund's short positions. Lastly, we study if hedge funds were aware of the bubbles and managed to time their exits in individual stocks before the price peaks and subsequent crashes through an event-study framework.

Our study finds that hedge funds do not always ride bubbles. When looking at the hedge funds' long holdings results, we identify two main trading strategies employed by our sample of hedge funds. During the run-ups to the coal bubble in 2008 and the electronic equipment bubble in 2000, the hedge funds held a greater proportion of their stock holdings in bubble stocks than the market portfolio. We interpret this as the hedge funds riding the bubble, as they increased their exposure when the price run-ups began and decreased them before the bubble burst. However, during the steel bubble in 2008 and the computer software and hardware bubbles in 2000, we find our sample of hedge funds employed the opposite strategy. The hedge funds instead attacked the bubbles by decreasing their holdings in the bubble stocks during the price run-up. The reason why our sample of hedge funds ride some bubbles and attack others is unclear, but we speculate that it could be due to different bubble or industry characteristics.

Second, due to data and method limitations, we are unable to strengthen these findings by analyzing the net weights held by our sample of hedge funds in the bubbles. Due to the large discrepancy between our long-only proportions and net weights, we run several robustness checks where we divide the bubbles into two time-periods, add noise to the returns and broaden the number of stocks included in each bubble. However, none of these tests provide net weights that are more aligned with the proportions found in the long-only analysis.

Lastly, by analyzing hedge funds timing exposure in individual stocks, we provide some evidence that our sample of hedge funds understood that the bubbles existed. That enabled them to capture the price run-ups and avoid the subsequent crashes in individual stocks. The bubbles that support this finding are the steel bubble in 2008, and the measurement & control equipment, electronic equipment and steel bubbles in 2000. During these bubbles, our sample of hedge funds managed to decrease their share of equity held in the quarter prior to the price peak. The computer hardware and computer software bubbles provide some evidence of the contrary, as the hedge funds either kept their share of the equity constant or increased it, despite the bubble bursting.

Altogether, in two of seven bubbles, we find that the hedge funds seemingly rode the bubbles. However, we also find that hedge funds chose to attack three bubbles by decreasing their holdings in the bubble industry. Hence, our overall results diverge from the findings of Brunnermeier and Nagel (2004). Although we cannot conclude hedge funds' general trading strategy during bubbles due to diverging results, our study opens up for interesting discussions of why hedge funds employ different trading strategies in different bubbles. Two commonly mentioned reasons explaining why hedge funds ride

[1] Form 13F is provided on the SEC website and includes a list of reporting requirements in the application form, which we use as a reference.

bubbles relate to synchronization risk discussed in Abreu and Brunnermeier (2002) and fundamental risk discussed in Wurgler and Zhuravskaya (2002). Further, our results that demonstrate that hedge funds chose to attack bubbles are in line with the efficient market hypothesis, (Fama, 1970), and findings by Akbas, et al. (2015) and Fung and Hsieh (2000).

We divide the remaining part of our study into the following sections. Section II presents previous literature on hedge funds' trading strategy and how our study contributes to the current literature. Section III is our data section and presents our bubbles identification, hedge fund holding data, market data, summary statistics, and data limitations. Section IV investigates hedge funds' long-only holdings in the bubbles and includes an analysis of net holdings. Both parts are structured in three main subsections: methodology, empirical results, and analysis. Section V is structured in the same way as Section IV and investigates whether hedge funds were able to successfully anticipate the crash in individual stocks and exit their positions before. In Section VI, we provide a future research analysis. Section VII concludes our findings.

II. Literature review

Whether hedge funds act as a correcting force by reverting stock prices back to fundamentals is a doubted area. To research hedge funds' general trading strategy in bubbles, we need a definition of bubbles and previous research on hedge funds' trading strategy. The closest literature for our study is *Hedge Funds and the Technology Bubble* by Brunnermeier and Nagel's (2004), published in the Journal of Finance.

A. Hedge fund trading strategy

According to the efficient market hypothesis, stocks always trade at fair value (Fama 1970). That is because whenever stock mispricing occurs, there will be rational arbitrageurs who revert prices back to their fundamentals. According to Akbas et al. (2015), in the aggregate, money flowing to hedge funds helps correct stock mispricing. Hence, hedge funds serve as rational arbitrageurs. This view is strengthened by Cao, Chen, Goetzmann and Liang (2018) who show that hedge funds buy undervalued stocks and help stock prices revert back to the security market plane, thereby correcting stock mispricings. However, multiple studies have found the opposite. For example, Abreu and Brunnermeier (2002) find that a single rational arbitrageur may benefit from staying invested in a mispricing until a more coordinated attack by many arbitrageurs occurs due to synchronization risk. DeLong et al. (1990) prove that when positive feedback traders exist, informed rational speculators can destabilize prices and drive them above their fundamental values. These two studies indicate that when stock prices do not trade at their fundamental value, rational arbitrageurs such as hedge funds may sometimes exacerbate the mispricings rather than correct them.

Many of the studies mentioned above refer to Brunnermeier and Nagel's (2004) paper. By analyzing the technology bubble in the 2000s, Brunnermeier and Nagel conclude that hedge funds exacerbated the bubble by riding it rather than acting as informed investors and reverting prices back to their fundamentals. Further, they conclude that among the sample of hedge funds they studied, Tiger management was the only fund that did not survive the technology bubble. It was also the fund with the lowest exposure to

technology stocks. Griffin, Harris, Shu, and Topaloglu (2011) find similar results for the technology bubble and challenge the essential part of market efficiency that sophisticated investors always seek to correct mispricing. Fung and Hsieh (2000) contradict this finding and show that hedge funds do not use positive feedback trading strategies. Further, they find little evidence that hedge funds systematically cause market prices to deviate from fundamentals.

B. Bubble definition

The American economist Euguene Fama argues that bubbles do not exist. He disagrees with the definition of a bubble which implies that a predictable substantial price decline occurs after an irrational strong price increase. That is because no valid evidence on predictable price declines exists, hence the definition of "bubbles" is based on beliefs rather than reliable evidence. Further, he contradicts the argument that price declines during a bubble should be viewed as market correction of unreasonable price increases by arguing that it is unclear which part, the up or the down, of the bubble that is irrational. (Fama 2014)

Greenwood, Shleifer, and You (2019) assess Fama's claim in their paper *Bubbles for Fama*, published in the Journal of Financial Economics. They agree with Fama's statement that a substantial industry portfolio price increase does not, on average, foresee a sharp industry portfolio price decline. However, they find that the probability of a crash is remarkably higher after a sharp industry portfolio price increase and that typical characteristics during a price run-up can help predict a possible crash and future returns. Hence, investors can use such attributes as indicators of bubbles, helping them time the bubble and earn superior returns. Their paper also identifies all US industries' price run-ups followed by a crash between 1928 and 2012 based on Fama and French (1997) 49 industry classifications. Since we study hedge funds' trading strategy in bubbles, we use Greenwood et al.'s identification of bubbles.

C. Our contribution

Common previous research areas regarding hedge funds' trading strategy include studies on rational arbitrageurs, the efficient hypothesis, and limits on arbitrage. (Akbas, et al., 2015; Fung and Hsieh, 2000; Abreu and Brunnermeier, 2002; DeLong et al. 1990) However, to our knowledge, previous research on whether hedge funds have a general trading strategy in bubbles is limited, which is why we delimit our scope to solely investigating trading strategy during bubbles. By applying a similar methodology as Brunnermeier and Nagel (2004) did on the technology bubble, but instead using seven other bubbles identified by Greenwood et al. (2019), we provide a new dimension to the research of hedge funds that can be applied to future analyses on hedge fund trading strategy during bubbles. Creating some predictability regarding hedge fund trading strategy in bubbles could play a role in handling future bubbles where hedge funds' behavior will affect financial markets due to their strong linkages to the global financial system (King and Maier, 2009).

III. Data

We obtain data on hedge fund holdings using 13F filings which have been consolidated by Thomson Refinitiv and WhaleWisdom. To access specific stock and returns data, we use the CRSP database.

A. Identifying bubbles

The first step to test whether hedge funds in general ride bubbles or revert prices back to fundamentals is to identify a sample of bubbles. We use the paper *Bubbles for Fama* written by Greenwood et al. (2019). This paper is based on Fama and French 49 industry classifications and identifies all price run-ups between 1928 and 2012 followed by a crash. They define an industry price run-up as raw returns of more than 100% in the past two years, 100% net of market returns in the past two years, and at least 100% returns on a five-year horizon. A crash is defined as a downturn of at least 40% within two years from the initial price run-up. We delimit our choice of bubbles to US industries, totaling 21 different price run-up episodes followed by a crash between 1928 and 2012. Due to the limited availability of hedge fund data before the 1990s, we exclude bubbles before 1995.

Our final sample of bubbles amounts to seven and occurs in two different time-periods: 1999-2000 and 2007-2008. Five of them occurred in 1999-2000, consisting of the computer hardware industry with 190 firms crashing in the third quarter of 2000, the computer software with 551 firms crashing in the first quarter of 2000, the electronic equipment industry with 347 firms crashing in the first quarter of 2000, the steel industry with 77 firms crashing in the third quarter of 2000, and the measurement & control equipment industry with 127 firms crashing in the first quarter of 2000. The two remaining bubbles in 2007-2008 include the steel industry, with 48 firms crashing in the second quarter of 2008, and the coal industry, with 13 firms crashing in the second quarter of 2008. (Greenwood et al., 2019)

Our method of identifying bubble stocks differs from Brunnermeier and Nagel's (2004) methodology. They divide all stocks on Nasdaq into five quintiles based on their price to sales ratio and define all stocks within the highest quintile as technology stocks. They validate their methodology by comparing their sample of stocks to Lewellen (2003) and find that 90% of internet stocks are included in the highest P/S quintile. Using Fama & French industries rather than broader price-fundamental ratios such as P/S, we identify more specific bubble segments. Another benefit is that this method allows us to analyze multiple bubbles that occurred during the same time-period individually.

B. Hedge fund data

1. Hedge fund holding data

To identify hedge funds' holdings during the two time-periods, we use 13F forms filed by the hedge funds. Form 13F is a SEC regulation that forces all institutional investment managers based in the US with assets under management exceeding USD 100 million to disclose their quarterly long equity holdings (SEC Form 13F). Hence, we limit our sample of hedge funds to US based firms only. However, short positions are exempted from Form

13F leading to an incomplete picture of the entire portfolio holdings. 13F forms shall be filed within 45 days after the last day of the calendar quarter, implying that funds have more than a month to change their holdings before filing the 13F (Shi, 2017; SEC Form 13F). We use Thomson Refinitiv to gain access to the consolidated holdings. For the bubbles in 2008, we obtain an initial sample consisting of roughly 2800 funds.

An issue with Form 13F is that the reporting institution is the manager and not the individual fund. As a result, investment advisors who manage both a mutual- and a hedge fund report the entire business' holdings, rather than reporting the holdings of the hedge fund and mutual fund separately. To cope with this limitation, we use the WhaleWisdom database as it enables us to filter the data on different types of investment advisors and delimit the data to only include hedge funds. Further, we only include hedge funds defined as large or mega according to WhaleWisdom, meaning their holdings have a market value of more than USD 10 billion dollars. For the steel and coal bubbles in 2008, we first identify large and mega hedge funds in Q1 2006. We then cross-check them with the large and mega hedge funds in Q2 2006 and Q1 2008 to guarantee that the hedge funds existed and were classified as large or mega during the entire bubble. We get a sample of 37 hedge funds. As a last step, we match the sample of hedge funds with the fund managers available in the 13F data to generate a final sample of 11 hedge funds: Barrow Hanley Mewhinney & Straus, D. E. Shaw & Co, Dimensional Fund Advisors, Geode Capital Management, Harris Associates, Jennison Associates, Marsico Capital Management, Eaton Vance Management, Oppenheimer Funds, Renaissance Technologies Corporation and Wellington Management Company. Instead of using the manager name which changes during the time-period, we use the manager number provided in the 13F filings.

Selecting hedge funds for the bubbles in the year 2000 was difficult due to inadequate access to data. On WhaleWisdom, we only have access to data from the first quarter of 2001, which enables us to only look at the largest hedge funds at that time. We then have to assume that these hedge funds were large and active from 1998 through 2001. The subsample of hedge funds in this time-period is similar to the sample of 2007-2008 and includes 12 funds: Invesco Capital Management, Wellington Management Company, Iridian Asset Management, Oppenheimer Funds, Jennison Associates, Neuberger Berman, Dimensional Fund Advisors, Barrow Hanley Mewhinney & Straus, Eaton, Vance Management, Loomis, Sayles & Company, Fred Alger Management, and Mackay Shields. Again, we use manager number instead of manager name since the manager numbers are more consistent.

Having identified our samples of managers, we delimit their holdings. The first step is to remove all fund holdings not being listed on either Nasdaq, AMEX or NYSE. Additionally, we only keep holdings in common stocks to avoid looking at exchange-traded funds for example. That proved difficult for the holdings before 1999 as the stocks lacked an exchange code to identify where they were traded. Hence, we remove these criterions for the sample of hedge funds selected for the bubbles in the year 2000.

2. Hedge fund return data

Except for the information in Form 13F, hedge funds are not required by law to file any other information about their portfolio. Therefore, finding data on, for instance, portfolio returns is challenging. Some funds disclose information to commercial databases, such as

Hedge Fund Research and TASS, but the information is limited. (Agarwal, Jiang, Tang and Yang, 2013; Barth, Joenvaara, Kauppila and Wermers, 2021) However, using the WhaleWisdom database, we can access performance data for hedge funds from 2001 and onwards, which implies we do not have performance estimates the bubbles in 2000. The manager performance on WhaleWidsom is generated through backtesting, which means they are estimated by creating a copy-cat portfolio replicating each hedge fund's top 20 holdings using the same weight as the manager and looking at the result of said portfolio. Further, hedge fund performance is generated annually using this method. To identify returns of quarter *t*, we look at the difference between the yearly returns found in quarter *t* and the yearly returns found in quarter *t-1* to generate an estimate of quarterly returns.

C. Market Data

To compare hedge funds' holdings with the market portfolio, we generate a market portfolio based on all stocks trading on Nasdaq, AMEX, and NYSE. We calculate the market capitalization for each stock based on the latest number of shares outstanding and the last price close. For some stocks, that price is missing. For these stocks, we follow CRSPs recommendation by using the last closing price available instead. Since we classify identified bubbles using Fama & French 49 industry codes, we map each stock to one of these industries, which enables us to calculate the share of the market portfolio that constituted bubble stocks in each quarter. To generate market returns, we use CRSP's monthly index, which we compound into quarterly returns.

D. Summary Statistics

Tables 1 and 2 summarize the hedge fund holding data for our sample of hedge funds. The first column specifies the number of hedge funds that reported holdings in each quarter. We have holding data for 11 hedge funds for the bubbles in 2008 and 12 hedge funds for the bubbles in 2000. Looking at table 2, we find that we are missing data from one fund during 1998. The fund missing is Oppenheimer Funds, and the reason behind it is unclear. It could be that the fund changed manager number during this period or that their holdings did not reach the USD 100 million threshold required to file 13F reports during 1998.

Table 1. Summary Statistics 2006-2009

The data for our 11 hedge funds originates from 13F holdings and is compiled by Thomson Refinitiv. The number of hedge funds column specifies how many fund managers reported in each quarter. The stock holdings are generated by summarizing the market value of all stocks that satisfy the criteria stated in the text held by our sample of hedge funds during each quarter. The number of stocks is the number of unique stocks held. Lastly, the aggregate holdings are the summarized holdings of all reporting hedge funds.

			Stock holdings per hedge fund		Number of stocks per hedge fund		Aggregate Holdings
Year	Quarter	Number of hedge funds	Mean (USD mn)	Median (USD mn)	Mean	Median	USD mn
2006	1	11	62,339	46,308	1,462	1,704	685,733
	2	11	61,297	43,886	1,491	1,692	674,272
	3	11	64,565	45,865	1,500	1,698	710,219
	4	11	69,505	48,925	1,505	1,766	764,553
2007	1	11	71,696	50,645	1,499	1,721	788,658
	2	11	76,492	58,242	1,505	1,721	841,417
	3	11	76,343	55,286	1,499	1,672	839,768
	4	11	72,333	54,426	1,548	1,635	795,666
2008	1	11	64,085	46,243	1,532	1,588	704,931
	2	11	65,251	48,987	1,539	1,590	717,764
	3	11	57,675	43,349	1,523	1,493	634,423
	4	11	43,865	34,614	1,509	1,465	482,520
2009	1	11	39,190	32,002	1,509	1,451	431,092
	2	11	45,462	36,900	1,483	1,399	500,080
	3	11	52,369	41,553	1,471	1,418	576,056
	4	11	54,280	44,524	1,452	1,414	597,085

Table 2. Summary Statistics 1998-2002

The data for our 12 hedge funds originates from 13F holdings and is compiled by Thomson Refinitiv. The number of hedge funds column specifies how many fund managers reported in each specific quarter. We generate the stock holdings by summarizing the market value of all stocks held by our sample of hedge funds during each quarter. The number of stocks is the number of unique stocks held. Lastly, the aggregate holdings are the summarized holdings of all reporting hedge funds.

			Stock holdings per hedge fund		Number of stocks per hedge fund		Aggregate Holdings
Year	Quarter	Number of hedge funds	Mean (USD mn)	Median (USD mn)	Mean	Median	USD mn
1998	1	11	27,170	19,743	978	687	298,866
	2	11	27,468	19,170	1,020	756	302,147
	3	11	23,590	15,428	981	697	259,485
	4	11	28,115	18,690	1,046	745	309,260
1999	1	12	29,560	17,954	1,074	1,065	354,717
	2	12	32,205	20,262	1,074	1,057	386,455
	3	12	33,977	22,998	1,059	1,045	407,718
	4	12	35,744	25,864	1,123	1,064	428,926
2000	1	12	39,685	25,353	1,186	1,264	476,224
	2	12	38,878	25,741	1,151	1,207	466,541
	3	12	41,529	25,236	1,213	1,193	498,348
	4	12	38,653	24,795	1,190	1,178	463,833
2001	1	12	34,758	24,711	1,163	1,187	417,093
	2	12	39,659	27,441	1,228	1,182	475,913
	3	12	33,218	23,710	1,253	1,099	398,620
	4	12	38,407	26,839	1,284	1,106	460,889
2002	1	12	39,392	28,704	1,263	1,063	472,699
	2	12	35,128	26,694	1,284	1,090	421,538
	3	12	29,151	21,732	1,265	1,113	349,811
	4	12	30,688	22,762	1,270	1,059	368,253

Next, the mean and median stock holdings per hedge fund are reported. Stock holdings are defined as the total market value of all bubble stock holdings in table 2. In table 1, only common stocks trading on either Nasdaq, AMEX, or NYSE are included. The mean holdings have increased between the bubbles in 2000 and the bubbles in 2008, which is natural considering the overall growth of the hedge fund industry during the same period (Stowell 2012). However, the mean holdings are large, and the median is lower than the mean, suggesting that the holdings are skewed to the right with a few funds being significantly larger than the average.

The third set of columns reports the mean and median number of stocks held per hedge fund. For both of our time-periods, our sample of hedge funds holds a large number of unique stocks, which is worrisome as active managers such as hedge funds often makes bets on a relatively small number of stocks or a specific segment in the market. However, in table 1, the mean number of stocks held is smaller than the median, implying that we have a skewed distribution to the left. The same finding does not hold for table 2. Overall, we question whether our sample of selected hedge funds hold too many stocks to plausibly be pure hedge funds and rather are investment managers managing other forms of funds as well.

Lastly, the aggregate holdings for the entire sample of hedge funds are reported. Table 1 shows how the aggregate holdings increased to a high of USD 841 million in the second quarter of 2007, and then started decreasing to a low of USD 431 million in the first quarter of 2009. The same pattern is not found during the bubbles in 2000, where the aggregate hedge fund holdings reached their peak in the third quarter of 2000, which is when all our identified bubbles have already burst.

E. Data limitations

Researching hedge funds is challenging due to the limited data availability. With 13F being the exception, reporting to other sources such as public hedge fund databases, including Lipper TASS and Hedge Fund Research is voluntary, leading to an incomplete picture of hedge fund holdings and performance (Agarwal, Jiang, Tang and Yang, 2013; Barth et al., 2021) The best source available, 13F filings, is only reported quarterly, which gives an inadequate picture of intra-quarter holdings and hedge fund behavior.

The first limitation of our study is the sample of hedge funds. As previously mentioned, a limitation of 13F filings is that the reporting institution is the manager, not the specific fund. We have tried to identify a particular sample of funds that we believe are pure hedge funds, but since we are dealing with funds from 2006, it is hard to ensure that they did not manage money using other methods, for example, through a mutual- or industry-specific fund. While all funds included in the sample are registered as hedge funds in WhaleWisdom's database, the high mean holdings and large number of stocks held by our selected funds create doubt regarding the accuracy of that classification.

A second limitation regards hedge fund performance. Our best estimates for hedge fund returns are generated by backtesting the long stock positions fund managers held. Estimating results this way implies that we do not account for any short positions, other derivatives or intra-quarter movements in holdings. Moreover, the results we have are on a yearly basis and have been converted to quarterly results, which may reduce accuracy further.

A final limitation is that we are working with data that is more than 20 years old. As a result, we have been unable to find any fund performance for the bubbles in the year 2000. Further, we have had to loosen some of the criterion placed on hedge fund holdings for those bubbles due to limited data.

IV. Hedge fund holdings in bubble stocks

In this section, we aim to determine whether hedge funds ride bubbles as the results found in Brunnermeier and Nagel (2004) suggest, or if they attack the bubbles by selling their holdings in the bubble sector or going short against it. We divide the section into three subsections. The first one investigates hedge funds' long holdings in bubble stock, the second and third subsection is an extension of the first one and includes hedge funds' short positions in bubble stocks. All subsections are structured in the same way, consisting of methodology, empirical results, and analysis.

A. Hedge fund long holdings in bubble stocks compared to the market portfolio

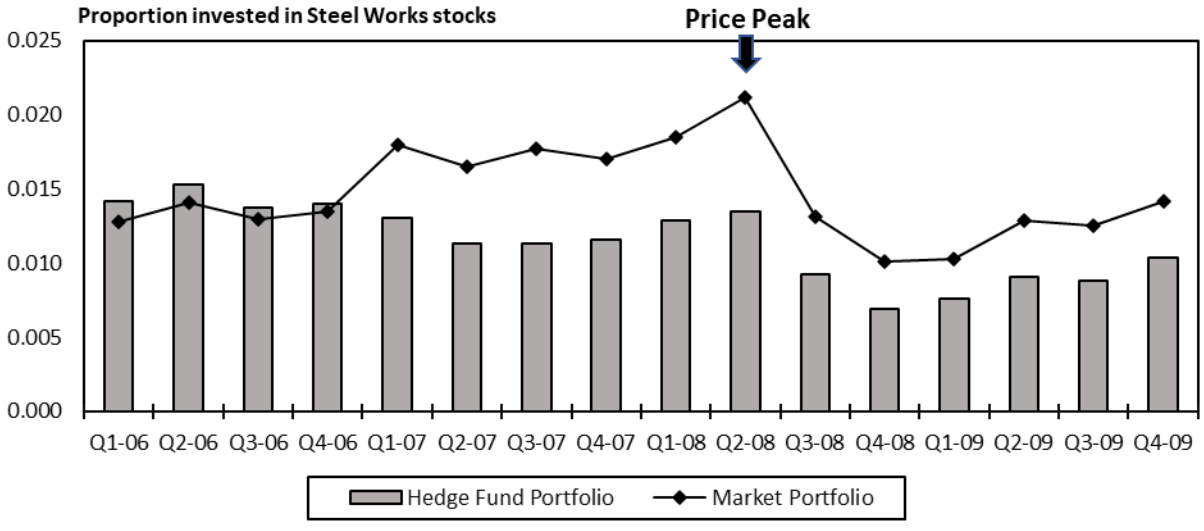
1. Methodology

To measure what proportion of overall stock holdings our sample of hedge funds held in bubble stocks, we calculate the market value of the bubble stocks in each quarter and compare that with the market value of their entire stock portfolio in that quarter. We then use the total market capitalization of bubble stocks in each quarter and compare it with the market capitalization of all stocks on Nasdaq, AMEX, and NYSE to identify what weight the bubble stocks held in the market portfolio. We apply the same methodology for all seven bubbles.

2. Empirical Results

a) Proportion invested in steel stocks, 2006-2009

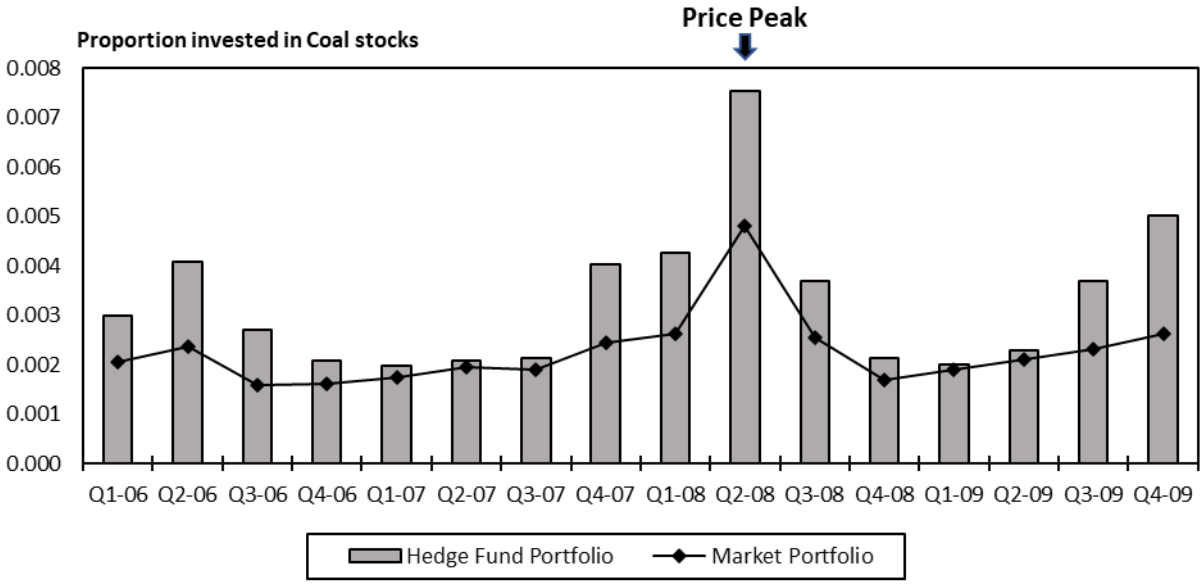
Figure 1. The proportion invested in steel stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in steel stocks, compared to the market value of all holdings. As a comparison, the weight of steel stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.



Initially, our sample of hedge funds and the market portfolio almost have identical proportions of their portfolio invested in steel stocks. However, as the price run-up for stocks in the steel industry began in 2007, our sample of hedge funds behaved differently from the market portfolio. Instead of drastically increasing their proportion held to mirror the market portfolio, our hedge funds initially decreased their proportion and then slightly increased it while the price run-up continued. As a result, when the bubble crashed in the second quarter of 2008, the hedge funds held less than 1.5% of their holdings in steel stocks, compared to a weight of more than 2% for the market portfolio. Following the crash, the gap narrows due to the market weight decreasing substantially more than the hedge fund holdings.

b) Proportion invested in coal stocks, 2006-2009

Figure 2. The proportion invested in coal stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in coal stocks, compared to the market value of all holdings. As a comparison, the weight of coal stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.



Compared to the steel bubble in the same time-period, our sample of hedge funds behaved differently during the price run-up and subsequent crash of stocks in the coal industry. While holding similar proportions as the market portfolio at the beginning of 2007, the hedge funds increased their holdings substantially at the end of 2007, to a much larger extent than the weight increase seen in the market portfolio. The increased exposure became even more significant in the second quarter of 2008, when hedge funds held nearly 0.8% of their stock holdings in coal stocks, compared to the market weight of 0.5%. After the crash in the same quarter, the hedge funds decreased their proportions back in line with the market portfolio.

c) Proportion invested in computer hardware, computer software, electronic steel, and measurement & control equipment, 1998-2002

Figure 3. The proportion invested in computer hardware stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in computer hardware stocks, compared to the market value of all holdings. As a comparison, the weight of computer hardware stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.

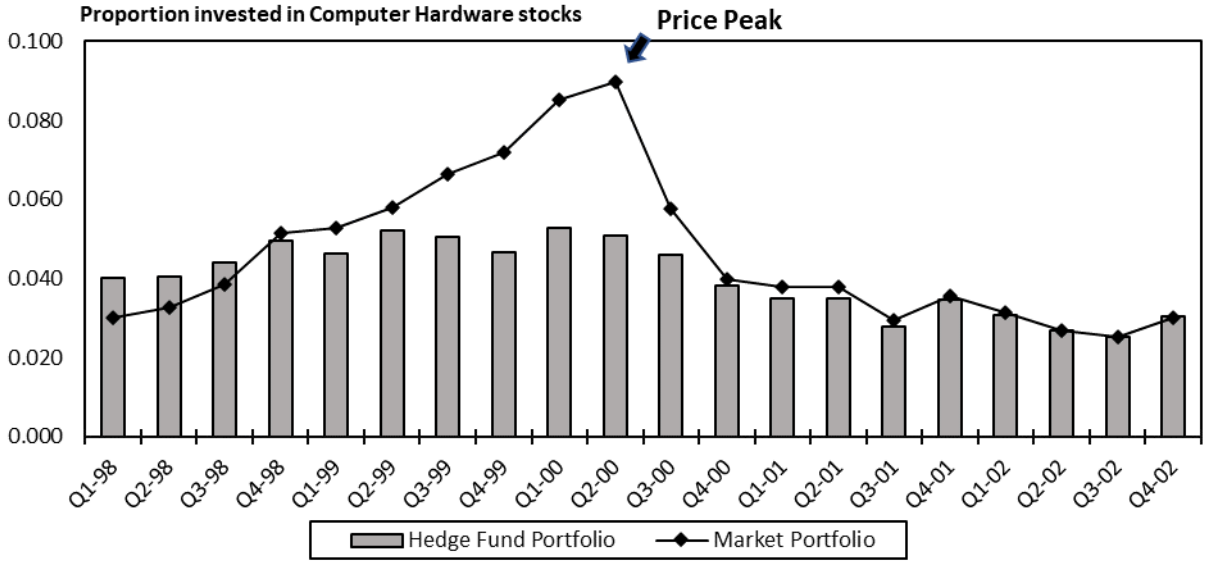


Figure 4. The weight proportion invested in computer software stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in computer software stocks, compared to the market value of all holdings. As a comparison, the weight of computer software stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.

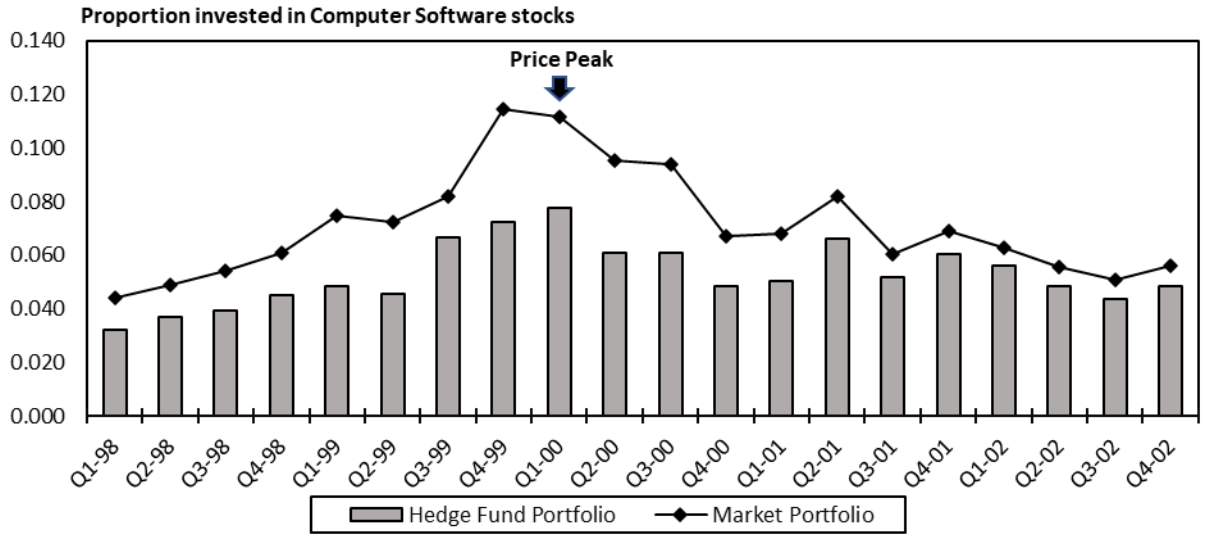
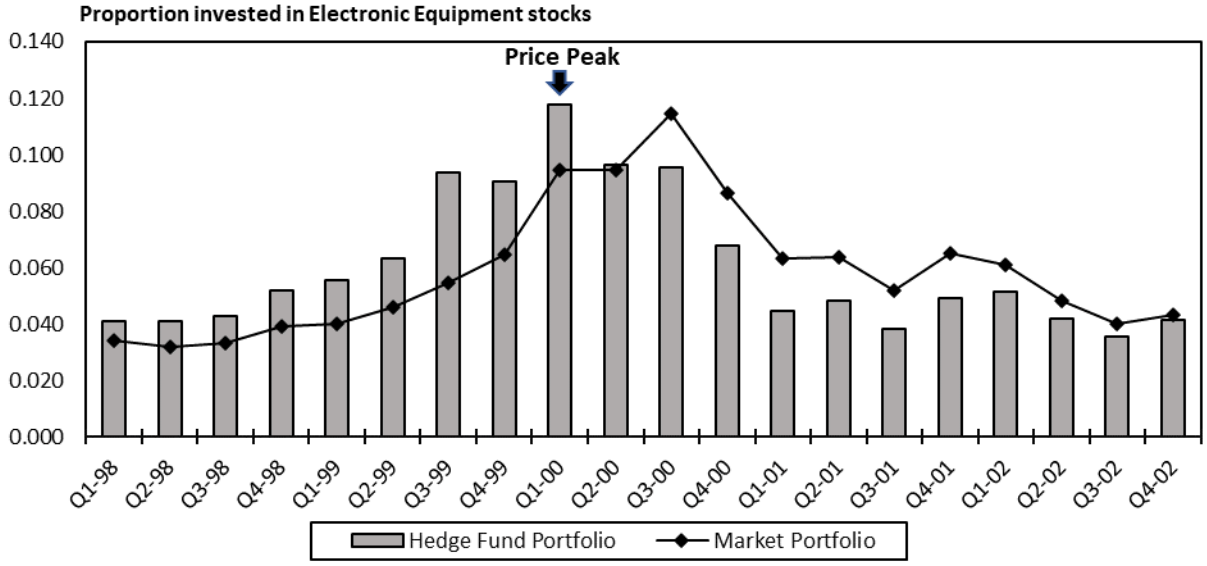


Figure 5. The weight proportion invested in electronic equipment stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in computer electronic equipment, compared to the market value of all holdings. As a comparison, the weight of electronic equipment stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.



Figures 3, 4 and 5 present how the proportions of hedge funds' long-only stock holdings in computer hardware, computer software and electronic equipment changed over the bubble periods. Further, figures 11 and 12 in the appendix present the same analysis on the steel, and measurement & control equipment bubbles. In general, our findings of the computer hardware and software bubbles show that our sample of hedge funds did not increase their holdings in line with the overall weight in the market portfolio. That implies that they were missing out on the price run-up but not taking as large losses as the market portfolio when the bubbles burst. The strategy is different for the remaining three bubbles. In the electronic equipment bubble, the holding pattern indicates that the hedge funds increased the proportion held during the price run-up and then decreased that proportion after the crash to a larger extent than the weight of the stocks in the market portfolio. In figure 11 in the appendix, it is further apparent that our sample of hedge funds held a larger proportion of their portfolio invested in the steel segment than the market portfolio. Still, there is no evident sell-off during the entire period. Lastly, as figure 12 in the appendix shows, the holdings in measurement & control stocks are also relatively stable and do not move much with the movement of the market portfolio.

3. Analysis

With our results for the steel bubble in 2008, we conclude that by keeping the share of their portfolio held in steel stocks constant while the weight increases in the market portfolio, the hedge funds were abstaining from riding the bubble, which is in line with what the efficient market hypothesis predicts. We see a similar pattern for computer hardware and software bubbles. We interpret this finding as our sample of hedge funds attacking the bubbles. By attacking the bubbles, hedge funds were less exposed to downturns and did not suffer as much as the market portfolio did when the bubbles burst. However, we also have examples of the opposite. For instance, in the coal and electronic equipment bubbles, the hedge funds held a larger proportion of their stock portfolio in bubble stocks than the market, which points to a

positive feedback trading strategy that contributes to the bubble. We interpret this finding as the hedge funds riding the bubbles.

Two common aspects discussed in the literature regarding why hedge funds ride bubbles instead of attacking them are synchronization risk and fundamental risk. According to Abreu and Brunnermeier (2002), synchronization risk, defined as the coordination required between investors' trading behaviors to affect market prices, helps explain why mispricing can persist at least for a while. Abreu and Brunnermeier (2003) further strengthen the synchronization aspect in their study by connecting asset bubbles to the coordination-failure model. They convey that unless many investors decide to correct mispricing by attacking the bubble, it will continue to grow. Therefore, it can be beneficial for investors to ride bubbles for a while until there are reasons to believe that other rational arbitrageurs will begin attacking the bubble. Hence, an explanatory factor for why our sample of hedge funds rode the coal and electronic equipment bubbles could be due to synchronization risk. The second explanatory factor relates to fundamental risk. Wurgler and Zhuravskaya (2002) argue that rational arbitrageurs avoid correcting mispricing when there is an absence of perfect substitutes that can be used to hedge their trades. A lack of close substitutes leads to a larger fundamental risk that the rational arbitrageur must bear. Hence, rational arbitrageurs' risk aversion restrains the aggressiveness, which during a bubble, would result in riding the bubble instead of attacking it.

One reason why our sample of hedge funds apply different trading strategies for different bubbles in the same time-period could be industry characteristics, such as the number of stocks included in the industry. When looking at differences in trading strategy across the two time-periods, one potential reason could be the differences in the sample of hedge funds used. However, there is some overlap between the two samples, and we therefore expect the trading strategy to be relatively similar. Therefore, the differences in trading strategy could rather be explained by differences in bubble characteristics, such as the external factors causing the bubble.

Besides the different trading strategies used in different bubbles, another finding is the low proportions invested in bubble stocks in 2008, both for our sample of hedge funds and for the market portfolio. During the technology bubble in 2000, Brunnermeier and Nagel (2004) present that hedge funds held 10-30% of their portfolio in the highest P/S-quintile of Nasdaq stocks. The corresponding proportion invested in the market portfolio was between 5-20%. That could be compared to our results for the steel bubble in 2008, where the proportion invested in steel stocks was 1-2% for both hedge funds and the market portfolio. One reason for this is the low number of stocks characterized as steel stocks, only amounting to 48 stocks, which is substantially fewer than one-fifth of all Nasdaq stocks. Further, during the technology bubble, Brunnermeier and Nagel (2004) present that hedge funds' proportion invested in the highest P/S-quintile was larger than the weight those stocks held in the market portfolio during the entire bubble. Most of our identified stocks in the computer hardware, computer software, and electronic equipment bubbles in 2000 are probably included in the highest P/S-quintile in Brunnermeier and Nagel's paper since 90% of internet stocks were included in the highest P/S-quintile (Brunnermeier and Nagel, 2004; Lewellen, 2003). Thus, we expect to find similar results, namely a larger proportion invested in technology stocks for our sample of hedge funds than the market portfolio during the entire bubble. However, one finding is that our results for the computer hardware and software bubbles diverge from Brunnermeier and Nagel's results. Only our results for the electronic equipment bubble are close to identical to their results.

B. Hedge fund holdings in bubble stocks, including short positions

With the working hypothesis that hedge funds do not have a general trading strategy in bubbles but rather apply different strategies to different bubbles, we test that this hypothesis still holds when accounting for short positions. Due to data limitations outlined above, we only run the regression on the bubbles in 2008 rather than our entire sample of seven bubbles.

1. Methodology

To identify short positions, we use an approach similar to Sharpe (1992) and Brunnermeier and Nagel (2004). We assume that hedge fund returns can be simplified as the weighted returns of two asset classes plus some idiosyncratic return. For the two bubbles we had returns data on, namely the coal and steel bubble in 2008, we assume that hedge funds invested their portfolio into two different asset classes: a market portfolio and a bubble portfolio, which only consists of stocks in the industry that peaked. The return of the market portfolio R_M is the value-weighted return of all stocks on Nasdaq, AMEX, and NYSE. The return of the bubble portfolio R_B is the return of the stocks included in the relevant Fama & French industry that are listed on either Nasdaq, AMEX or NYSE. R_B will either be R_S or R_C, depending on whether we are analyzing the steel bubble or coal bubble. We then assume that portfolio managers can allocate b to these two asset classes. Assuming that they allocate a fraction g of their portfolio value to the bubble stocks, the remaining amount $(b - g)$ will then be invested in the market portfolio. Therefore, the return for a hedge fund investing in the bubbles can be written as:

$$R_t = (b - g)R_{M,t} + gR_{B,t} + e_t \quad (1)$$

Where e_t is the idiosyncratic return and R_B is either R_S if we consider the steel bubble, or R_C if we consider the coal bubble.

We have already estimated the proportion of hedge fund long holdings invested in the bubble stocks, compared to the overall long holdings and the proportion bubble stocks held in the market portfolio. The weights of the bubble stocks in the market portfolio are denoted m_B, and can be either m_S for the steel bubble or m_C for the coal bubble. This implies that in total, the hedge fund exposure to bubble stocks will consist of g, which is the proportion they invest in bubble stocks directly, and $(b - g) * m_B$, which is the indirect exposure they get from investing in the market portfolio. The latter contains some bubble stocks itself, denoted as m_B. Thus, the net investment in bubble stocks as a proportion of the total hedge fund portfolio is $g + (b - g)m_B$. The total net investment in stocks is still b, which implies that the net investment in bubble stocks compared to the total investment, after rearranging the terms, equals:

$$w_B = m_B + \frac{b}{g}(1 - m_B) \quad (2)$$

Where w_B equals the net proportion invested in the bubble stocks and will take the values w_S and w_C for the steel and coal bubble, respectively. For a hedge fund that tracks the market portfolio, $b = 0$ and $g = 0$, which implies that $w_B = m_B$.

Next, we aim to estimate w_B. To estimate b and g, we rearrange equation (1) to get the following equation:

$$R_{i,t} = \alpha + \beta R_{M,t} + \gamma\left(R_{B,t} - R_{M,t}\right) + \epsilon_t \quad (3)$$

Using our assumptions, it is easy to show that $\beta = b$ and $\gamma = g$. $\left(R_{B,t} - R_{M,t}\right)$ will be $\left(R_{S,t} - R_{M,t}\right)$ when analyzing the steel bubble and $\left(R_{C,t} - R_{M,t}\right)$ when analyzing the coal bubble. We estimate b and g by running a panel regression on equation (3), with R_i being the quarterly returns between 2007 and 2009 for each of the 11 hedge funds we have included in our sample. This regression has two independent variables. The first independent variable is the return on the market portfolio, represented by the value-weighted returns of all stocks listed on Nasdaq, AMEX, and NYSE. The second independent variable is the excess return of the stocks included in the relevant bubble industry compared to the market portfolio return. All variables are standardized, which means that $\alpha = 0$. Since we have returns data for 11 different hedge funds, a panel regression allows us to attain more specific results than if we would take the weighted average of the 11 hedge funds since we can increase the number of observations from 11 to 132.

Our method is a simplification of the diverse and dynamic trading strategies that hedge funds use. For example, Fung and Hsieh (1997) demonstrates that a linear model is inaccurate for describing the dynamic trading strategies that hedge funds can use in their trading. However, it should provide some guidance towards our sample of hedge funds' exposure to our bubble sectors.

2. Empirical results

Table 3. Hedge fund net exposure to the bubble stocks: return regression. This table reports the results of a panel regression on the quarterly returns of 11 hedge funds during 2007 - 2009 on two independent variables, R_M, the value-weighted return of the market portfolio, and $(R_B - R_M)$, the excess return of the bubble stocks compared to the return on the market portfolio. The bubble stocks are defined through Fama & French industry classification.

$$R_{i,t} = \alpha + \beta R_{M,t} + \gamma\left(R_{B,t} - R_{M,t}\right) + \varepsilon_t$$

The t-statistics for the coefficients are reported in parentheses. β and γ are used to estimate w_B, the net weight of the bubble stocks in the hedge fund portfolios using equation (2).

	Factor loadings			Implied net-weights	
Bubbles in 2008	β	γ	Adj. R^2	w_S	w_C
Steel Bubble	0.51 (6.08)	0.63 (7.81)	0.43	0.44	
Coal Bubble	0.22 (2.63)	0.01 (0.08)	0.40		0.02

The regression gives us a beta estimate of 0.51 and gamma estimate of 0.63 for the steel bubble, translating into a net portfolio weight of 0.44. For the coal bubble, the beta estimate is 0.22, and the gamma estimate is 0.01, which translates into a net portfolio weight of 0.02. While both the gamma- and beta estimates are statistically significant at conventional significance levels for the steel bubble, only the gamma estimate is statistically significant for the coal bubble. That implies that we cannot draw any conclusions from the results for the coal bubble.

However, the implied net weight for the steel bubble that these estimates provide are not sensible compared to the proportions found using long-only holdings. The previous section concluded that the gross proportions held by hedge funds in steel stocks was roughly 1.5%. Our results imply that the net proportion, including short positions and derivatives, invested in steel stocks is 44%, and that the hedge funds hold a net proportion of 56% in the market portfolio.

3. Analysis

Rather than strengthening the findings from the analysis on long-only holdings, including short positions led to portfolio weights that are drastically different from the proportions found in the long-only section. As a result, despite our findings being statistically significant for the steel bubble, we cannot confirm our hypothesis that our sample of hedge funds attacked the steel bubble as we find in the long-only section. Due to a statistically insignificant beta estimate for the coal bubble, we cannot confirm our hypothesis that they rode that bubble either. Instead, to identify how our sample of hedge funds changed their holdings during the bubble, we divide the bubble in two periods, the first six quarters and the last six quarters. The results can be found in table 6 in the appendix. Now, both the gamma and beta estimates are statistically significant at conventional significance levels for the steel and the coal bubbles in both periods. For the steel bubble in the first period, the net portfolio weight is 61% in steel stocks and 39% in the market portfolio. For the second period, the implied net portfolio weight in steel stocks is 190% and -90% in the market portfolio. For the coal bubble in the first period, the net portfolio weight is -109% in coal stocks and 209% in the market portfolio. The implied portfolio net weight in coal stocks in the second period is 308% and -208% in the market portfolio. While the weights are still very different from the proportions found in the long-only section, the results imply that our sample of hedge funds increased the net weight of their portfolio invested in bubble stocks after compared to before the price peak. This is not in line with figure 1, where we find that hedge funds decreased their holdings after the price peak. Therefore, the robustness check does not help provide proof that our findings hold even when accounting for short positions.

Our inability to generate accurate proportions when accounting for short positions is unclear, but there are several possible reasons. First, our hedge fund returns have been generated through backtesting the long-only holdings of hedge fund managers. These returns will not be the actual returns including short positions. To combat this shortcoming, we did a robustness check by adding noise to our sample of hedge fund returns, to see whether that affects the implied portfolio weights. The results are found in table 7 in the appendix, where noise with a standard deviation of 0.5% has been added. Our results show net weights of 44% in steel stocks and 66% in the market portfolio for the steel bubble, and 0% in coal stocks and 100% in the market portfolio for the coal bubble. While both estimates are statistically significant for the steel bubble, the beta estimate for the coal bubble is not statistically significant, which means we cannot draw any conclusion about the implied net weight for the coal bubble. However, our implied net weight for the steel bubble is nearly identical with the implied net weights in table 3. Hence, our results are not sensitive to adding noise to the returns.

A second reason why our results are unrealistic could be our method of classifying bubble stocks. By defining bubble stocks using Fama & French' industries rather than looking at a broader sample of stocks, such as the top quintile of Nasdaq stocks sorted on P/S ratios, we are examining a significantly smaller sample of stocks. While the methodology used in Brunnermeier and Nagel (2004) worked well for the broad dot-com bubble with a large number of stocks included, it proved less beneficial for the smaller steel and coal bubbles. Alas, in the

next section, we try to combat this issue by applying a different methodology of selecting stocks to achieve a larger sample of stocks characterized as bubble stocks.

C. Hedge fund holdings using a broader definition of the bubble segment

1. Methodology

To broaden the sample, we look at which stocks' returns have been the most sensitive to coal and steel prices developments, instead of looking at the stocks included in the Fama & French steel and coal industries. We look at the monthly returns from investing in steel futures and the monthly price developments of Australian and South African coal from the IMF to accomplish this. We then compare these returns to the monthly returns of individual stocks and the monthly market portfolio returns, using the following panel regression:

$$R_{i,t} = \alpha + \beta R_{M,t} + \gamma R_{B,t} + \varepsilon_t \quad (4)$$

Where R_i is the return of hedge fund i, R_M is the return of the market portfolio, and R_B is the monthly returns on steel futures and coal prices, depending on which bubble we are analyzing. The β signifies the stock's return sensitivity to the market, and the γ signifies the stock's return sensitivity to steel or coal prices. We run the panel regression above with the quarterly returns between 2007 and 2009 for each of the 11 hedge funds included in our sample. All variables are standardized, which means that $\alpha = 0$. Next, we divide all stocks into quintiles based on their γ, which estimates how sensitive the stock's return is to the price developments of steel and coal and select the top quintile to include the most sensitive stocks to steel and coal prices. Using this new sample, we conduct the same analysis on how the proportion of long-only holdings for hedge funds have changed over the bubble period. We then re-run a panel regression on equation (3) using the returns of our new sample of bubble stocks instead of the old sample to control whether our findings for long-only holdings are supported when accounting for short positions.

2. Empirical results

a) Proportion of hedge fund long holdings invested in bubble stocks

When we broaden our sample of stocks, the results in figure 6 show that the proportion of stock holdings that our sample of hedge funds held in high steel-price sensitive stocks largely resemble the weights they constitute in the market portfolio. We can no longer distinguish the difference between how our sample of hedge funds behaved, compared to the overall market portfolio behavior, which could be due to looking at a larger sample of stocks.

Similarly, in figure 7 we find that the proportions of stock holdings that hedge funds held in high coal-price sensitive stocks largely resemble the weights held in the market portfolio, albeit constantly being slightly lower.

Figure 6. The proportion invested in high steel-price sensitive stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in the high steel-price sensitivity quintile, compared to the market value of all holdings. As a comparison, the weight of the stocks in the high steel-price sensitivity quintile in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.

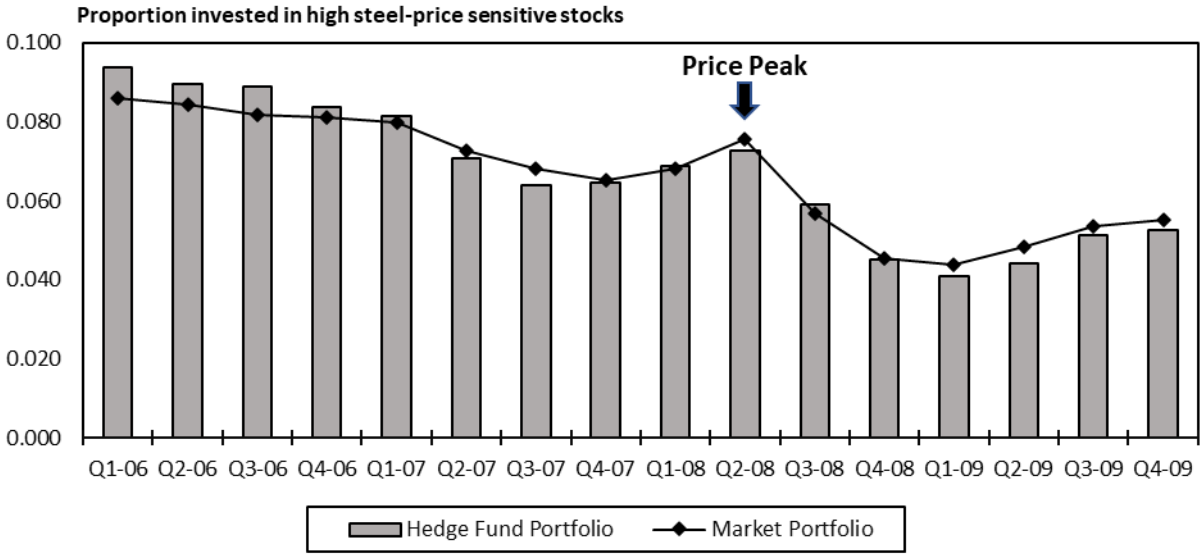
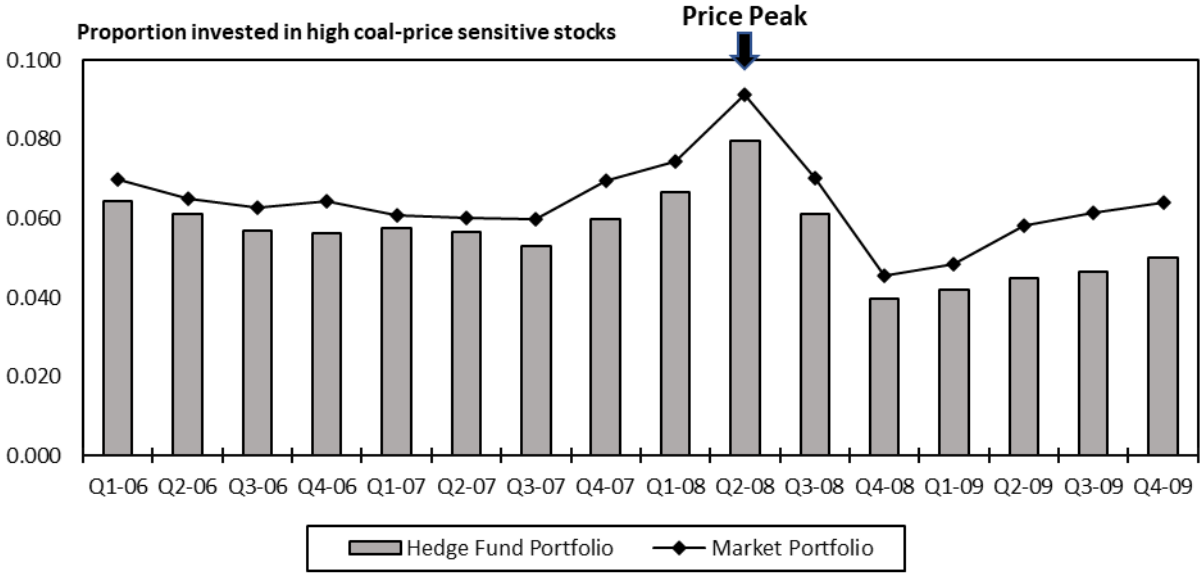


Figure 7. The proportion invested in high coal-price sensitive stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in the high coal-price sensitivity quintile, compared to the market value of all holdings. As a comparison, the weight of the stocks in the high coal-price sensitivity quintile in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.



b) Proportion of hedge fund holdings invested in bubbles stocks, including short positions

Table 4. Hedge fund net exposure to the bubble stocks: return regression. This table reports the results of a panel regression on the quarterly returns of 11 hedge funds during 2007 - 2009 on two independent variables, R_M, the value-weighted return of the market portfolio, and $(R_B - R_M)$, the excess return of the bubble stocks compared to the return on the market portfolio. The bubble stocks are defined as the stocks in the highest quintile ranked by how sensitive their returns are compared to the price development of steel and coal, respectively.

$$R_{i,t} = \alpha + \beta R_{M,t} + \gamma\left(R_{B,t} - R_{M,t}\right) + \varepsilon_t$$

The t-statistics for the coefficients are reported in parentheses. β and γ are used to estimate w_B, the net weight of the bubble stocks in the hedge fund portfolios using equation (2).

	Factor loadings			Implied net-weights	
Bubbles in 2008 using quintiles	β	γ	Adj. R^2	w_S	w_C
Steel Bubble	0.46 (5.79)	0.32 (4.13)	0.47	0.71	
Coal Bubble	0.68 (7.06)	-0.07 (-0.77)	0.40		-0.03

Lastly, table 4 depicts the results of the same regression that was used previously, but with bubble returns defined as the value-weighted results of the quintile of stocks most sensitive to returns in coal and steel prices, instead of the stocks belonging to the correct Fama & French industry. The regression gives us a beta estimate of 0.46 and gamma estimate of 0.32 for the steel bubble, translating into a net portfolio weight of 0.71. For the coal bubble, the beta estimate is 0.68, and the gamma estimate is -0.07, which translates into a net portfolio weight of -0.03. While both the gamma- and beta estimates are statistically significant at conventional significance level for the steel bubble, only the beta estimate is statistically significant for the coal bubble. That implies that we cannot draw any conclusion from the results for the coal bubble. Our results imply that the net proportion invested, including short positions and derivates, invested in steel stocks is 71%, and that the net proportion invested in the market portfolio is 29%.

3. Analysis

By increasing the number of stocks included in the bubble segments, we find that the long-only proportion held in bubble stocks increases to roughly 8% of the total stock holdings. Similarly, we find that the net weight held in steel stocks increases compared to using a narrower definition of the bubble segment. Increasing the number of stocks included in the bubble also brings a loss of specificity, as we find the hedge fund long holdings now largely track the market portfolio. However, the regression still produces very different net weights compared to the long-only proportions, which means that increasing the number of stocks included in the bubble segment does not help us confirm our hypotheses that our sample of hedge funds attacked the steel bubble and rode the coal bubble.

V. Hedge funds and individual stock timing

Having established partial evidence that our sample of hedge funds was riding two of the bubbles, we now move to deduce whether they were aware of the bubbles and timed their exit in individual stocks before the price peaks. This analysis aims to determine that hedge funds rode the bubble deliberately rather than failing to understand that a bubble had formed.

A. Methodology

To determine whether our sample of hedge funds managed to time their exposure in individual stocks, we look at the stocks included in the different bubble industries and create a quarterly total return index for these stocks during the bubble period. We then identify the quarter in which the stock price peaked, defined as the quarter in which the index took its maximum value. We apply some bubble-specific constraints. For example, we ignore coal and steel stocks that peaked before the first quarter of 2007, as that is when the price-run up began, and those that peaked after 2008. Similarly, for the bubbles in 2000, we disregard stock that peaked before 1999, and after 2000.

We then calculate the proportion of outstanding shares held by hedge funds for each stock and quarter. To calculate hedge fund holdings in each quarter, we look at the proportion of outstanding equity that our sample of hedge funds held in our sample, measured by the number of shares owned compared to overall shares outstanding. The holdings are then value-weighted based on the total value of the stocks in the aggregate hedge fund portfolio, defined as the shares owned timed by the share price. Lastly, we align the quarterly series of hedge fund holdings using an event study framework, where event-time quarter zero is the quarter of the price peak. Next, we disregard stocks for which we lacked data four quarters before or after the price peak. Whereas the coal bubble is synchronized with all stocks peaking during the same quarter, this finding does not hold for all bubbles. For example, table 5 below presents the distribution of peaks for stocks in the steel bubble in 2008. While a large number of stocks peaked in the second quarter of 2008, some stocks peaked before that, in 2007. The distribution of stock peaks for the remaining bubbles can be found in the appendix, table 8 to 12.

Table 5. The distribution of stock peaks for the steel bubble in 2008. For each stock, we construct a returns index that summarizes the quarterly returns between 2006 and 2009 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 2007 and 2008.

Year	Quarter	Number of peaks
2007	1	3
	2	2
	3	5
	4	4
2008	2	10
	3	1

B. Empirical results

Figure 8. The average share of equity held by our sample of hedge funds during the individual stock price peaks in the steel and coal bubbles in 2008. We create a quarterly return index for each stock included in the bubbles and determine the quarter in which this index peaks. We also calculate the share of equity held, defined as the proportion of outstanding shares held by our sample of hedge funds for each stock and quarter. For stocks that peaked in 2007 or 2008, we align the value-weighted holdings in event-time where the quarter the price peaked is event-time 0.

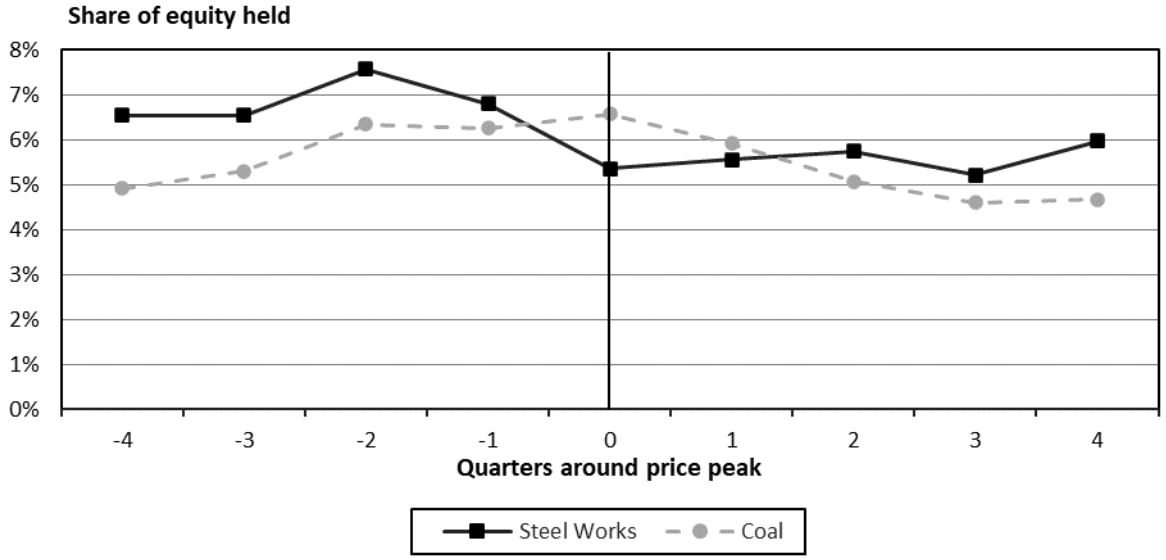


Figure 8 presents the results for the two bubbles in 2008. For the steel bubble, our sample of hedge funds on average began to exit their positions and decrease their share of equity held one quarter before the quarter of the price peak. For the coal bubble, we find that our sample of hedge funds increased the share of equity held moving up to the peak and then began to sell their holdings in the quarters after the peak. That is consistent with the findings in figure 2, which is not surprising considering the synchronization of stock peaks.

Figure 9. The average share of equity held by our sample of hedge funds during the individual stock price peaks in the computer hardware, computer software, electronic equipment, and measurement & control equipment bubbles in 2000. We create a quarterly return index for each stock included in the bubbles and determine the quarter in which this index peaks. We also calculate the share of equity held, defined as the proportion of outstanding shares held by our sample of hedge funds for each stock and quarter. For stocks that peaked in 1999 or 2000, we align the value-weighted holdings in event-time where the quarter the price peaked is event-time 0.

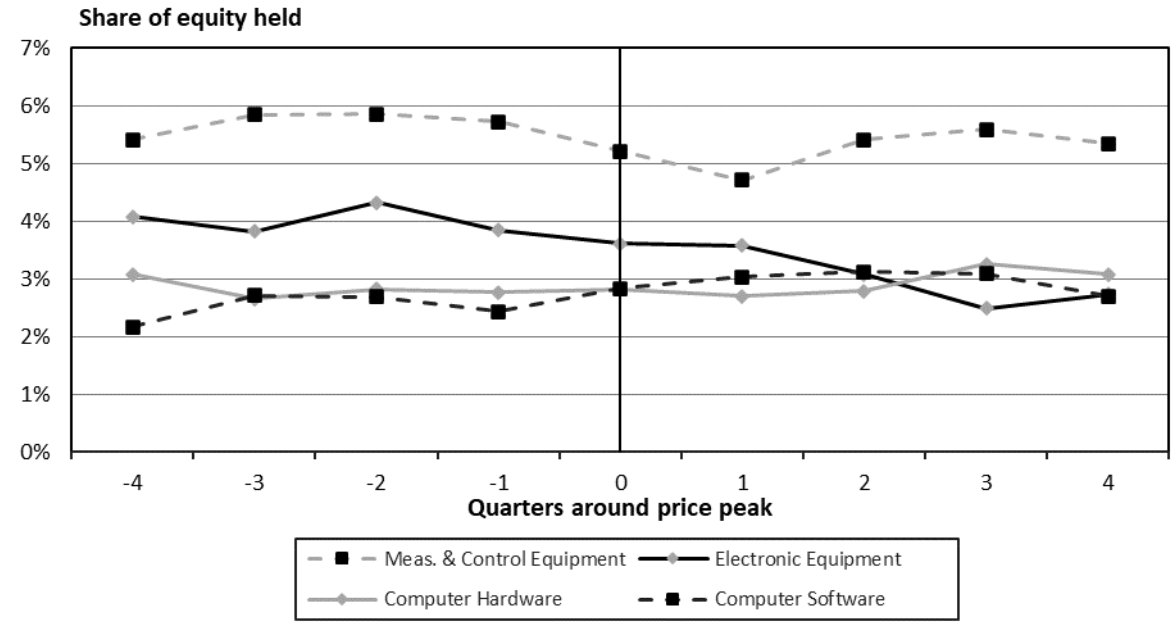


Figure 10. The average share of equity held by our sample of hedge funds during the individual stock price peaks in the steel bubble in 2000. We create a quarterly return index for each stock included in the bubbles and determine the quarter in which this index peaks. We also calculate the share of equity held, defined as the proportion of outstanding shares held by our sample of hedge funds for each stock and quarter. For stocks that peaked in 1999 or 2000, we align the value-weighted holdings in event-time where the quarter the price peaked is event-time 0.

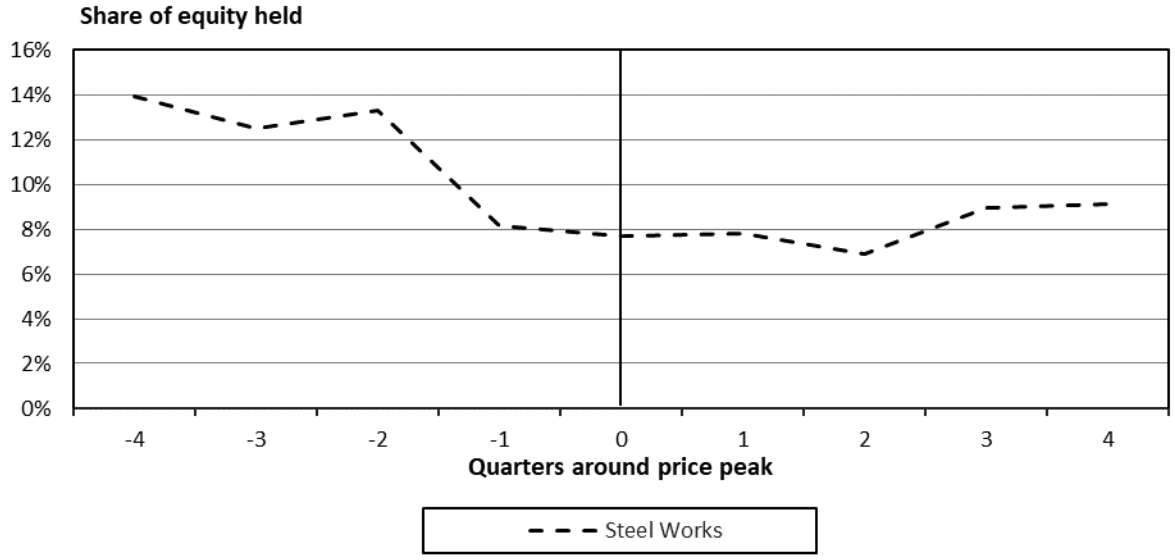


Figure 9 presents the results for the measurement & control equipment, computer hardware, electronic equipment, and computer software bubbles in 2000. For the measurement & control equipment bubble, our sample of hedge funds began to decrease their holdings one quarter before the quarter of the price peak. They continued to decrease their holdings until one quarter after the peak and then increased them again. We find a similar behavior during the run-up to the price peak for stocks in the electronic equipment bubble. However, the behavior differs after the bubble as our sample of hedge funds continued to decrease their holdings after the bubble, which is different from the results found for the measurement & control equipment bubble. For the computer software bubble, we find a different pattern. Instead of decreasing the holdings before the price peak, our sample of hedge funds began to increase their holdings in the quarter of the price peak and continued to increase them slightly until two quarters after the peak. For the computer hardware bubble, our hedge funds held a relatively constant proportion during the entire bubble. Lastly, in figure 10, we find a sharp decrease in the share of equity held one quarter prior to the quarter of the price peak in steel stocks.

C. Analysis

The results for the steel bubble in 2008, the measurement & control equipment, electronic equipment, and steel bubble in 2000 show evidence of our sample of hedge funds being able to anticipate price peaks in individual stocks and exiting their positions before the downturn. The two bubbles that diverge from this finding are the computer hardware and computer software bubbles in 2000. In these bubbles, our sample of hedge funds do not seem to be aware of the bubble as they either increase their share of equity held, or keep it constant, despite the price run-up and subsequent crash. The coal bubble in 2008 does not provide further insights due to the synchronization of the individual stocks. Therefore, we cannot determine whether our sample of hedge funds timed their exposure in individual stocks.

Including results from both hedge funds' long positions in bubble stocks and their ability to time price peaks in individual stocks, we find diverging results. The coal bubble in 2008 and the electronic equipment bubble in 2000 show the most decisive proof of positive feedback trading strategies. We interpret these results as our sample of hedge funds being aware of the bubbles' existence and that they were about to burst. However, in the steel bubble in 2008, our sample of hedge funds chose to abstain from taking part in the price run-up, instead attacking the bubble by decreasing their holdings in the bubble industry and potentially acting as a correcting force on stock mispricing. The hedge funds also traded against the computer hardware and software bubbles in 2000 based on their long holdings. However, when including the stock-by-stock analysis, this pattern is diminished as the hedge funds instead increased the holdings in computer software stocks before the price peak and maintained a relatively constant proportion in computer hardware stocks.

VI. Future research

Our considerable data limitations have reduced the accuracy of our results. Thus, for future research, it would be of great interest to increase the accuracy of our results by accessing a complete dataset with actual hedge fund returns rather than backtested ones. Other data improvements are also possible. First, one could analyze a larger data set of hedge funds. Second, one could run the analysis on hedge funds outside the US and compare hedge funds' trading strategy during bubbles in different countries. It would also be useful to consider that

different hedge funds may invest in different types of securities and industries. We also believe that having the reporting institution for 13F forms be specific funds, rather than investment managers who may manage different types of funds, could improve the selection of hedge funds. Finally, we believe that our methodology could be run on a larger or different sample of bubbles to enhance the scope of our findings.

One yet relatively unexplored bubble is Covid-19. Since Covid-19 has affected industries differently, it would be interesting to identify whether any bubbles have arisen and study whether our findings on hedge fund trading strategy are applicable. Another common discussion area regarding hedge funds, is whether the regulatory framework is sufficient. In January 2022, the SEC proposed a motion to increase Form PF's reporting requirement for certain investment advisors to increase the transparency of investment advisors´ holdings (SEC, 2022). Given that the SEC will extend the regulatory framework for hedge funds, it would be interesting to run a similar analysis as we did to see if hedge funds' trading strategy are affected.

VII. Conclusion

In conclusion, our findings show some evidence that hedge funds acted as a correcting force on mispricing in two bubbles. However, the opposite is true for other examined bubbles. Hence, we cannot draw a general conclusion on hedge funds' trading strategy in bubbles. According to the efficient market hypothesis, smart money and rational arbitrageurs such as hedge funds will act as a correcting force whenever stock prices diverge from their fundamental values (Fama 1970). This paper tests this notion by analyzing hedge fund strategy during seven different bubbles including the steel and coal bubble during 2008, and the computer hardware, computer software, electronic equipment, steel and measurement & control equipment bubbles in 2000. Our results show that hedge funds apply different strategies for different bubbles. On the one hand, during the computer hardware and software bubbles in 2000, and steel bubble in 2008, our sample of hedge funds held the bubble stocks to a smaller extent than the market portfolio. This suggests that they were actively attacking these bubbles. On the other hand, our sample of hedge funds invested a higher proportion of their portfolio than the market portfolio during the run-ups to the coal bubble in 2008 and the electronic equipment bubble in 2000. That suggests that hedge funds were indeed riding those bubbles. We are unable to strengthen our findings by looking at the net position of hedge funds. Despite several robustness checks, we cannot identify the reasons behind the large discrepancies between the long-only proportions and the net weights. Lastly, looking at a stock-by-stock analysis, we find some evidence that our sample of hedge funds were able to anticipate the price peaks and start selling off their positions before the bubble burst. However, we also find some evidence of the contrary, as we have two bubbles where our sample of hedge funds either increased their share of equity or held it constant despite the bubble bursting. Overall, our results partly diverge from those found by Brunnermeier and Nagel (2004). We find that hedge funds do not always ride bubbles, but sometimes choose to attack them, by decreasing their holdings in the relevant industry. However, our results further partly diverge from Akbas et al. (2015), who show that money flowing to hedge funds in the aggregate helps correct mispricings, and Fung and Hsieh (2000), who show that hedge funds do not use positive feedback trading strategies. In general, hedge funds apply a broad selection of trading strategies, which means that one strategy that fits an entire sample of hedge funds does not exist.

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IX. Appendix

A. Hedge fund holding data

To map each stock in the 13F holdings data to their Fama & French industry, we use the standard industrial classification (SIC) codes provided in CRSP. To accomplish this, we use the CUSIP for each stock and cross-reference them with the NCUSIPs found in CRSP, where NCUSIPs are provided together with individual SIC codes. Next, we use Judson Caskey's Stata script for mapping SIC codes to Fama & French industry codes.

B. Long proportions for the bubbles in 2000

Figure 11. The proportion invested in steel stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in steel stocks, compared to the market value of all holdings. As a comparison, the weight of steel stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.

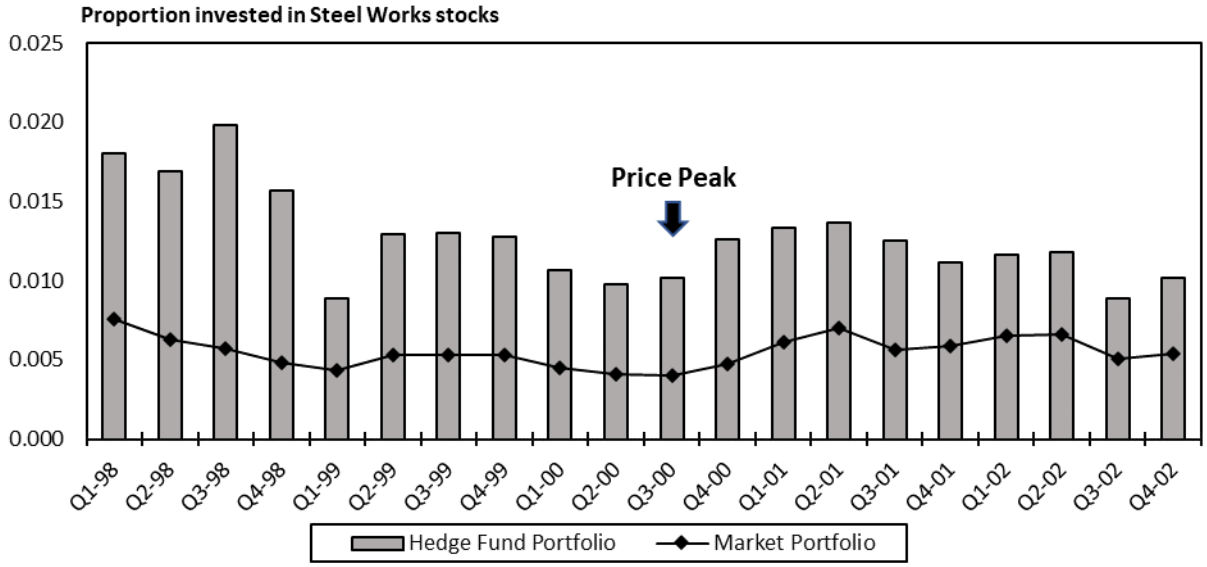
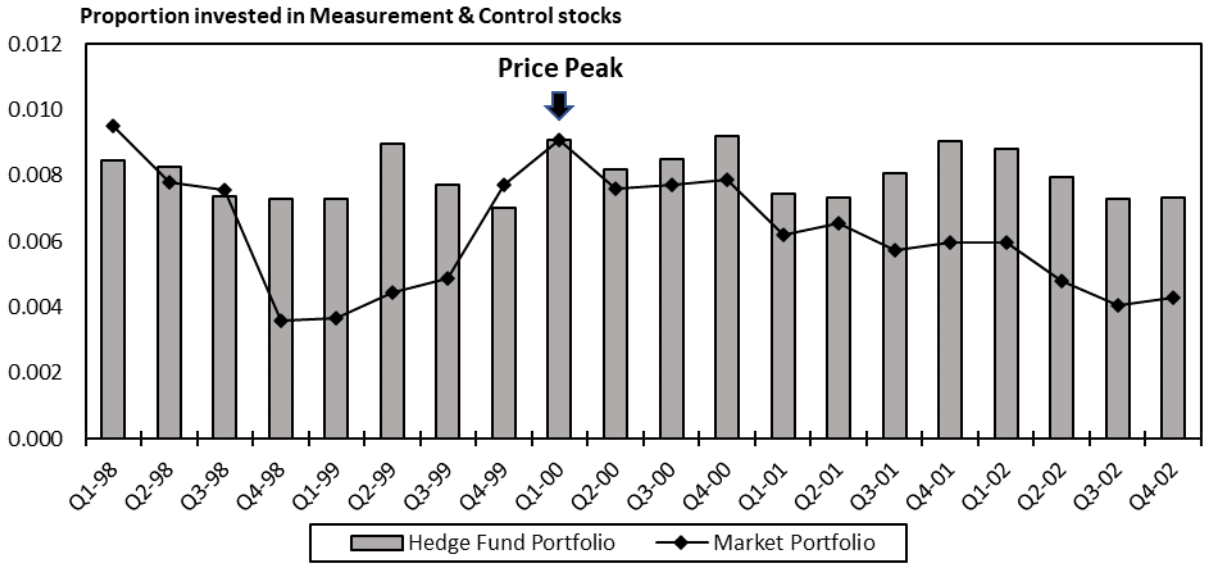


Figure 12. The proportion invested in measurement & control stocks in the aggregate hedge fund portfolio compared to the market portfolio. The hedge fund portfolio proportion is calculated as the total market value of the holdings in measurement & control stocks, compared to the market value of all holdings. As a comparison, the weight of measurement & control stock stocks in the market portfolio is also reported, where the market portfolio is defined as all the stocks on Nasdaq, AMEX and NYSE.



C. Short position robustness checks

Table 6. Hedge fund net exposure to the bubble stocks: return regression. This table reports the results of a panel regression on the quarterly returns of 11 hedge funds during two time-periods, the first regression is based on the first quarter of 2007 to the second quarter of 2008. The second regression is based on the third quarter of 2008 to the fourth quarter of 2009. Both regressions have two independent variables, R_M, the value-weighted return of Nasdaq, AMEX and NYSE, and $(R_B - R_M)$, the excess return of the bubble stocks compared to the return on the market portfolio. The bubble stocks are defined through Fama & French industry classification.

$$R_{i,t} = \alpha + \beta R_{M,t} + \gamma\left(R_{B,t} - R_{M,t}\right) + \varepsilon_t$$

The t-statistics for the coefficients are reported in parentheses. β and γ are used to estimate w_B, the net weight of the bubble stocks in the hedge fund portfolio using equation (2).

	Factor loadings			Implied net-weights	
Period 1 - Q1-07 through Q2-08	β	γ	Adj. R^2	w_S	w_C
Steel Bubble	0.43 (3.72)	0.26 (2.25)	0.27	0.61	
Coal Bubble	0.41 (3.88)	-0.45 (-4.21)	0.40		-1.09
Period 2 - Q3-08 through Q4-09	β	γ	Adj. R^2	w_S	w_C
Steel Bubble	0.32 (3.38)	0.61 (6.45)	0.73	1.90	
Coal Bubble	0.23 (2.65)	0.71 (8.24)	0.79		3.08

Table 7. Hedge fund net exposure to the bubble stocks: return regression. This table reports the results of a panel regression on the quarterly returns of 11 hedge funds during 2007 - 2009 with some noise ξ added to all hedge fund returns. The noise has a mean of 0 and a std.dev of 0.5%. The regression is based on two independent variables, R_M, the value-weighted return of Nasdaq, AMEX and NYSE, and $(R_B - R_M)$, the excess return of the bubble stocks compared to the return on the market portfolio. The bubble stocks are defined through Fama & French industry classification.

$$R_{i,t} + \xi_{i,t} = \alpha + \beta R_{M,t} + \gamma\left(R_{B,t} - R_{M,t}\right) + \varepsilon_t$$

The t-statistics for the coefficients are reported in parentheses. β and γ are used to estimate w_B, the net weight of the bubble stocks in the hedge fund portfolios using equation (2).

	Factor loadings			Implied net-weights	
Bubbles in 2008 with Noise	β	γ	Adj. R^2	w_S	w_C
Steel Bubble	0.51 (6.07)	0.22 (2.60)	0.43	0.44	
Coal Bubble	0.63 (1.32)	0.00 (3.62)	0.40		0.00

D. Hedge funds and individual stock timing

Table 8. The distribution of stock peaks for the computer hardware bubble in 2000. For each stock, we construct a returns index that summarizes the quarterly returns between 1998 and 2002 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 1999 and 2000.

Year	Quarter	Number of peaks
1999	1	3
	2	3
	4	9
2000	1	17
	2	5
	3	10
	3	2

Table 9. The distribution of stock peaks for the computer software bubble in 2000. For each stock, we construct a returns index that summarizes the quarterly returns between 1998 and 2002 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 1999 and 2000.

Year	Quarter	Number of peaks
1999	1	2
	2	2
	3	2
	4	37
2000	1	42
	2	12
	3	25
	3	9

Table 10. The distribution of stock peaks for the electronic equipment bubble in 2000. For each stock, we construct a returns index that summarizes the quarterly returns between 1998 and 2002 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 1999 and 2000.

Year	Quarter	Number of peaks
1999	2	3
	4	11
2000	1	46
	2	39
	3	35
	3	5

Table 11. The distribution of stock peaks for the steel bubble in 2000. For each stock, we construct a returns index that summarizes the quarterly returns between 1998 and 2002 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 1999 and 2000.

Year	Quarter	Number of peaks
1999	2	3
	3	1
	4	4
2000	1	2
	2	1
	3	2
	3	1

Table 12. The distribution of stock peaks for the measurement & control equipment bubble in 2000. For each stock, we construct a returns index that summarizes the quarterly returns between 1998 and 2002 and determines which quarter end the index takes its highest value. The table below summarizes the number of peaks during 1999 and 2000.

Year	Quarter	Number of peaks
1999	3	2
	4	2
2000	1	13
	2	10
	3	6
	3	4