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Hedge Funds and Stock Market Efficiency

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We measure misvaluation using the discounted residual income model. As shown in the literature, this measure of stocks' misvaluation significantly explains their future cross-sectional returns. We measure the market-level misvaluation (market inefficiency) by the misvaluation spread: the difference in the misvaluation of the most overvalued and undervalued shares. We show that the misvaluation spread is a strong predictor of a misvaluation-based long–short portfolio's returns, reinforcing the hypothesis that it proxies for the level of mispricing in the stock market. Using data on hedge fund returns, hedge fund industry assets under management, flows, and individual hedge fund holdings, we present evidence that hedge funds' trading reduces market-level misvaluation. Our results are robust across different time periods and are not driven by market liquidity. Moreover, we find that mutual funds do not have the price-correcting effect that hedge funds have.

Keywords: hedge funds; misvaluation; stock market efficiency
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1. Introduction

In his review article, Stulz (2007) argues that hedge funds can play a valuable role in the financial markets since they look for mispriced securities, and their trading can bring prices closer to fundamental values. Stulz also argues that hedge funds can potentially improve financial market efficiency more effectively than mutual funds, since the use of short sales and derivatives allows hedge funds to "reduce mispricings more forcefully than mutual funds" (p. 181). Not all agree with this positive role of hedge funds in promoting stock market efficiency. For instance, Brunnermeier and Nagel (2004) and Griffin et al. (2011) present evidence that hedge funds invested in the technology bubble, suggesting that hedge funds can sometimes nurture mispricing in the financial markets. Their findings are in line with Abreu and Brunnermeier (2003), who show that it can be optimal for rational investors to invest in overpriced securities if they believe that other rational investors will not yet start trading against the bubble. Adding to the debate, Stein (2009) argues that it is not necessary that an increase in the amount of sophisticated investors, such as hedge funds, leads to greater market efficiency. Given the controversy, it is an empirical question whether hedge funds typically promote stock market efficiency. As Stultz notes, there is so far little direct evidence on this issue.

In this paper, we bring forth evidence on whether hedge funds promote stock market efficiency by looking at the effect of hedge funds on stocks' misvaluations. To estimate stocks' misvaluations, we first model the firms' fundamental values using the discounted residual income model of Ohlson (1990, 1995). This model has received strong support in the literature as a measure for firms' fundamental value. For example, Frankel and Lee (1998a) document that the residual income model has high explanatory power for stock prices in an international setting with 21 countries, and Frankel and Lee (1998b) show that the ratio of estimated fundamental value to price (measure of misvaluation) outperforms the beta and the book-to-price ratio in predicting long-term returns in the cross section of stocks. Confirming previous findings in this literature, we show that a misvaluation-based long–short portfolio, long in the 30% most undervalued and short in the 30% most overvalued stocks in our sample of U.S. stocks, generates significantly positive annualized returns (4.2% p.a.) during our sample period from 1991 until 2010. Moreover, the misvaluation-based long–short strategy has a positive and significant annualized Carhart (1997) four-factor alpha of 3.6%. Other papers that have relied on this measure to evaluate mispricing include, for example, Lee et al. (1999), D'Mello and Schroff (2000), Dong et al. (2006, 2007), and Doukas et al. (2010).[1]

We propose to measure the overall level of stock market misvaluation by the misvaluation spread, defined as the difference in the misvaluations of the 30% most overvalued and 30% most undervalued stocks. The misvaluation spread (our measure of market inefficiency) is a powerful predictor of the misvaluation-based long–short portfolio's returns, reinforcing the hypothesis that it proxies for the level of mispricing in the stock market. For instance, following time periods when misvaluations have been the lowest (periods that belong to the lowest quintile of the misvaluation spread), the misvaluation-based long–short portfolio generates, on average, a negative return of 3.9% In turn, following time periods that belong to the highest misvaluation spread quintile, the average annualized returns on this long–short portfolio are 9.9% p.a. Furthermore, a regression explaining three-year future returns on the misvaluation-based long–short portfolio with the misvaluation spread has an astonishing R-squared value of 56%.[2]

Our misvaluation spread measure and our finding that it forecasts misvaluation-based long–short portfolios' returns are closely related to the results in Asness et al. (2000), who show that value stocks' returns relative to growth stocks can be forecasted using a "value spread" measure. Assness et al. define value and growth stocks as the stocks that belong to the extreme deciles of stocks in a ranking based on the stocks' industry-adjusted book-to-price, sales-to-price, and earnings-to-price ratios. Their value spread measure is based on the ratios of the median values of the above three ratios in the value and the growth stock portfolios. In another closely related paper, Cohen et al. (2003) define the value spread to be the difference between the Fama and French (1993) "high" and "low" portfolios' book-to-market ratios, and they show that this value spread measure forecasts the Fama and French HML factor returns. Both of the above-mentioned papers recognize that their long–short portfolios' returns can be driven by misvaluations or risk premia, just as we and Ali et al. (2003) note is the case for the misvaluation-based long–short portfolio's returns. To that extent, the fact that our misvaluation spread forecasts the misvaluation-based long–short portfolios' returns can alternatively be interpreted as evidence that the level of the misvaluation spread reflects factor risk premia. It is simply not possible to distinguish between these two possible explanations for the return predictability. In this paper, for expositional reasons, we always take the extreme view that our fundamental value estimates are correct and call all price deviations from our estimates of the fundamental values misvaluations.

Armed with our measure of the aggregate amount of misvaluation in the stock market, the misvaluation spread, we investigate whether hedge funds promote market efficiency. We start by regressing the misvaluation spread on the hedge fund industry's assets under management (AUM). Our idea here is to see whether the overall market level of misvaluation (the misvaluation spread) is lower in time periods when the arbitrage capital to hedge funds is abundant. Supporting the arguments that hedge funds promote market efficiency, we find that hedge fund industry AUM is negatively associated with the level of the misvaluation spread. Furthermore, hedge fund industry flows significantly reduce the misvaluation spread. Also, the hedge funds' funding liquidity matters, as the treasury-to-eurodollar spread (TED spread) is positively associated with the level of the misvaluation spread, and increases in TED spread increase the misvaluation spread.[3] In contrast, we find mixed evidence on the effect of mutual fund industry's total net assets on the misvaluation spread. In fact, our results suggest that the marginal effect of mutual funds (after controlling for the effect of hedge funds) has typically been price distorting.

We study the robustness of our finding that hedge funds reduce misvaluations in several ways. We repeat our regression analysis on the relationship between the hedge fund AUM and the misvaluation spread for subsamples of liquid and illiquid stocks, and we repeat the regressions in two different time periods. The results are consistently qualitatively similar. We also look at the effect of hedge fund AUM separately on the misvaluations of undervalued and overvalued shares. In both cases, the hedge

[1] In §4, we show that these misvaluation-based long–short returns are significantly negatively exposed to market excess returns and momentum, whereas they are significantly positively exposed to the Fama and French high minus low (HML) and small minus big (SMB) factors. The negative exposure of the misvaluation-based long–short returns to market excess returns and momentum explains why portfolios loading on the misvaluation-based long–short returns, market excess returns, and momentum have had extremely attractive annualized Sharpe ratios (up to 1.2) during our sample period, well exceeding the annualized Sharpe ratios obtainable from portfolios merely exposed to the Fama–French–Carhart factors (up to 1.0).

[2] Our misvaluation spread is correlated with another measure of market inefficiency, the closed-end fund discount. The correlation between the two measures is 0.36. Pontiff (1997) shows that closed-end funds exhibit excess volatility, consistent with the idea that the closed-end funds are commonly misvalued in the market.

[3] TED spread is a common proxy for the availability of funding liquidity to hedge funds; see, e.g., Brunnermeier et al. (2009). Ang et al. (2011) also show evidence that the TED spread affects hedge funds' leverage. The idea that arbitrageurs' borrowing costs affect their ability to conduct arbitrage was first presented in Pontiff (1996).

fund AUM is negatively associated with the levels of the misvaluations. Additionally, again in line with the idea that hedge funds promote market efficiency, we find that hedge fund index returns are positively exposed to the returns of a portfolio of undervalued shares, but they are not dependent on the returns of a portfolio of overvalued shares. Finally, using hedge funds' holdings data from their 13F filings, we show that hedge funds invest more in undervalued than in overvalued shares at times when the misvaluation spread is high, and vice versa when the misvaluation spread is low.

Changes in hedge funds' stockholdings also suggest that their trading affects the misvaluation spread: the quarters when the misvaluation spread declines are associated with higher hedge fund purchases of undervalued stocks compared with overvalued stocks (suggesting that hedge funds' trading has a price impact). Similarly, the quarters when the misvaluation spread increases are associated with more hedge fund purchases of overvalued stocks than undervalued stocks. Finally, to address causality concerns, we show that hedge funds' net holdings of undervalued shares (that is, their holdings of undervalued shares minus their holdings of overvalued shares) significantly increase in quarters that begin with high levels of misvaluation but, in fact, slightly decrease in quarters that begin with low levels of misvaluation. Finally, in support of our other analysis, we find that quarterly changes in TED spread and quarterly hedge fund industry flows affect the hedge funds' holdings of undervalued and overvalued shares in the expected direction. Given this evidence, our finding that hedge funds actively reduce misvaluations, as measured by the discounted residual income model, seems highly robust.

Our paper is closely related to the literature on limits of arbitrage; see, e.g., Shleifer and Vishny (1997) or Gromb and Vayanos (2010). Varying investor preferences, lack of information, misperceptions, or even exogenous constraints can lead to differences in investors' portfolio allocations. With limited arbitrage capital, and a market-clearing price setting for each security, situations may arise where even highly similar securities trade at very different prices. In this literature, it is typically argued that the price-correcting speculation is constrained by the speculators' limited equity capital (assets under management), their degree of risk aversion, and their access to funding capital (see, e.g., Gromb and Vayanos 2002, Brunnermeier and Pedersen 2009). Our findings are consistent with the idea that hedge funds reduce the valuation differences in the stock market that are due to limits of arbitrage but that the hedge funds' speculative activity is constrained by their limited assets under management and their limited funding capital.

Our study contributes to the existing literature on the effect of hedge funds on market misvaluations, which so far has documented contradictory evidence from different markets and situations. Papers that suggest a positive, efficiency-improving role for hedge funds include Mitchell et al. (2007), who show evidence that capital constraints for hedge funds lead to greater misvaluations in the convertible bond and equity markets. Jylhä et al. (2014), in turn, show that hedge funds enter into short-term reversal trades, thus providing liquidity to the stock market, promoting price efficiency in the stock market at a short trading horizon. In addition, they show that the hedge fund flows typically reduce stock price volatility. Jones (2010) plots decay rates of return performance for numerous factors and anomalies—namely, value, momentum, earnings surprise, accrual, analyst revisions, and stock price reversals. For all these factors, the performance of the factors was weaker (as evidenced by lower information ratios) during a more recent sample period, consistent with an increased amount of capital being deployed to exploit mispricing with respect to these factors and the idea that increased hedge fund capital has promoted market efficiency and affected expected factor returns. Green et al. (2011), in turn, show that the returns on the accrual anomaly have decreased in a pattern that is consistent with the increase in hedge funds' investments based on the accrual anomaly, supporting the view of adaptive market efficiency. Finally, Ellul et al. (2011) show that the price effect of bond downgrades are more pronounced when the capital of potential outside buyers (e.g., hedge funds) is relatively scarce.[4, 5]

[4] Akbas et al. (2015) present related evidence on the effects of speculative capital on market efficiency by showing that the flow of speculative capital to "quant mutual funds" affects the returns to a quantitative trading strategy capitalizing on observed anomalies. Related to previous studies, Johnson and Schwartz (2002) show that the returns to the post-earnings-announcement drift strategy became smaller after the publication of the Bernard and Thomas (1989, 1990) papers, consistent with investors (including hedge funds) using this strategy to arbitrage the anomaly afterward. Similarly, McLean and Pontiff (2012) study 82 characteristics that have been documented by prior studies to predict future stock returns. They find that after academic research documented that these characteristics predict future stock returns, the cross-sectional predictability of the characteristics decline about 35%. These authors also document that post publication stocks in characteristic portfolios experience higher volume, variance, short interest, and correlations with portfolios based on public characteristics, consistent with increased informed trading after the publication of academic research papers that documented these anomalies. Academic research that increases the sophistication of investors, therefore, appears to be another force that affects market efficiency alongside the arbitrageurs' capital. Fortunately for us, the two effects can be identified separately.

[5] Our research is also related to the literature on the effect of speculative capital on hedge funds' returns. Note that our results indicate

Other researchers have documented more negative evidence on the role of hedge funds in promoting market efficiency. Jylhä et al. (2014) and Kang et al. (2014) show that in case of the stocks that have the most volatile short-term returns, hedge funds do not provide, but instead appear to demand, liquidity, thus creating volatility. Kang et al. (2014) show that this effect is strongest for illiquid stocks. There is also evidence that hedge funds were large sellers in the 2007–2009 financial crisis, contributing to market volatility (see, e.g., Ben-David et al. 2012). In addition, the results in Ben-David et al. (2013) suggest that hedge funds have manipulated prices, which also implies that hedge funds can increase price inefficiencies.

Given the controversial expectations of the effect of hedge funds on market efficiency, it is important to obtain empirical estimates of the net effect of hedge funds on market performance. The main contribution of our paper is to provide an estimate of the effect of hedge funds on the overall level of stock market misvaluations in the U.S. equity markets. To our knowledge, we are the first ones to try to do so. To estimate the stocks' misvaluations, one must necessarily adopt some measure for the firms' fundamental values. Such a measure is necessarily imperfect, creating noise in the analysis. In addition, accurately measuring the activities of the hedge funds, and even the assets of the hedge funds, is problematic. Despite the difficulties, our evidence that hedge funds reduce misvaluations in the stock market (when those are measured using the residual income model) is strong and in line with the arguments presented in Stultz (2007). Importantly, we also show that mutual funds and hedge funds are very different in regard to their impact on market efficiency. As the regulation of hedge funds around the globe is continuously evolving, and it is often guided only by anecdotal evidence, it is important to develop academic research on the effect of hedge funds on the functioning and efficiency of stock markets.

2. Measuring Mispricing

To study whether hedge funds improve stock market efficiency, we must first measure stocks' misvaluation. Following Frankel and Lee (1998b), we measure mispricing by comparing stock prices to an estimate of fundamental value obtained using the discounted residual income model of Ohlson (1990, 1995). In this approach, the fundamental (intrinsic) value of a stock is defined as the discounted value of its future dividends; that is,

$$V_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r_e)^i}, \tag{1}$$

where V_t is the time t fundamental value of the stock; $E_t(D_{t+i})$, $i = 1, 2, \ldots$, are the expected future dividends; and r_e is the cost of equity capital. Furthermore, assuming clean surplus accounting, i.e., that all changes in the book value of equity (except transactions with owners) are reflected in income, a firm's fundamental value can be written as the book value of equity plus the present value of expected future residual income. Namely, letting B_{t+i} denote the (per-share) book value of equity at time $t+i$, NI_{t+i} the net income, and ROE_{t+i} the after-tax return on book equity, the fundamental value of a firm's stock can be expressed as

$$\begin{aligned} V_t &= B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - (r_e B_{t+i-1})]}{(1+r_e)^i} \\ &= B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e) B_{t+i-1}]}{(1+r_e)^i}. \end{aligned} \tag{2}$$

To empirically estimate the fundamental value, we follow the approach in Frankel and Lee (1998b). First, let us define the variables needed in the estimation: the book values, forecasted returns on equity (denoted as *FROE*), and the costs of equity. To estimate the forecasted returns on equity, we use the one-year-ahead and two-years-ahead consensus earnings forecasts (denoted as FY_1 and FY_2, respectively) from the Institutional Brokers' Estimate System (I/B/E/S). To avoid inflated estimates of *FROE* as a result of unusually low book value in period $t-1$, we use the return on average equity:

$$FROE_t = \frac{FY_1}{(B_{t-1} + B_{t-2})/2} \quad \text{and} \quad FROE_{t+1} = \frac{FY_2}{(B_t + B_{t-1})/2}. \tag{3}$$

Here, the estimated book value at time t, where t refers to the year of portfolio formation, is defined as

$$B_t = B_{t-1}[1 + FROE_t(1-k)], \tag{4}$$

where k is the dividend payout ratio. Similarly, let

$$B_{t+1} = B_t[1 + FROE_{t+1}(1-k)]. \tag{5}$$

The final building block of a two-period expansion of the residual income model used in Frankel

that hedge fund flows reduce mispricings in the stock market, thus increasing the contemporaneous returns to misvaluation-based long–short trading strategies, but lead to a smaller future return on such investment strategies. Consistent with this, Barquero and Verbeek (2009) document a positive contemporaneous relation between hedge fund flows and returns, and Avramov et al. (2013) find evidence of a negative relation between hedge fund flows and future returns.

and Lee (1998b), the cost of equity, is estimated as an industry-specific rate using the Fama–French 48-industry classification and the three-factor pricing model (Fama and French 1997).[6] We are now ready to express the two-period expansion of the residual income model as

$$\hat{V}_t = B_t + \frac{FROE_t - r_e}{(1+r_e)} B_t + \frac{FROE_{t+1} - r_e}{(1+r_e) r_e} B_{t+1}. \quad (6)$$

Here, the last term represents a terminal value where the forecasted *ROE* in period $t+1$ is assumed to be earned in perpetuity.[7]

Our measure of misvaluation, denoted by $MISV_t$, is then defined to be the natural logarithm of the price-to-fundamental value ratio,

$$MISV_t = \ln(P_t / \hat{V}_t). \quad (7)$$

We rank stocks into deciles using (7). Our main measure of the amount of misvaluation in the stock market is the *misvaluation spread*: the difference in the average misvaluation of the three highest and three lowest misvaluation deciles.

The residual income model has received strong support in the literature as a measure for mispricing. For example, Frankel and Lee (1998b) show that the V/P ratio—that is, the ratio of estimated value to price—outperforms the beta and the book-to-price ratio in predicting long-term returns in the cross section of stocks. Lee et al. (1999) use the residual income model to estimate the intrinsic value of the Dow 30 stocks and find that the V/P measure has statistically reliable predictive power, whereas traditional multiples such as book to price, earnings to price, and the dividend yield perform poorly. Ali et al. (2003) examine whether the predictive power of V/P is due to omitted risk factors or market mispricing, and they conclude that their results are consistent with the mispricing explanation. Mispricing measures based on the residual income model have also been used in explaining the drivers of mergers and acquisitions (Dong et al. 2006), corporate investment (Dong et al. 2007), and the timing of share repurchases (D'Mello and Schroff 2000).

3. Data

Our data are standard. We use price and return data on all common stocks in NYSE, NASDAQ, and AMEX provided by the Center for Research in Securities Prices (CRSP), combined with accounting data from Compustat and monthly consensus (mean) earnings forecasts from I/B/E/S. Our sample period is from January 1991 to December 2010 since prior to the 1990s, the role of hedge funds was minor.

Following Fama and French (1992, 1993), we define *book equity* as Compustat common shareholder equity plus deferred taxes (if any) minus preferred shares. For preferred shares, we use the redemption value, the liquidation value, or the par value (in that order). Firms with negative book equity are excluded. The firm-specific dividend payout ratio (k) is obtained by dividing the common stock dividends paid in the most recent year by the net income. Following Frankel and Lee (1998b), among others, we divide dividends by 6% of total assets for firms with negative net income, since 6% reflects the average long-run return on assets. To remove clear outliers, we restrict the dividend payout ratio to be between 0% and 100% and remove stocks whose price is below $1 in any month (since we use monthly rebalancing). To ensure that all accounting information is known when calculating the misvaluation measure (7), we allow a minimum of six months between the end of the fiscal year and forming the misvaluation measures. Thus the misvaluation measures are estimated in June of year t, using accounting data from year $t-1$. We then use these accounting variables until the June of year $t+1$, when their values are updated. To study the effect of misvaluation on stock returns, we form monthly-rebalanced decile portfolios of the stocks, where portfolio formation is based on the misvaluation rank of the previous month. In calculating the decile break points, we use stocks listed in the NYSE only and define the undervalued (overvalued) portfolio to consist of three of the lowest (highest) deciles of the misvaluation rank.[8] We also construct a zero investment portfolio (henceforth, long–short misvaluation portfolio) long in undervalued and short in overvalued stocks.

It is difficult to obtain reliable monthly estimates for the hedge fund industry's AUM dating back in time. In estimating the hedge fund capital, we follow Jylhä and Suominen (2011) and Jylhä et al. (2014). First, we use the annual estimates of the hedge fund industry's AUM from Hedge Fund Research, Inc. (HFR). In addition, we use the Lipper TASS database, which provides monthly observations on individual funds during our entire sample period and covers a large but time-varying proportion of the total hedge fund industry. To form a monthly series of the hedge fund

[6] Frankel and Lee (1998b) investigate the sensitivity of their results to different specifications of the discount rate, and they find that the industry-specific rate performs well.

[7] Equation (6) assumes that there is no growth in the future forecasted returns on equity. Frankel and Lee (1998b) estimate several versions of the residual income model and conclude that their results are robust to the different specifications. The same two-period expansion is also used by Doukas et al. (2010).

[8] Using three deciles in the misvaluation portfolios is consistent with the formation of the Fama and French (1993) book-to-market portfolios. However, our results are robust to using only the most extreme deciles or quintiles in the misvaluation portfolios.

AUM, we start with the annual estimates of the total hedge fund AUM by HFR. Next, we calculate asset-weighted averages of returns and new asset flows to all the funds included in the Lipper TASS database for each month. As the year-to-year asset growth of the Lipper TASS funds does not match the growth in the hedge fund industry indicated by the estimates provided by HFR, because of the changing coverage in Lipper TASS, we make the assumption that each year, the difference between the two growth figures accumulates steadily over the year. Hence, our estimated hedge fund AUM growth is the asset-weighted average growth in the AUM of the hedge funds reporting to the Lipper TASS database plus 1/12 of the difference in the current year's asset growth estimates obtained from HFR and the Lipper TASS database. In this way, we get a monthly estimate of the hedge fund AUM whose end-of-year figure matches the estimates of HFR and whose monthly growth pattern resembles as closely as possible that of the population of funds reporting to the Lipper TASS database.

Our estimate of the hedge fund industry's asset flow is based on all funds in the Lipper TASS database and our AUM estimates. We calculate an estimate of the percentage asset flow to each fund and each month when reported asset and return figures are available, take an asset-weighted average of these percentage flows, and multiply this by our estimate of the total hedge fund industry AUM to obtain an estimate of the flow in dollar terms. Our estimates of the mutual fund industry total net assets (TNA), in turn, are based on the CRSP Mutual Fund Database, which lists all U.S. mutual funds. Our sample includes only funds that invest in equity. The mutual fund flows are calculated as in Frazzini and Lamont (2008) and aggregated across the funds. Finally, we normalize both the hedge fund AUM, the mutual fund TNA, and the hedge fund and mutual fund flows by the U.S. stock market capitalization.[9]

Descriptive statistics for the equally weighted portfolios, and several other relevant variables, are given in Table 1. The annualized mean return on the undervalued minus overvalued long–short portfolio is 4.2%, which is well in line with the estimates in, for example, Frankel and Lee (1998b) and Ali et al. (2003).

Table 1 also presents the average measure of misvaluation for the two portfolios and the misvaluation spread. Since misvaluation is measured as the natural logarithm of the price-to-value ratio, the misvaluation measure for the undervalued portfolio is usually negative and positive for the overvalued portfolio. The average number of firms in the undervalued (overvalued) portfolio is 518 (596). On average, undervalued firms are smaller and have higher book-to-price (B/P) ratios than overvalued firms. This finding parallels Frankel and Lee (1998) and Ali et al. (2003), who also document a relation between mispricing, size, and book-to-market ratios.

[9] Most of the hedge funds' AUM, 56% in 2010, is in equity-related equity hedge and event-driven funds. We include also the AUM of all other funds, as many of them may also engage in long–short equity trading either directly or indirectly via equity market derivatives.

Table 1 Descriptive Statistics

	Undervalued	Overvalued	Long–short
Mean (annualized)	0.182	0.137	0.045
SD (annualized)	0.190	0.192	0.113
Skewness	−0.328	−0.758	0.570
Kurtosis	5.744	2.557	7.812
Average number of firms	518	596	—
Average ln(P/V)	−0.159	1.185	1.345
SD of ln(P/V)	0.227	0.253	0.152
Average B/P	1.387	0.302	—
Average size	1,510.491	5,104.133	—

Notes. This table gives descriptive statistics for three equally weighted misvaluation-based portfolios with monthly rebalancing. The means and standard deviations are reported as annualized figures. In addition, the table reports the skewness; kurtosis; the average number of firms in the portfolios; the average and the standard deviation of the misvaluation measure defined as ln(P/V), where P is the market price of the stock and V denotes the fundamental value based on the residual income model; the average book-to-price ratio; and average size (in millions). The undervalued (overvalued) portfolio consists of three of the lowest (highest) deciles. Decile break points are based on NYSE firms only. The long–short portfolio is long in undervalued and short in overvalued stocks. The sample period is from January 1991 to December 2010.

4. Returns on the Misvaluation Portfolios and the Misvaluation Spread

In this section, we explore the return properties of the portfolios consisting of undervalued and overvalued shares, as well as the long–short misvaluation portfolio. The mean monthly equally weighted CRSP market return during our sample was 17% p.a., implying, given the numbers in Table 1, that the undervalued shares portfolio has overperformed the market, whereas the overvalued portfolio has underperformed the market, consistent with the idea that they are indeed made up of undervalued and overvalued shares. Table 2 presents the Carhart (1997) four-factor alpha for the undervalued minus the overvalued long–short portfolio. As Table 2 shows, the misvaluation-based long–short returns have a statistically significant positive alpha at the 5% confidence level.

Figure 1, in turn, plots the time series of the misvaluation spread defined in §1 (along with the hedge fund industry AUM). The misvaluation spread remained fairly stable throughout the earlier part of our sample period, but its volatility has increased

Table 2 **Factor α**

DV: *Return on long–short misvaluation portfolio*		
	Coefficient	t-Statistic
α	0.003	2.286^{**}
MKT	−0.073	-1.962^{*}
SMB	0.178	3.655^{***}
HML	0.654	10.812^{***}
MOM	−0.400	-8.287^{***}
R-squared	0.760	

Notes. The first column of the table shows the results of regressing the return on our long–short misvaluation portfolio on the market factor (*MKT*), the size factor (*SMB*), the value factor (*HML*), and Carhart's (1997) momentum factor (*MOM*). The second column shows the heteroskedasticity and autocorrelation consistent t-statistics. Our sample period is from January 1991 to December 2010 ($N = 241$). DV, dependent variable.

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

after the late 1990s. There is no clear time trend. In general, an increase in misvaluation has typically resulted in a fairly quick downward correction, which could imply that the investment opportunities due to mispricing are quickly exploited. The technology bubble shows up as a significant peak in the misvaluation spread; the increase from 1.99 in December 1997 to 2.97 in March 2000 represents a percentage increase of almost 50%. Furthermore, the 2008 financial crisis resulted in another considerable peak, though mispricing did not reach levels as high as during the technology bubble.

To test the relevance of the misvaluation spread as a measure of market wide misvaluation we explore whether it can predict 12- to 36-month returns on the long-short misvaluation portfolio. We follow common practice in the literature and use the forecasting regression proposed by Fama and French (1988a, 1988b). Namely, we run the following regression:

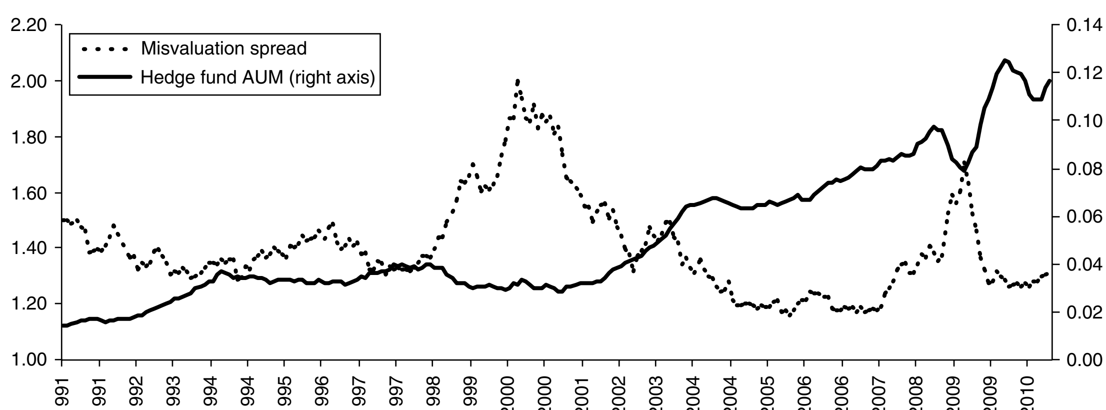
$$\sum_{k=1}^{K} r_{t+k} = a_K + b_K MISV_t + \varepsilon_{t+K,K}, \qquad (8)$$

where r_{t+k} is the k months ahead monthly (log) return on the long–short misvaluation portfolio, and $MISV_t$ is the level of misvaluation spread at time t. Here, K is either 12 months, 24 months, or 36 months, respectively. As is commonly done in the literature, we use overlapping observations. Using overlapping data causes some econometric problems because it induces autocorrelation in the residuals. To account for this, we use generalized method of moments (GMM) standard errors with the Hansen and Hodrick (1980) correction. In addition, since the explanatory variable is persistent, the results could suffer from the small sample bias suggested by Kendall (1954), which was popularized in financial economics by Stambaugh (1999). To correct for this bias, we apply the augmented regression framework proposed by Amihud and Hurvich (2004).

Table 3 gives the results of estimating Equation (8) for three different horizons: 12 months (panel A), 24 months (panel B), and 36 months (panel C).

The first column estimates the model with ordinary least squares (OLS). All results are significant at the 1% level. The next column, labeled ARM OLS, corrects for the small sample bias and estimates the augmented regression model (ARM) using OLS. The results do not change significantly from the simple OLS estimation. The last column, ARM GMM, estimates the augmented regression model with GMM. In this case, the coefficient for the misvaluation spread in 12-month return forecasting

Figure 1 **Misvaluation Spread and Hedge Fund AUM**



Notes. This figure plots the misvaluation spread (our measure of market-level misvaluation) together with the hedge fund AUM. The AUM has been scaled by the average CRSP stock market capitalization of the previous 12 months. The misvaluation spread is defined as the difference in the misvaluations of the highest three deciles of stocks and the lowest three deciles of stocks ranked by their misvaluations. The decile break points are calculated using NYSE stocks only. The misvaluation spread corresponds with the difference in the misvaluations of the overvalued and the undervalued portfolios defined in the text and in Table 1.

Table 3 Regressions Explaining Cumulative Returns on the Undervalued Minus Overvalued Long–Short Portfolio

	OLS	ARM OLS	ARM GMM
	Panel A: 12 months		
Constant	−0.485***	−0.477***	−0.477
	(−5.584)	(−5.463)	(−1.420)
MISV	0.367***	0.361***	0.361
	(5.998)	(5.839)	(1.410)
R-squared	0.137		
	Panel B: 24 months		
Constant	−1.164***	−1.153***	−1.153***
	(−10.528)	(−10.305)	(−3.730)
MISV	0.868***	0.860***	0.860***
	(11.122)	(10.866)	(3.780)
R-squared	0.366		
	Panel C: 36 months		
Constant	−1.604***	−1.616***	−1.616***
	(−15.311)	(−15.306)	(−5.610)
MISV	1.191***	1.199***	1.199***
	(16.126)	(16.078)	(6.170)
R-squared	0.563		

Notes. This table shows the results of regressing the cumulative return on the undervalued minus overvalued long-short portfolio on the level of the misvaluation spread (*MISV*) of the previous month. The results are given for three different horizons: 12 months, 24 months, and 36 months. The first model is estimated using OLS with heteroskedasticity and autocorrelation consistent standard errors. The second model (ARM OLS) is estimated with OLS and the augmented regression method of Amihud and Hurvich (2004). The third model (ARM GMM) is estimated using the augmented regression method and GMM standard errors with the Hansen and Hodrick (1980) correction.

*** denotes statistical significance at the 1% level.

regression turns insignificant. However, the coefficients for the misvaluation spread in the 24-month and 36-month forecasting regressions remain significant at the 1% level.

The results in Table 3 show that the misvaluation spread has strong predictive power to forecast two- and three-year future returns on the long-short misvaluation portfolio. The coefficients are positive and significant at the 1% level. Moreover, the adjusted R-squared value from the OLS regression for the three-year horizon is as high as 56%. Thus the level of the misvaluation spread can explain a significant proportion of the cumulative future returns on the long–short misvaluation portfolio. This reinforces the idea that the misvaluation spread can be seen as a proxy for stock market inefficiency.

5. Do Hedge Funds Affect Marketwide Misvaluation?

Figure 1 plotted the misvaluation spread together with the hedge fund AUM (scaled by the average CRSP market capitalization in the previous 12 months). A visual inspection of the figure already suggests that there is a negative relation between the two series. We now examine more carefully the idea that hedge funds negatively affect the misvaluation spread by regressing the misvaluation spread on the hedge fund industry's AUM and the mutual fund industry's TNA. We also include the TED spread in all regressions to proxy for the hedge funds' use of leverage. Since hedge funds' leverage is likely to adjust only gradually to changes in the TED spread, we use the 12-month average of the TED spread in our regressions. The results are given in Table 4.[10]

The first three columns of Table 4 report the results without a correction for the small sample bias of Kendall (1954), and the last three columns the results from using the ARM that corrects for this bias.[11] To avoid problems with multicollinearity, we orthogonalize one of the variables in each regression. The orthogonalized variables are denoted by "residual" in Tables 4–7.[12] Our expectation is that hedge fund AUM is negatively associated with the misvaluation spread, whereas the TED spread is positively associated with it, consistent with the idea that hedge funds foster market efficiency. The idea is that when the TED spread is high, hedge funds' funding liquidity and leveraging ability is low, resulting in limits to arbitrage and a higher misvaluation spread. We do not expect to find similar results with the mutual funds' TNA.

The results in Table 4 show that hedge fund AUM is indeed negatively associated with the level of the misvaluation spread since the coefficient on hedge fund AUM is negative and highly significant in some form in every specification. In addition, the coefficient for the TED spread is positive and significant, as expected. These results remain intact irrespective of whether we use the level of the hedge funds' AUM (first column) or the orthogonalized measure of hedge funds' AUM (residual, second column). Moreover, the results for the mutual funds' TNA are at best inconclusive. The coefficient on the mutual fund TNA is negative and significant (second column). However, after controlling for the effect of hedge funds, the marginal effect of mutual funds (the residual) is positive and significant at the 1% level. This suggests that

[10] The hedge fund industry AUM in our sample amounts to nearly 12% of the total CRSP stock market capitalization in 2010 and to 1.5% in 1991. When evaluating the potential of hedge funds on the stock market, one must keep in mind that hedge funds are typically highly levered. McGuire et al. (2005) report leverage ratios of up to 12:1.

[11] In the case of several explanatory variables in the regressions, we use the generalization of the ARM proposed by Amihud et al. (2009).

[12] The orthogonalized variables are the residuals from a regression of hedge fund AUM (mutual fund TNA) on a constant, mutual fund TNA (hedge fund AUM) and the TED spread. Our results are qualitatively similar if we do not orthogonalize the variables.

Table 4 Regressions Explaining the Misvaluation Spread

	OLS			ARM		
Constant	1.436***	1.460***	1.240***	1.432***	1.454***	1.233***
	(70.011)	(61.567)	(19.156)	(70.017)	(57.280)	(19.358)
HF AUM	−3.361***		−0.461	−3.677***		−1.205
	(−8.013)		(−0.541)	(−8.381)		(−1.339)
MF TNA		−0.773***			−0.846***	
		(−6.591)			(−6.772)	
HF residual		−6.878***			−7.520***	
		(−6.324)			(−6.874)	
MF residual	1.555***			1.700***		
	(4.427)			(4.821)		
TED spread	26.351***	21.564***	61.528***	26.988***	21.752***	59.168***
	(7.658)	(6.856)	(4.292)	(8.291)	(7.462)	(4.084)
HF AUM × *TED spread*			−472.207***			−421.685**
			(−2.882)			(−2.542)
R-squared	0.526	0.526	0.4714	0.564	0.564	0.516

Notes. This table shows the results of regressing the misvaluation spread (average overvaluation in the three highest misvaluation deciles minus the average undervaluation in the three lowest misvaluation deciles) on the hedge fund industry AUM (*HF AUM*), the mutual fund industry TNA (*MF TNA*), and a 12-month average of the TED spread (*TED spread*). The variable *HF residual* consists of the residuals from a regression of hedge fund AUM on a constant, mutual fund TNA, and the average TED spread. The variable *MF residual* is defined analogously. Decile break points are calculated using NYSE stocks only. In the first three columns, all models are estimated using OLS, whereas in the last three columns, all models are estimated using the augmented regression method of Amihud et al. (2009). Our sample period is from January 1991 to December 2010 ($N = 241$).

** and *** denote statistical significance at the 5% and 1% levels, respectively.

in contrast to hedge funds, mutual funds may have acted as an efficiency deteriorating force in the stock market during our sample period.

When we correct for the small sample bias in the last three columns of Table 4, our results remain both qualitatively and quantitatively similar as before the correction. Thus, our results suggest that hedge funds narrow the misvaluation spread and, in that sense, increase stock market efficiency, but mutual funds do not. In the remaining tables in this section (with the exception of Table 8), we only report results obtained with the augmented regression model.[13]

Sadka and Scherbina (2007) argue that increases in aggregate liquidity help the convergence of market prices to their fundamentals. To ensure that our results are not merely driven by liquidity, we sort all the stocks in our sample based on Amihud's (2002) liquidity measure, divide them into two subsamples, and calculate the misvaluation spread within that subsample. We then run the same regressions as before separately for the most liquid and the least liquid stocks. The results are given in Table 5. Analyzing liquid (first three columns) and illiquid (last three columns) stocks separately, our results show that qualitatively the effect of hedge funds is similar between the two categories. In both cases, the coefficients on hedge fund AUM in some form are negative and significant. However, the results are even stronger for liquid stocks. For example, the coefficient on the hedge fund residual for liquid stocks is roughly twice the coefficient for illiquid stocks. This result is in line with the conjecture that liquid stocks are easier to arbitrage. Moreover, the positive marginal effect of mutual funds is substantially larger for liquid stocks with the coefficient on the mutual fund residual for liquid stocks being roughly three times higher than the coefficient for illiquid stocks.[14]

Hedge funds can also have had a different impact on market efficiency in different time periods during our sample window. For example, in the latter half of our sample period, the size of the hedge fund industry was much larger. Moreover, there are two major crises (the burst of the technology bubble and the 2008 subprime crisis) in the second half of our sample. To analyze the possibly different impact of hedge funds on the stock market efficiency over time, we

[13] Our results are economically significant as the estimates in Table 4 suggest that if hedge funds held 10% more of the market, other things equal, the misvaluation spread would be 0.34, or two standard deviations lower. Compared with the historical average of the misvaluation spread, this would correspond with a 24% lower misvaluation spread. Using the average market values of the undervalued and overvalued firms, assuming that the correction in misvaluation would accrue equally much to undervalued and overvalued firms, we estimate that such a reduction in misvaluation spread would have reduced equity market misvaluations on average by roughly one trillion U.S. dollars during our sample period.

[14] When looking at the average misvaluation across liquidity deciles, we find that illiquid stocks are more likely to be underpriced, and liquid stocks are more likely to be overpriced (consistent with liquidity premium). Consistent with the idea that liquid stocks are easier to arbitrage and more accurately priced, we find that in the decile of the most illiquid stocks, the coefficient of variation of misvaluation, a normalized measure of its standard deviation over time, is more than double that of the most liquid stocks (1.47 versus 0.68). We also performed the regression in Table 5 for the middle category of stocks sorted by their measure of illiquidity. The results were qualitatively similar to the illiquid stocks.

Table 5 Misvaluation, Hedge Funds, and Liquidity

	Liquid stocks			Illiquid stocks		
Constant	1.501***	1.509***	1.191***	1.307***	1.354***	1.197***
	(77.823)	(63.382)	(18.372)	(101.168)	(85.533)	(31.529)
HF AUM	−3.975***		−0.130	−2.712***		−1.289***
	(−7.611)		(−0.170)	(−9.217)		(−2.285)
MF TNA		−0.834***			−0.767***	
		(−6.261)			(−9.545)	
HF residual		−8.906***			−4.167***	
		(−6.324)			(−5.178)	
MF residual	2.181***			0.643**		
	(4.882)			(2.438)		
TED spread	23.797***	17.861***	75.759***	18.651***	15.281***	37.613***
	(7.539)	(7.026)	(5.244)	(9.307)	(8.942)	(4.487)
HF AUM × *TED spread*			−675.543***			−246.793***
			(−4.312)			(−2.539)
R-squared	0.561	0.561	0.521	0.556	0.556	0.557

Notes. This table shows the results of regressing the misvaluation spread for two subsamples based on liquidity on the hedge fund industry AUM (*HF AUM*), the mutual fund industry TNA (*MF TNA*), and a 12-month average of the TED spread (*TED spread*). The variable *HF residual* consists of the residuals from a regression of hedge fund AUM on a constant, mutual fund TNA, and the average TED spread. The variable *MF residual* is defined analogously. The classification of stocks to liquid and illiquid stocks (five deciles of stocks in both groups) is done based on the Amihud's (2002) ILLIQ measure. Decile break points are calculated using the NYSE stocks only. All models are estimated using the augmented regression method of Amihud et al. (2009). Our sample period is from January 1991 to December 2010 ($N = 241$).

** and *** denote statistical significance at the 5% and 1% levels, respectively.

split our sample into two subperiods. The results from analyzing these two subperiods are given in Table 6.

The results for the two subperiods (1991–2000, given in the first three columns, and 2001–2010, given in the last three columns) seem to be in line with our previous findings. In the first subperiod, the coefficient for the hedge fund AUM is negative (albeit not significant), and the marginal effect of the hedge funds (the residual) is negative and highly significant ($t = -6.6$). In the second period, the coefficient for the hedge fund AUM is also negative and significant at the 1% level, whereas the coefficient for the residual is insignificant. Our proxy for the hedge funds' leverage, the TED spread, remains significantly positive in both periods. For mutual funds in the first period, the coefficients on both the level of the TNA and the residual are positive and significant at the 1% level. In the second period, however, the coefficients for the mutual fund TNA become negative and significant, suggesting that mutual funds have became less price distorting over time.[15]

[15] Reasons why mutual funds can be more price distorting than hedge funds on average include their arguably lower level of sophistication compared to hedge funds, lower managerial incentives, and a structure that exposes them to rapid fund withdrawals that may cause price pressure. As discussed in the introduction, similar to the case of hedge funds, mutual funds also seem to engage in end-of-quarter gaming and window-dressing activities; see, e.g., Carhart et al. (2002). One reason why mutual funds appear to have become less price distorting over time could be that they have become increasingly sophisticated as research on capital market anomalies has become available (in line with McLean and Pontiff 2012).

Next we analyze the effect of hedge funds on the levels of undervaluation and overvaluation separately by regressing our overvaluation and undervaluation measures on hedge fund AUM. The results for the undervalued stocks are given in the first three columns of Table 7. Since undervaluation is on average a negative value, a positive coefficient for the hedge fund AUM implies that hedge fund industry AUM reduces undervaluation. This is exactly what we find. The coefficients of both the hedge fund industry AUM and the residual are positive and significant at the 1% level. The last three columns give the results for the overvalued stocks. In this case, since overvaluation is a positive figure, a negative coefficient for hedge fund AUM would imply that it decreases overvaluation. We find that the estimated coefficient is indeed negative and significant in some form in every specification. According to our results, therefore, hedge funds narrow the misvaluation spread both through undervalued and overvalued stocks. It appears that the effect of hedge funds is stronger for reducing the overvaluation of overvalued shares compared with reducing the undervaluation of undervalued shares. The t-statistics and the R-squared value of the regression for the overvalued shares are larger, and consistent with the observation that the borrowing constraints are particularly relevant in shorting, we find that the TED spread when interacted with the hedge fund AUM is significant only in the regression of the overvalued stocks.

In contrast, mutual funds do not seem to have a similar effect, consistent with our earlier results. After controlling for the effect of hedge funds, the marginal

Table 6 Misvaluation Spread and Hedge Funds in 1991–2000 and 2001–2010

	First period (1991–2000)			Second period (2001–2010)		
Constant	1.091***	0.996***	1.624***	1.508***	1.863***	1.522***
	(19.265)	(19.952)	(9.402)	(44.817)	(32.771)	(18.685)
HF AUM	−0.678		−14.577**	−4.253***		−4.446***
	(−0.465)		(−2.245)	(−8.117)		(−3.247)
MF TNA		0.675***			−2.365***	
		(3.225)			(−10.983)	
HF residual		−24.065***			1.849	
		(−6.598)			(1.504)	
MF residual	3.768***			−3.160***		
	(7.213)			(−6.222)		
TED spread	75.384***	66.930***	2.306	21.502***	15.417***	17.659
	(8.529)	(7.708)	(0.066)	(9.054)	(8.051)	(1.027)
HF AUM × *TED spread*			2523.000*			40.290
			(1.891)			(0.192)
R-squared	0.731	0.731	0.558	0.728	0.728	0.577

Notes. This table shows the results of regressing the misvaluation spread on the hedge fund industry AUM (*HF AUM*), the mutual fund industry TNA (*MF TNA*), and a 12-month average of the TED spread (*TED spread*). The variable *HF residual* consists of the residuals from a regression of hedge fund AUM on a constant, mutual fund TNA, and the average TED spread. The variable *MF residual* is defined analogously. The analysis is run separately for two time periods, 1991–2000 and 2001–2010. All models are estimated using the augmented regression method of Amihud et al. (2009).

*, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7 Undervaluation, Overvaluation, and Hedge Fund AUM

	Undervalued stocks			Overvalued stocks		
Constant	−0.609***	−0.615***	−0.589***	0.824***	0.840***	0.644
	(−45.100)	(−37.720)	(−16.341)	(79.458)	(64.823)	(18.702)
HF AUM	1.193***		1.018*	−2.484***		−0.187
	(6.206)		(1.808)	(−8.612)		(−0.425)
MF TNA		0.276***			−0.570***	
		(4.378)			(−7.576)	
HF residual		2.428***			−5.092***	
		(5.151)			(−6.758)	
MF residual	−0.546***			1.154***		
	(−3.327)			(4.852)		
TED spread	−14.076***	−12.381***	−15.482*	12.912***	9.371***	43.686***
	(−6.880)	(−6.192)	(−1.931)	(7.391)	(6.536)	(5.518)
HF AUM × *TED spread*			19.633			−402.052***
			(0.203)			(−4.526)
R-squared	0.406	0.406	0.363	0.610	0.610	0.588

Notes. This table shows the results of regressing the average misvaluation measures of the portfolio of undervalued stocks (first three columns) and the portfolio of overvalued stocks (last three columns) on the hedge fund industry AUM (*HF AUM*), the mutual fund industry TNA (*MF TNA*), and a 12-month average of the TED spread (*TED spread*). The variable *HF residual* consists of the residuals from a regression of hedge fund AUM on a constant, mutual fund TNA, and the average TED spread. The variable *MF residual* is defined analogously. All models are estimated using the augmented regression method of Amihud et al. (2009). Our sample period is from January 1991 to December 2010 ($N = 241$).

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

effects of the mutual funds seem to be that they increase the undervaluation of underpriced stocks (the coefficient on the residual being negative and significant) and increase the overvaluation of overpriced stocks (the coefficient on the residual being positive and significant). Hence again, our evidence suggests that on average the mutual funds have had an opposing effect on market efficiency from the hedge funds.[16]

So far, our analysis has focused on the effect of hedge funds' AUM on the level of the misvaluation spread. Next, we study changes in misvaluation and regress the annual changes in the misvaluation spread

[16] Although it is conceivable that hedge fund industry AUM is correlated with alternative factors that might affect market efficiency, such as transaction costs, this is less likely to be the case for the marginal effect (the residuals) of hedge fund capital and the hedge fund flows. In the next two sections, we analyze hedge funds' exposure to the returns on undervalued and overvalued shares as well as the hedge funds' holdings of those shares to provide additional evidence that our results are not merely the result of time variation in transaction costs.

Table 8 Changes in the Misvaluation Spread and Hedge Fund Flow

Dependent variable: *Annual change in the misvaluation spread*			
Constant	0.030	0.024	0.025
	(−1.532	(−0.715	(−1.231)
HF Flow	−7.030***		−7.380***
	(−3.215)		(−2.976)
MF Flow		−2.058	0.585s
		(−0.996)	(0.442)
Change in TED	18.978***	12.441***	19.163***
	(3.657)	(3.623)	(3.565)
R-squared	0.499	0.289	0.501

Notes. This table shows the results of regressions explaining annual changes in the misvaluation spread. The explanatory variables are the hedge fund industry flow (*HF Flow*), mutual fund industry flow (*MF Flow*), and the change in the TED spread (*Change in TED*). Heteroskedasticity- and autocorrelation-consistent t-values are in parentheses.

*** denotes statistical significance at the 1% level.

on hedge fund flow, mutual fund flow, and changes in the TED spread. The flows are defined as the cumulative flow during the year and are scaled by the average 12-month stock market capitalization from CRSP. Our results, given in Table 8, show that hedge fund flow is negatively and significantly (at the 1% level) related to changes in the misvaluation spread, whereas the effect of mutual funds is insignificant.[17]

6. Additional Evidence from Returns and Holdings Data

6.1. Evidence from Hedge Fund Returns

To provide yet alternative evidence on the hedge funds' exposure to misvalued shares, in this section, we investigate the investments of hedge funds in undervalued and overvalued securities by regressing the returns on the HFR Composite Hedge Fund Index on the returns on the portfolios of undervalued stocks and the portfolio of overvalued stocks. The three Fama and French (1993) factors and Carhart's (1997) momentum factor are included as controls. The results are given in Table 9.

The coefficient for the undervalued portfolio is positive and significant (t-value of 1.92). This result implies that hedge funds seem to invest in undervalued shares, which supports our previous finding that hedge fund flows reduce the undervaluation of undervalued shares. The coefficient for the overvalued portfolio is insignificant.

6.2. Holdings Data

Next, we look for additional evidence that hedge funds affect the level of the misvaluation spread by analyzing the hedge funds' stock holdings from their

[17] We also run similar regressions for monthly and quarterly changes in the misvaluation spread. The results are qualitatively similar but lack statistical significance and are thus omitted.

Table 9 Regressions Explaining Hedge Fund Returns

Dependent variable: *Return on all hedge funds index*			
Constant	0.007***	0.007***	0.007***
	(8.210)	(8.259)	(7.736)
UNDERV	0.064**		0.061*
	(1.924)		(1.808)
OVERV		0.038	0.016
		(0.657)	(0.281)
MKT	0.297***	0.319***	0.284***
	(8.034)	(4.880)	(4.282)
MOM	0.078***	0.053***	0.075***
	(4.362)	(3.336)	(4.130)
SMB	0.122***	0.146***	0.117***
	(3.453)	(4.094)	(2.940)
HML	−0.042	−0.001	−0.039
	(−1.099)	(−0.033)	(−1.023)
R-squared	0.761	0.759	0.761

Notes. This table shows the results of regressing the return on the HFR all hedge funds (composite) index on the return on the undervalued portfolio (*UNDERV*; first column), the return on the overvalued portfolio (*OVERV*; second column), and the returns on both misvaluation portfolios together (third column). The market factor (*MKT*), the momentum factor (*MOM*), the size factor (*SMB*), and the book-to-market factor (*HML*) are used as controls. The misvaluation measure is calculated each month using accounting data from year $t-1$ (updated each June) and the corresponding month's market price. Heteroskedasticity- and autocorrelation-consistent t-values are in parentheses.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

13F filings. Our data are from Thomson Reuters. To identify hedge funds' equity holdings, we follow the approach of Brunnermeir and Nagel (2004) and Griffin and Xu (2009).

We first compile a list of hedge fund management companies from Lipper TASS. We then manually match this list to the quarterly institutional portfolio holdings reports (Form 13F). The 13F filings include various types of institutional investors. To ensure that our sample includes only hedge funds, we check whether the institutions in our initial list of potential hedge fund managers are registered as investment advisers with the U.S. Securities and Exchange Commission (SEC). As in Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we manually check the "ADV forms" that institutional investors submit to the SEC. To be included in our sample, we require that the institutions classify more than 50% of their clients as "high-net-worth individuals" or "other pooled investment vehicles." Finally, we use various online sources to check whether the institutions declare that their main line of business is to manage hedge funds. It is worth noting that our procedure excludes institutional investors that manage hedge funds but are also involved in other investment activities. Thus our sample does not include large investment banks and brokers (e.g., Goldman Sachs, J.P. Morgan). Applying the filters described above, our final sample includes 255 hedge fund management companies.[18]

To measure the funds' quarterly stock holdings, we follow Chen et al. (2000) and compute the following measure of aggregate holdings at the stock level:

$$FracHoldings_{i,t} = \frac{NumberSharesHeld_{i,t}}{NumberSharesOustanding_{i,t}} \times 100, \quad (9)$$

where the numerator is the number of shares in stock i held by the hedge funds on aggregate at the end of quarter t, and the denominator is the number of shares outstanding for stock i at the end of quarter t. Furthermore, we measure the aggregate trading activity of hedge funds by calculating the quarterly change in the aggregate holdings; that is,

$$Trades_{i,t} = FracHoldings_{i,t} - FracHoldings_{i,t-1}. \quad (10)$$

As argued by Chen et al. (2000), the advantage of this measure of trading (where positive values correspond with purchases and negative with sales) compared with some alternative measures—for example, the portfolio change measure of Grinblatt and Titman (1993)—is that it tracks only active trading by funds and is not affected by passive changes in portfolio weights driven by price changes. If there are no net buys or sells by hedge funds on aggregate in a given quarter, our measure of trades is equal to zero.

6.3. Hedge Funds' Holdings, Trades, and Misvaluation

To analyze how hedge funds' stockholdings and trading are related to our measure of misvaluation, we first divide our sample into subperiods corresponding to periods with high, medium, and low misvaluation spread, classifying roughly one-third of the periods into each category. We then calculate hedge funds' aggregate holdings in the most undervalued and overvalued stocks conditional on the level of the misvaluation spread. Here, we define the most undervalued (most overvalued) stocks as those belonging to the lowest (highest) decile of stocks ranked according to our misvaluation measure. Fair-valued stocks are here defined to be between percentile points 40 and 60.[19]

The results related to periods with high and low misvaluation spread are given in panel A of Table 10

Table 10 Hedge Funds' Stockholdings and Trades

	Undervalued	Fairly valued	Overvalued
Panel A: Misvaluation spread and holdings			
High spread	1.750	1.425	1.580
Low spread	2.328	2.264	2.680
Panel B: Change in misvaluation spread and trades			
Δ Spread < 0	0.070	0.062	0.012
Δ Spread ≥ 0	0.011	0.034	0.050
Panel C: Lagged misvaluation spread and trades			
High spread ($t-1$)	0.103	0.049	0.035
Low spread ($t-1$)	0.046	0.056	0.057

Notes. This table shows the hedge funds' aggregate stock holdings (panel A) and net purchases (panels B and C) in undervalued, fairly valued, and overvalued stocks conditional on the level of misvaluation spread (panel A), change in the misvaluation spread (panel B), or lagged level of misvaluation spread (panel C). Undervalued (overvalued) stocks are here defined to be those that belong to the lowest (highest) decile of stocks when sorted according to our mispricing measure. Fairly valued stocks belong between percentile points 40 and 60. In panel A, we divide the sample into periods that correspond to a high level of the misvaluation spread and a low level of the misvaluation spread, respectively. Both groups contain roughly 30% of the observations in each tail of the distribution. The hedge funds' aggregate percentage holdings are calculated as a fraction of market capitalization as defined in Equation (9) in the text. In panel (B), we divide the sample into periods of decreasing and increasing misvaluation spread and calculate the hedge funds' net purchases conditional on the direction of the quarterly change in the misvaluation spread. Net purchases are calculated as changes in the aggregate holdings, as defined in Equation (10). Panel (C) shows the hedge funds' aggregate trades in undervalued, fairly valued, and overvalued stocks conditional on the level of the misvaluation spread in the previous quarter. The sample period is from Q1 1991 to Q4 2010. Hedge fund holdings are calculated by matching the management companies in the TASS database to the management companies in the 13F filings provided by Thomson Reuters.

(to save space we do not report the results related to periods with medium level of misvaluation). When the misvaluation spread is high, hedge funds on average own 1.75% of the market capitalization of the most undervalued stocks. The corresponding fraction for the most overvalued stocks is 1.58%. In contrast, when the misvaluation spread is low, hedge funds own an average of 2.33% of the most undervalued and 2.68% of the most overvalued stocks. The interpretation of these results is quite straightforward. When the misvaluation spread is large, hedge funds invest relatively more in the most undervalued shares than in the most overvalued shares, thus causing a negative effect on the misvaluation spread. When the misvaluation spread is low, hedge funds, in turn, hold relatively more the overvalued stocks. The fact that holdings are larger in periods with low misvaluation spread is consistent with our idea that these are periods with more abundant hedge fund capital.

Panel B of Table 10 gives the results for the hedge fund trades (net purchases of undervalued minus overvalued shares) as defined in Equation (10). Our analysis of hedge funds' trades provides additional

[18] The Lipper TASS database includes information at the fund level, whereas the 13F holdings are consolidated at the management company level, so the matching is done at the management company level.

[19] If we instead classify the three lowest (highest) deciles to be the undervalued (overvalued) stocks, our results are qualitatively similar, but the differences in hedge funds' stock holdings across states are slightly smaller in magnitude.

Table 11 Hedge Funds' Relative Trading (Trades in Undervalued Stocks Minus Trades in Overvalued Stocks)

Panel A: Relative trades conditional on lagged level of the misvaluation spread and changes in TED spread		
	ΔTED < 0	ΔTED ≥ 0
High spread ($t-1$)	16.914	−11.451
Low spread ($t-1$)	9.337	−26.148
Panel B: Relative trades conditional on lagged level of the misvaluation spread and hedge fund flow		
	Flow ≥ 0	Flow < 0
High spread ($t-1$)	9.382	−4.018
Low spread ($t-1$)	−0.676	−40.379

Notes. This table shows hedge funds' relative trading defined as the difference between their trades in undervalued shares and their trades in overvalued shares. In the table, we calculate the relative trades conditional on the lagged (end of previous quarter) level of the misvaluation spread and the sign of the change in the TED spread (panel A) and positive or negative net flow (panel B). The sample period is from Q1:1991 to Q4:2010. Hedge fund holdings are calculated by matching the management companies in the TASS database to the management companies in the 13F filings provided by Thomson Reuters.

evidence that their trading influences the misvaluation spread. Namely, in quarters when the misvaluation spread declines, hedge funds tend to purchase considerably more undervalued than overvalued shares. In contrast, in quarters when the misvaluation spread increases, hedge funds purchase more overvalued than undervalued shares. This is consistent with the idea that hedge funds' trading affects the misvaluation spread. Panel C, in turn, shows that hedge funds' net purchases of undervalued shares are larger in quarters starting with a high level of the misvaluation spread than in quarters starting with a low level of the misvaluation spread, where hedge funds, in fact, purchase more overvalued than undervalued stocks.[20]

Finally, in Table 11 we provide evidence that the hedge funds' trades are affected by their capital constraints. We now calculate the trades conditional on the sign of the change in the TED spread in the relevant quarter (panel A) and the quarterly hedge fund industry flow (panel B). We do this separately for both the high and low misvaluation periods. The results show that hedge funds' (relative) buying activity of undervalued stocks is associated with periods of increasing hedge fund capital, resulting either from a decline in TED spread or from positive hedge fund industry flow. In contrast, periods of hedge funds' (relative) selling of undervalued stocks are coupled with periods of rising TED and negative hedge fund flows. Furthermore, as expected, increases in hedge fund capital are associated with purchases of undervalued shares especially in periods with high misvaluation spread.

All in all, the results in this section are consistent with our earlier results. Hedge funds seem to be able to identify undervalued shares and their holdings and trades concentrate on mispriced shares. When misvaluations are large, hedge funds hold and purchase relatively more the undervalued shares, thus influencing positively market efficiency. We find evidence that they are capital constrained in the sense that increases (decreases) in hedge fund capital lead to net purchases (net selling) of undervalued shares.

[20] Consistent with the growth of the industry, we find that the hedge fund holdings of undervalued (overvalued) shares are significantly larger at times of high (low) misvaluation spread in the latter half of our sample. Similarly, their net purchases of undervalued shares at times of declining misvaluation spread are larger in the latter half of the sample, as are their net purchases of overvalued shares at times of rising misvaluation spread.

7. Conclusions

To summarize, to the extent that the residual income model provides good estimates of stocks' misvaluations, our findings systematically indicate, as argued by Stulz (2007), that hedge funds act as a correcting force in the stock market and reduce the amount of misvaluation. Moreover, it appears that mutual funds do not have the price-correcting effect that hedge funds have.

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References

Abreu D, Brunnermeier MK (2003) Bubbles and crashes. *Econometrica* 71:173–204.

Akbas F, Armstrong WJ, Sorescu SM, Subrahmanyam A (2015) Capital market efficiency and arbitrage efficacy. *J. Financial Quant. Anal.* Forthcoming.

Ali A, Hwang LS, Trombley MA (2003) Residual-income-based valuation predicts future stock returns: Evidence on mispricing vs. risk explanations. *Accounting Rev.* 78:377–396.

Amihud Y (2002) Illiquidity and stock returns: Cross-section and time-series effects. *J. Financial Markets* 5:31–56.

Amihud Y, Hurvich CM (2004) Predictive regressions: A reduced bias estimation method. *J. Financial Quant. Anal.* 39:813–841.

Amihud Y, Hurvich CM, Wang Y (2009) Multiple-predictor regressions: Hypothesis testing. *Rev. Financial Stud.* 22:413–434.

Ang A, Gorovyy S, Van Inwegen GB (2011) Hedge fund leverage. *J. Financial Econom.* 102:102–126.

Asness CS, Friedman JA, Krail RJ, Liew JM (2000) Style Timing: Value versus growth. *J. Portfolio Management* 26:50–60.

Avramov D, Barras L, Kosowski R (2013) Hedge fund predictability under the magnifying glass. *J. Financial Quant. Anal.* 48:1057–1083.

Baquero G, Verbeek M (2009) A portrait of hedge fund investors: Flows, performance, and smart money. Unpublished working paper, ESMT European School of Management and Technology, Berlin.

Ben-David I, Franzoni F, Moussawi R (2012) Hedge funds stock trading during the financial crisis of 2007–2009. *Rev. Financial Stud.* 25:1–54.

Ben-David I, Franzoni F, Landier A, Moussawi R (2013) Do hedge funds manipulate stock prices? *J. Finance* 68:2383–2434.

Bernard VL, Thomas JK (1989) Post-earnings-announcement drift: Delayed price response or risk premium? *J. Accounting Res.* 27:1–48.

Bernard VL, Thomas JK (1990) Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *J. Accounting Econom.* 13:305–340.

Brunnermeier MK, Nagel S (2004) Hedge funds and the technology bubble. *J. Finance* 59:2013–2040.

Brunnermeier MK, Pedersen LH (2009) Market liquidity and funding liquidity. *Rev. Financial Stud.* 22:2201–2238.

Brunnermeier MK, Nagel S, Pedersen LH (2009) Carry trades and currency crashes. Acemoglu D, Rogoff K, Woodford M, eds. *NBER Macroeconomics Annual* 2008, Vol. 23 (University of Chicago Press, Chicago), 313–347.

Carhart MM (1997) On persistence in mutual fund performance. *J. Finance* 52:57–82.

Chen HL, Jegadeesh N, Wermers R (2000) The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *J. Financial Quant. Anal.* 35:343–368.

Cohen RB, Polk C, Vuolteenaho T (2003) The value spread. *J. Finance* 58:609–642.

D'Mello R, Schroff PK (2000) Equity undervaluation and decisions related to repurchase tender offers: An empirical investigation. *J. Finance* 55:2399–2424.

Dong M, Hirshleifer D, Teoh SH (2007) Stock market misvaluation and corporate investment. Unpublished working paper, University of California, Irvine, Irvine.

Dong M, Hirshleifer D, Richardson S, Teoh SH (2006) Does investor misvaluation drive the takeover market? *J. Finance* 61:725–762.

Doukas JA, Kim C, Pantzalis C (2010) Arbitrage risk and stock mispricing. *J. Financial Quant. Anal.* 45:907–934.

Ellul A, Jotikasthira C, Lundblad CT (2011) Regulatory pressure and fire sales in the corporate bond market. *J. Financial Econom.* 101:596–620.

Fama EF, French KR (1988a) Dividend yields and expected stock returns. *J. Financial Econom.* 22:3–25.

Fama EF, French KR (1988b) Permanent and temporary components of stock prices. *J. Political Econom.* 96:246–273.

Fama EF, French KR (1992) The cross-section of expected stock returns. *J. Finance* 47:427–465.

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *J. Financial Econom.* 33:3–56.

Fama EF, French KR (1997) Industry costs of equity. *J. Financial Econom.* 43:153–193.

Frankel R, Lee CMC (1998a) Accounting diversity and international valuation. Working paper, University of Michigan, Ann Arbor.

Frankel R, Lee CMC (1998b) Accounting valuation, market expectation, and cross-sectional stock returns. *J. Accounting Econom.* 25:283–319.

Frazzini A, Lamont O (2008) Dumb money: Mutual fund flows and the cross-section of stock returns. *J. Financial Econom.* 88:299–322.

Green J, Hand JRM, Soliman MT (2011) Going, going, gone? The apparent demise of the accruals anomaly. *Management Sci.* 57:797–816.

Griffin JM, Xu J (2009) How smart are the smart guys? A unique view from hedge fund stock holdings. *Rev. Financial Stud.* 22:2531–2570.

Griffin JM, Harris J, Shu T, Topaloglu S (2011) Who drove and burst the tech bubble? *J. Finance* 66(4):1251–1290.

Grinblatt M, Titman S (1993) Performance measurement without benchmarks: An examination of mutual fund returns. *J. Bus.* 66:47–68.

Gromb D, Vayanos D (2002) Equilibrium and welfare in markets with financially constrained arbitrageurs. *J. Financial Econom.* 66:361–407.

Gromb D, Vayanos D (2010) Limits of arbitrage: The state of the theory. *Annual Rev. Financial Econom.* 2:251–275.

Hansen LP, Hodrick RJ (1980) Forward exchange rates as optimal predictors of future spot rates: An econometric analysis. *J. Political Econom.* 88:829–853.

Johnson WB, Schwartz W (2002) Learning curve: Investors apply evidence of how earnings surprises affect returns. *Investors Relations Quart.* 4:30–57.

Jones RC (2010) Maybe it really is different this time. *J. Portfolio Management* 36:60–72.

Jylhä P, Suominen M (2011) Speculative capital and currency carry trades. *J. Financial Econom.* 99:60–75.

Jylhä P, Rinne K, Suominen M (2014) Do hedge funds supply or demand liquidity. *Rev. Finance* 18:1259–1298.

Kang N, Kondor P, Sadka R (2014) Do hedge funds reduce idiosyncratic risk? *J. Financial Quant. Anal.* 48:843–877.

Kendall MG (1954) Note on bias in the estimation of autocorrelation. *Biometrika* 41:403–404.

Lee CMC, Myers J, Swaminathan B (1999) What is the intrinsic value of the Dow? *J. Finance* 54:1693–1741.

McGuire P, Remolona E, Tsatsaronis K (2005) Time-varying exposures and leverage in hedge funds. *BIS Quart. Rev.* (March): 59–72.

McLean RD, Pontiff J (2012) Does academic research destroy stock return predictability? Unpublished working paper, University of Alberta, Edmonton, AB, Canada.

Mitchell M, Pedersen LH, Pulvino T (2007) Slow moving capital. *Amer. Econom. Rev.* 97:215–220.

Ohlson J (1990) A synthesis of security valuation theory and the role of dividends, cash flows, and earnings. *Contemporary Accounting Res.* 6:648–676.

Ohlson J (1995) Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Res.* 11:661–687.

Pontiff J (1996) Costly arbitrage: Evidence from closed-end funds. *Quart. J. Econom.* 111:1135–1151.

Pontiff J (1997) Excess volatility and closed-end funds. *Amer. Econom. Rev.* 87:155–169.

Sadka R, Scherbina A (2007) Analyst disagreement, mispricing, and liquidity. *J. Finance* 62:2367–2403.

Shleifer A, Vishny RW (1997) The limits of arbitrage. *J. Finance* 52:35–55.

Stambaugh RF (1999) Predictive regressions. *J. Financial Econom.* 54:375–421.

Stein J (2009) Presidential address: Sophisticated investors and market efficiency. *J. Finance* 64:1517–1548.

Stulz RM (2007) Hedge funds: Past, present, and future. *J. Econom. Perspect.* 21:175–194.