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# The mean–variance relation and the role of institutional investor sentiment

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## HIGHLIGHTS

- We test the role of institutional investor sentiment in the mean–variance relation.
- Returns are negatively related to conditional volatility over bullish periods.
- Returns are positively related to conditional volatility over bearish periods.
- The evidence indicates that institutional investors can also be sentiment traders.

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ABSTRACT

This paper investigates the role of institutional investor sentiment in the mean–variance relation. We find market returns are negatively (positively) related to market's conditional volatility over bullish (bearish) periods. The evidence indicates institutional investors to be sentiment traders as well.



## 1. Introduction

Rational asset pricing theories posit a positive mean–variance relation, i.e. the risk-return tradeoff. However, empirical evidence is quite mixed.[1] From a behavioral approach, Yu and Yuan (2011) state that unsophisticated investors are likely to misestimate variance of returns and they prefer taking long positions to short positions. Hence, an elevated level of unsophisticated investors over high-sentiment periods would distort the positive mean–variance relation while over low-sentiment periods, the positive relation would appear, which is empirically supported by their findings.

Extending Yu and Yuan (2011), we offer a new perspective by probing the role of institutional investor sentiment in determination of the mean–variance relation. While institutional investors are typically regarded sophisticated and are less likely to succumb to misestimation of variance of returns, more recent research by DeVault et al. (2018) show that in contrast to theoretical models, institutional rather than individual investors tend to be sentiment traders. Based on these, we argue that if institutional investors are sentiment traders, the distorted risk-return tradeoff would be observed when institutional investor sentiment is high.

## 2. Sentiment, market returns, and volatility models

### 2.1. Institutional investor sentiment

We collect institutional investor sentiment data from Investors Intelligence (II) that compiles weekly sentiment from investment newsletter writers including current or retired professionals who categorize themselves as bullish, bearish, or neutral (Brown and Cliff, 2004). The II considers the norm sentiment level to be 45% bulls, 35% bears, and 20% neutral, indicating that when the proportion of bulls (*Bull%*) exceeds 45%, institutional investors would generally be bullish and when the proportion of bears (*Bear%*) is over 35%, they would normally be bearish. Unlike Yu and Yuan

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[1] Extant evidence on the mean–variance relation appears three streams: positive, negative, and mixed (see, e.g., French et al., 1987; Whitelaw, 1994; Rossi and Timmermann, 2015; Wang et al., 2017).

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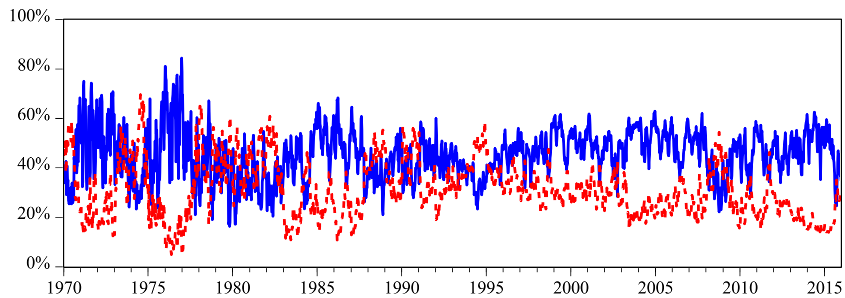


**Fig. 1.** Historical *Bull%* and *Bear%* weekly movement, 1970–2015. This figure presents the historical *Bull%* and *Bear%* weekly movement from 1970 to 2015. The solid and dotted lines represent *Bull%* and *Bear%*, respectively.

(2011) grouping the entire sample into high- and low-sentiment subsamples, we split ours into bullish, bearish, along with neutral subsamples. This is because separately exploring neural periods provides the standard state of the mean–variance relation when institutional investors are neither optimistic nor pessimistic, which seems more realistic in practice.

The approach to identify sentiment regimes largely follows Yu and Yuan (2011) and Antoniou et al. (2016). One period is at least one year to avoid too frequent conversions between three regimes. We compute annual *Bull%* and *Bear%* in calendar year $T$ by averaging the weekly *Bull%* and *Bear%* within the calendar year $T$, which is used to classify the sentiment regime for the next calendar year ($T+1$). In particular, the next calendar year ($T+1$) is categorized into bullish if *Bull%* is over 45%, bearish if *Bear%* is over 35%, and neutral otherwise.

While our separation is based on the II, one concern is that we do not disentangle the impact of individual investor sentiment—that is, this separation may reflect individual investor sentiment given its potential synchronous trend with institutional investor sentiment. If it is the case, our separation would not exclusively reflect the role of institutional investor sentiment in the mean–variance relation. To address this issue, we compute the correlation between *Bull%* and four widely-applied individual investor measures including consumer confidence of the Conference Board, consumer sentiment of the University of Michigan, and raw and orthogonalized BW sentiment index from Baker and Wurgler (2006).[2] The unreported correlations are 0.141 (*prob.* = 0.001), 0.332 (*prob.* = 0.000), −0.122 (*prob.* = 0.039), and −0.106 (*prob.* = 0.013), respectively, all of which are not prohibitively high. In this sense, our separation is mainly driven by institutional investor sentiment.

Table 1 shows that the historical averages of *Bull%* and *Bear%* are 0.453 (45.3%) and 0.310 (31.0%), respectively. In our sample containing 46 years, 24 and 14 years are identified as bullish and bearish periods, accordingly. The rest 8 years are then neutral periods. The movement of historical *Bull%* and *Bear%* is illustrated in Fig. 1, exhibiting that institutional investor sentiment fluctuates around the norm level, but at times it can deviate from the norm a lot.

### 2.2. Stock market

We collect value- and equal-weighted NYSE/AMEX market returns from the CRSP compiled by the WRDS. Table 2 shows that the mean of realized volatility is, by definition, close to the variance of market returns, and the difference between two figures is due to Jensen's inequality (Ghysels et al., 2005).

[2] We consider *Bull%* here since high (low) sentiment corresponds to high (low) values in *Bull%*, which is consistent with other individual investor sentiment measures. However, for *Bear%*, high (low) sentiment corresponds to low (high) values in *Bear%*, which is not commonly used in individual investor sentiment proxies.

**Table 1**
Summary statistics of *Bull%* and *Bear%*, 1970–2015.

| | $\mu$ | $\sigma$ | *Max.* | *Min.* | Number of years |
|---|---|---|---|---|---|
| *Bull%* | 0.453 | 0.099 | 0.844 | 0.163 | 24 |
| *Bear%* | 0.310 | 0.092 | 0.487 | 0.118 | 14 |

This table presents the summary statistics of *Bull%* and *Bear%*. In particular, we report the mean ($\sigma$), the standard deviation ($\sigma$), the maximum value (*Max.*), the minimum value (*Min.*), and the number of years for each subsample.

### 2.3. Volatility models

To measure conditional variance, we adopt four approaches including the rolling window (RW), GARCH, GJR-GARCH, and EGARCH models considering that the presented mean–variance relation depends on the choice of volatility models (Ghysels et al., 2005). The RW model follows,

$$Var_t\,(R_{t+1}) = \sigma_t^2 = \frac{22}{N_t}\sum_{d=1}^{N_t} r_{t-d}^2, \tag{1}$$

where $Var_t(R_{t+1})$ is conditional volatility for forecasting next-month market returns $R_{t+1}$; $\sigma_t^2$ is realized volatility in month $t$; $r_{t-d}$ is the demeaned daily return in month $t$, computed by subtracting the within-month mean daily return from the daily raw returns; $N_t$ is the actual number of trading days in month $t$, and 22 is the conventionally adopted number of trading days in one month. For GARCH, GJR-GARCH, and EGARCH models, we first estimate the mean equation,

$$r_{t+1} = \mu + \varepsilon_{t+1}, \tag{2}$$

where $r_{t+1}$ is the daily market return at day $(t+1)$; $\mu$ is the conditional mean of the daily return. The daily conditional volatility of market returns is filtered from,

$$\sigma_{t+1}^2 = \omega + \alpha\varepsilon_t^2 + \beta\sigma_t^2, \tag{3}$$

$$\sigma_{t+1}^2 = \omega + \alpha_1\varepsilon_t^2 + \alpha_2 I_t\varepsilon_t^2 + \beta\sigma_t^2, \tag{4}$$

$$\sigma_{t+1}^2 = exp\left\{\omega + \alpha_1[|\varepsilon_t|/\sqrt{\sigma_t^2}] + \alpha_2[\varepsilon_t/\sqrt{\sigma_t^2}] + \beta ln\sigma_t^2\right\}, \tag{5}$$

for GARCH, GJR-GARCH, and EGARCH models, accordingly. The term $I_t$ in Eq. (4) is the dummy variable for good news to account for the leverage effect (Glosten et al., 1993). We store daily conditional volatility series from these three specifications and apply them to the following,

$$Var_t\,(R_{t+1}) = E_t(\sum_{d=1}^{N_t}\sigma_{t+d}^2), \tag{6}$$

where the monthly conditional volatility, $Var_t(R_{t+1})$, is computed from the linear sum of daily conditional volatility, as specified in Engle (2001).