



# Evaluating the size of the bootstrap method for fund performance evaluation<sup>☆</sup>



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## HIGHLIGHTS

- Gauge the size of bootstrap methods with and without cross-sectional dependence.
- Without cross-sectional dependence, the size of the fund-by-fund bootstrap is good.
- With cross-sectional dependence, the fund-by-fund bootstrap is biased.
- We propose a new panel bootstrap model with unobservable interactive effects.
- Caution to use the bootstrap to distinguish skills from luck in the future.

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## ABSTRACT

We investigate the validity and reliability of the bootstrap approach in fund performance evaluation by gauging the size. Monte Carlo simulations suggest that cross-sectional dependence may alter the size of this test and we propose a new panel bootstrap approach.

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## 1. Introduction

One of the cornerstones of the Market Efficiency Hypothesis (EMH) is the principle that active investors (e.g., fund managers) do not have skills to beat the market in a persistent way. In the last decade, the bootstrap method has become an increasingly popular way to evaluate the performance of mutual funds (e.g., Kosowski et al. (2006); Fama and French (2010)), hedge funds (e.g., Kosowski et al. (2007)), pension funds (e.g., Blake et al. (2013)) and even individual investors Meyer et al. (2012). The great appeal of this

method comes from its simplicity and its ability to circumvent any ex ante parametric assumption on fund alphas (e.g., Kosowski et al. (2006); Fama and French (2010)). This method allows for the generation of the cross-sectional distribution of fund alphas purely due to sampling variability (“luck”), against which, the cross-section of realized alphas obtained from estimating a benchmark model is compared. A significant difference between them is regarded as evidence of genuine skill.

Given the popularity and the seeming superiority of this approach for separating skill from luck, it is surprising that no rigorous statistics analysis has been conducted to examine whether it can actually lead to correct inferences on managers’ skill as researchers presumed. Such analysis is essential to the understanding of the recent literature and the appropriate application of bootstrap in future research. Our paper fills this gap. While it is difficult, if not impossible, to examine the validity and reliability of

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the bootstrap approach, Monte Carlo simulation appears to be the natural choice for this need.

We explicitly investigate the two potential concerns on the bootstrap method in fund performance evaluation. First, the validity and reliability of this approach hinge on sample variations, i.e., the cross-sectional number of funds and time-series observations in the fund performance evaluation area. If sample variation is not enough, the bootstrap method may inevitably lead to a partial instead of a full picture of the underlying population due to the canonical type I error, which prompts us to gauge the size of the application of this method to fund evaluation. This question roots in the strand of literature about hedge fund evaluation, which usually suffers from the short time span of data (Kosowski et al., 2007). Moreover, the traditional fund-by-fund bootstrap does not take into account of the cross-sectional dependence, brought by the commonly held assets of the fund managers (e.g., Blake et al. (2014)).

We gauge the size of the fund-by-fund bootstrap performance evaluation method in two scenarios: with and without cross-sectional dependence in fund returns. Without cross-sectional dependence, our Monte Carlo simulations demonstrate that the size of the fund-by-fund bootstrap method approaches the conventional statistical significance level (0.05) even when we use a realistic small number of funds and time-series observations, which means that the fund-by-fund bootstrap method has excellent statistical properties in distinguishing skill from luck if the fund returns are not cross-sectionally dependent. With cross-sectional dependence in fund returns, however, the size of the fund-by-fund bootstrap method becomes much larger than 0.05 at any quantiles including the extreme tails, which means that the statistical inferences of this approach are severely biased towards identifying “skills” of fund managers. The “skills” of fund managers identified by this approach in the previous literature may be spurious and simply due to the cross-sectional dependence in fund returns associated with common asset holding. Although to some extent “luck” has been taken into account in this method, cross-sectional dependence in fund returns has not.

Following the recent development on cross-sectional dependence in econometrics (e.g., Bai (2009); Bai and Li (2014)), we take them into account by extending the traditional bootstrap method to a panel case with interactive effects and unobservable factors. This is very different with the existing literature in which all factors are observable (e.g., Kosowski et al. (2006, 2007); Fama and French (2010); Blake et al. (2013, 2014)). It is evident that not all factors are observable (Harvey and Liu, 2017a), given the development in the literature of the earlier CAMP-type single-factor market model to the multi-factor models such as the Fama–French 3-factor, 4-factor, and 5-factor models. It is promising that more factors may be discovered in the future and we treat them as unobservable now. Indeed, one advantage of our model is that it adopts a “let-data-speak” approach to gauge the number of unobservable factors via a principle component analysis addon Bai (2009). Moreover, it is easy to see that the usual fixed effects panel data model (e.g., Blake et al. (2014)) is a special case of our panel data model with interactive effects.

The remainder of the paper proceeds as follows. In Section 2, we introduce our panel data model with unobservable interactive effects. Sections 3 and 4 present the bootstrap procedure and Monte Carlo simulation, respectively. We omit the classical fund-by-fund bootstrap approach for brevity, as it has been well summarized in the extant literature (e.g., Kosowski et al. (2006, 2007); Fama and French (2010); Blake et al. (2013, 2014)). Section 5 concludes.

## 2. Panel data model with unobservable interactive effects

We propose the following panel data model with unobservable interactive effects to take into account of the cross-sectional dependence:

$$\begin{aligned} r_{it} &= \alpha_i + \beta_i r_{mt} + \varepsilon_{it}, \text{ for } i = 1, \dots, N, t = 1, \dots, T, \\ \varepsilon_{it} &= \lambda_i^\top F_t + e_{it}, \end{aligned} \tag{1}$$

where  $\beta_i$  is fund  $i$ 's risk loading on the market return  $r_{mt}$  and  $\alpha_i$  is the abnormal return, which is used to measure the fund performance,  $F_t (r \times 1)$  is a vector of unobserved common factors,  $\lambda_i$  contains the factor loadings and  $e_{it}$  is an idiosyncratic error term.

As mentioned in Blake et al. (2014), the standard framework has the problem that it is potentially incomplete since it excludes fund-specific variables and other common factors which might influence performance. With our approach, this problem can be well solved, as it can capture not only the observed factors but also unobserved or hidden factors. Note that  $r_{mt}$  can be correlated with  $\lambda_i$  alone or with  $F_t$  alone, or can be simultaneously correlated with  $\lambda_i$  and  $F_t$ . We know that if this correlation exists, then  $E(r_{mt} \varepsilon_{it}) \neq 0$ , so the traditional ordinary least squares (OLS) estimators of  $\alpha_i$  and  $\beta_i$  will be biased and inconsistent.

It is easy to see that model (1) can be rewritten as

$$r_{it} = \alpha_i + \gamma_i^\top z_t + e_{it}, \tag{2}$$

where  $\gamma_i = (\beta_i, \lambda_i^\top)^\top$  and  $z_t = (r_{mt}, F_t^\top)^\top$ . Here  $\gamma_i^\top z_t$  can capture all the possible cross-sectional dependence among the  $N$  funds, which includes the cross-sectional dependence resulted from not only the observed factor  $r_{mt}$  but also the unobserved term  $\lambda_i^\top F_t$ .

Obviously, model (2) can be written as

$$u_{it} = r_{it} - \gamma_i^\top z_t, \quad u_{it} = \alpha_i + e_{it}. \tag{3}$$

Ideally, we estimate  $\alpha_i$  by the following two steps.

- First, we extract cross-sectional dependence  $\gamma_i^\top z_t$  by principle component estimation. Let  $\widehat{\gamma_i^\top z_t}$  denotes the estimated values of  $\gamma_i^\top z_t$ . Under some regularity conditions, we can show that  $\widehat{\gamma_i^\top z_t}$  is a consistent estimator of  $\gamma_i^\top z_t$  (see, e.g., Bai (2009)).
- Second, we obtain  $\widehat{u}_{it}$  by  $\widehat{u}_{it} = r_{it} - \widehat{\gamma_i^\top z_t}$ . Then from model (3), it is easy to see that a estimator of  $\alpha_i$  will be

$$\widehat{\alpha}_i = \frac{1}{T} \sum_{t=1}^T \widehat{u}_{it}. \tag{4}$$

Then we obtain  $\widehat{e}_{it} = \widehat{u}_{it} - \widehat{\alpha}_i$ .

Since the extant literature (e.g., Kosowski et al. (2006, 2007); Fama and French (2010); Blake et al. (2013, 2014)) has unanimously proposed zero skills as their null hypothesis, we, in this paper, focus on the type I error and the size of the bootstrap approach for performance evaluation, which can help alleviate the probability of falsely refusing the EMH.

## 3. Panel bootstrap procedure for fund performance evaluation

Consider the hypothesis testing problem

$$H_0 : \alpha^{(q)} = 0 \text{ versus } H_1 : \alpha^{(q)} \neq 0,$$

for  $q = 0.01, 0.02, 0.03, 0.04, 0.05, \dots$

where  $\alpha^{(q)}$  denotes the  $q$ th quantile of the cross-sectional distribution of  $\alpha$ .

We evaluate the  $p$  value of the test for each quantile via the following bootstrap.

**Step 1:** Estimate model (2) and obtain  $\widehat{e}_{it}$  and  $\widehat{\gamma_i^\top z_t}$  for  $i = 1, 2, \dots, N$  and  $t = 1, 2, \dots, T$ .

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