

# FRACTALS WITH POINT IMPACT IN FUNCTIONAL LINEAR REGRESSION

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This paper develops a point impact linear regression model in which the trajectory of a continuous stochastic process, when evaluated at a sensitive time point, is associated with a scalar response. The proposed model complements and is more interpretable than the functional linear regression approach that has become popular in recent years. The trajectories are assumed to have fractal (self-similar) properties in common with a fractional Brownian motion with an unknown Hurst exponent. Bootstrap confidence intervals based on the least-squares estimator of the sensitive time point are developed. Misspecification of the point impact model by a functional linear model is also investigated. Non-Gaussian limit distributions and rates of convergence determined by the Hurst exponent play an important role.

**1. Introduction.** This paper investigates a linear regression model involving a scalar response  $Y$  and a predictor given by the value of the trajectory of a continuous stochastic process  $X = \{X(t), t \in [0, 1]\}$  at some unknown time point. Specifically, we consider the *point impact* linear regression model

$$(1) \quad Y = \alpha + \beta X(\theta) + \varepsilon$$

and focus on the time point  $\theta \in (0, 1)$  as the target parameter of interest. The intercept  $\alpha$  and the slope  $\beta$  are scalars, and the error  $\varepsilon$  is taken to be independent of  $X$ , having zero mean and finite variance  $\sigma^2$ . The complete trajectory of  $X$  is assumed to be observed (at least on a fine enough grid that it makes no difference in terms of accuracy), even though the model itself only involves the value of  $X$  at  $\theta$ , which represents a “sensitive” time point in terms of the relationship to the response. The main aim of the paper is to show that the precision of estimation of  $\theta$  is driven by *fractal* behavior in  $X$ , and to develop valid inferential procedures that adapt to a broad range of such behavior. Our model could easily be extended in various ways, for example, to allow multiple sensitive time points or further covariates, but, for simplicity, we restrict attention to (1).

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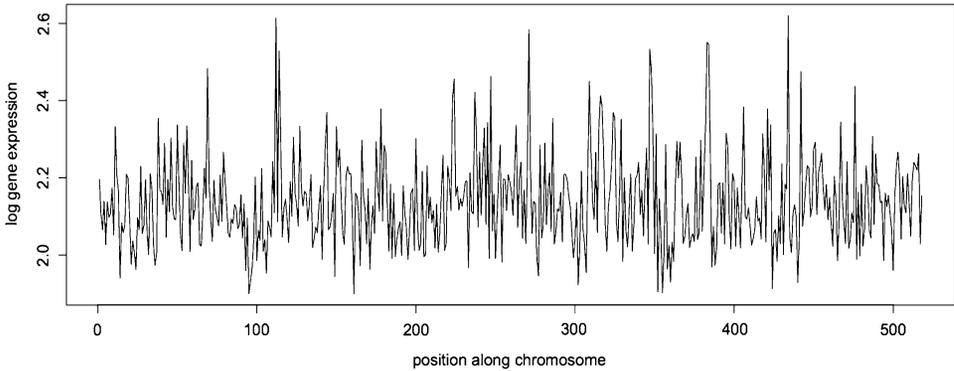


FIG. 1. *Log gene expression at 518 loci along chromosome 17 in tissue from a breast cancer patient.*

Our motivation for developing this type of model arises from genome-wide expression studies that measure the activity of numerous genes simultaneously. In these studies, it is of interest to locate genes showing activity that is associated with clinical outcomes. Emilsson et al. [10], for example, studied gene expression levels at over 24,000 loci in samples of adipose tissue to identify genes correlated with body mass index and other obesity-related outcomes. Gruvberger-Saal et al. [13] used gene expression profiles from the tumors of breast cancer patients to predict estrogen receptor protein concentration, an important prognostic marker for breast tumors; see also [5]. In such studies, the gene expression profile across a chromosome can be regarded a functional predictor, and a gene associated with the clinical outcome is identified by its base pair position  $\theta$  along the chromosome; see Figure 1. Our aim here is to develop a method of estimating a confidence interval for  $\theta$ , leading to the identification of chromosomal regions that are potentially useful for diagnosis and therapy. Although there is extensive statistical literature on gene expression data, it is almost exclusively concerned with multiple testing procedures for detecting differentially expressed genes; see, for example, [8, 30].

Gene expression profiles (as in Figure 1) clearly display fractal behavior, that is, self-similarity over a range of scales. Indeed, fractals often arise when spatiotemporal patterns at higher levels emerge from localized interactions and selection processes acting at lower levels, as with gene expression activity. Moreover, the recent discovery [19] that chromosomes are folded as “fractal globules,” which can easily unfold during gene activation, also helps explain the fractal appearance of gene expression profiles.

A basic stochastic model for fractal phenomena is provided by fractional Brownian motion (fBm) (see [22]), in which the so-called Hurst exponent  $H \in [0, 1]$  calibrates the scaling of the self-similarity and provides a natural measure of trajectory roughness. It featured prominently in the pioneering work of Benoît Mandelbrot, who stated ([23], page 256) that fBm provides “the most manageable

mathematical environment I can think of (for representing fractals).” For background on fBm from a statistical modeling point of view, see [11].

The key issue to be considered in this paper is how to construct a confidence interval for the true sensitive time point  $\theta_0$  based on its least squares estimator  $\hat{\theta}_n$ , obtained by fitting model (1) from a sample of size  $n$ ,

$$(2) \quad (\hat{\alpha}_n, \hat{\beta}_n, \hat{\theta}_n) = \arg \min_{\alpha, \beta, \theta} \sum_{i=1}^n [Y_i - \alpha - \beta X_i(\theta)]^2.$$

We show that, when  $X$  is fBm, both the rate of convergence  $r_n$  and limiting distribution of  $\hat{\theta}_n$  depend on  $H$ . In addition, we construct bootstrap confidence intervals for  $\theta_0$  that *do not require knowledge of  $H$* . This facilitates applications (e.g., to gene expression data) in which the type of fractal behavior is not known in advance; the trajectory in Figure 1 has an estimated Hurst exponent of about 0.1, but it would be very difficult to estimate precisely using data in a small neighborhood of  $\hat{\theta}_n$ , so a bootstrap approach becomes crucial. We emphasize that nothing about the distribution of  $X$  is used in the construction of the estimators or the bootstrap confidence intervals; the fBm assumption will only be utilized to study the large sample properties of these procedures. Moreover, our main results will make essential use of the fBm assumption only *locally*, that is, in a small neighborhood of  $\theta_0$ .

The point impact model (1) can be regarded as a simple working model that provides interpretable information about the influence of  $X$  at a specific location (e.g., a genetic locus). Such information cannot be extracted using the standard functional linear regression model [27] given by

$$(3) \quad Y = \alpha + \int_0^1 f(t)X(t) dt + \varepsilon,$$

where  $f$  is a continuous function and  $\alpha$  is an intercept, because the influence of  $X(t)$  is spread continuously across  $[0, 1]$  and point-impact effects are excluded. In the gene expression context, if only a few genes are predictive of  $Y$ , then a model of the form (1) would be more suitable than (3), which does not allow  $f$  to have infinite spikes. In general, however, a continuum of locations is likely to be involved (as well as point-impacts), so it is of interest to study the behavior of  $\hat{\theta}_n$  in misspecified settings in which the data arise from combinations of (1) and (3).

Asymptotic results for the least squares estimator (2) in the correctly specified setting are presented in Section 2. In Section 3 it is shown that the residual bootstrap is consistent for the distribution of  $\hat{\theta}_n$ , leading to the construction of valid bootstrap confidence intervals without knowing  $H$ . The nonparametric bootstrap is shown to be inconsistent in the same setting. The effect of misspecification is discussed in Section 4. A two-sample problem version of the point impact model is discussed in Section 5. Some numerical examples are presented in Section 6, where we compare the proposed bootstrap confidence interval with Wald-type confidence

intervals (in which  $H$  is assumed to be known); an application to gene expression data is also discussed. Concluding remarks appear in Section 7. Proofs are placed in Section 8.

**2. Least squares estimation of the sensitive time point.** Throughout we take  $X$  to be a fBm with Hurst exponent  $H$ , which, as discussed earlier, controls the roughness of the trajectories. We shall see in this section that the rate of convergence of  $\hat{\theta}_n$  can be expressed explicitly in terms of  $H$ .

First we recall some basic properties of fBm. A (standard) fBm with Hurst exponent  $H \in (0, 1]$  is a Gaussian process  $B_H = \{B_H(t), t \in \mathbb{R}\}$  having continuous sample paths, mean zero and covariance function

$$(4) \quad \text{Cov}\{B_H(t), B_H(s)\} = \frac{1}{2}(|t|^{2H} + |s|^{2H} - |t - s|^{2H}).$$

By comparing their mean and covariance functions,  $B_H(at) \stackrel{d}{=} a^H B_H(t)$  as processes, for all  $a > 0$  (self-similarity). Clearly,  $B_{1/2}$  is a two-sided Brownian motion, and  $B_1$  is a random straight line:  $B_1(t) = tZ$  where  $Z \sim N(0, 1)$ . The increments are negatively correlated if  $H < 1/2$ , and positively correlated if  $H > 1/2$ . Increasing  $H$  results in smoother sample paths.

Suppose  $(X_i, Y_i), i = 1, \dots, n$ , are i.i.d. copies of  $(X, Y)$  satisfying the model (1). The unknown parameter is  $\eta = (\alpha, \beta, \theta) \in \Xi = \mathbb{R}^2 \times [0, 1]$ , and its true value is denoted  $\eta_0 = (\alpha_0, \beta_0, \theta_0)$ . The following conditions are needed:

- (A1)  $X$  is a fBm with Hurst exponent  $H \in (0, 1)$ .
- (A2)  $0 < \theta_0 < 1$  and  $\beta_0 \neq 0$ .
- (A3)  $E|\varepsilon|^{2+\delta} < \infty$  for some  $\delta > 0$ .

The construction of the least squares estimator  $\hat{\eta}_n = (\hat{\alpha}_n, \hat{\beta}_n, \hat{\theta}_n)$ , defined by (2), does not involve any assumptions about the distribution of the trajectories, whereas the asymptotic behavior does. Our first result gives the consistency and asymptotic distribution of  $\hat{\eta}_n$  under the above assumptions.

**THEOREM 2.1.** *If (A1) and (A2) hold, then  $\hat{\eta}_n$  is consistent, that is,  $\hat{\eta}_n \xrightarrow{P} \eta_0$ . If (A3) also holds, then*

$$(5) \quad \begin{aligned} \zeta_n &\equiv (\sqrt{n}(\hat{\alpha}_n - \alpha_0), \sqrt{n}(\hat{\beta}_n - \beta_0), n^{1/(2H)}(\hat{\theta}_n - \theta_0)) \\ &\xrightarrow{d} \left( \sigma Z_1, |\theta_0|^{-H} \sigma Z_2, \arg \min_{t \in \mathbb{R}} \left\{ 2 \frac{\sigma}{|\beta_0|} B_H(t) + |t|^{2H} \right\} \right) \equiv \zeta, \end{aligned}$$

where  $Z_1$  and  $Z_2$  are i.i.d.  $N(0, 1)$ , independent of the fBm  $B_H$ .

*Remarks.*

1. It may come as a surprise that the convergence rate of  $\hat{\theta}_n$  increases as  $H$  decreases, and becomes arbitrarily fast as  $H \rightarrow 0$ . A heuristic explanation is that

fBm “travels further” with a smaller  $H$ , so independent trajectories of  $X$  are likely to “cover different ground,” making it easier to estimate  $\theta_0$ . In a nutshell, the smaller the Hurst exponent, the better the design.

2. It follows from (a slight extension of) Lemmas 2.5 and 2.6 of Kim and Pollard [15] that the third component of  $\zeta$  is well defined.
3. Using the self-similarity of fBm, the asymptotic distribution of  $\hat{\theta}_n$  can be expressed as the distribution of

$$(6) \quad \Delta \equiv \left( \frac{\sigma}{|\beta_0|} \right)^{1/H} \arg \min_{t \in \mathbb{R}} (B_H(t) + |t|^{2H}/2).$$

This distribution does not appear to have been studied in the literature except for  $H = 1/2$  and  $H = 1$  (standard normal). When  $H = 1/2$ ,  $X$  is a standard Brownian motion and the limiting distribution is given in terms of a two-sided Brownian motion with a triangular drift. Bhattacharya and Brockwell [2] showed that this distribution has a density that can be expressed in terms of the standard normal distribution function. It arises frequently in change-point problems under contiguous asymptotics [24, 34, 37].

4. From the proof, it can be seen that the essential assumptions on  $X$  are the self-similarity and stationary increments properties in some neighborhood of  $\theta_0$ , along with the trajectories of  $X$  being Lipschitz of all orders less than  $H$ . Note that any Gaussian self-similar process with stationary increments and zero mean is a fBm (see, e.g., Theorem 1.3.3 of [9]).
5. The trajectories of fBm are nondifferentiable when  $H < 1$ , so the usual technique of Taylor expanding the criterion function about  $\theta_0$  does not work and a more sophisticated approach is required to prove the result.
6. Note that  $(\hat{\alpha}_n, \hat{\beta}_n)$  has the same limiting behavior as though  $\theta_0$  is known, and  $\hat{\theta}_n$  and  $(\hat{\alpha}_n, \hat{\beta}_n)$  are asymptotically independent.
7. The result is readily extended to allow for additional covariates [cf. (11)], which is often important in applications. The limiting distribution of  $\hat{\theta}_n$  remains the same, and the other regression coefficient estimates have the same limiting behavior as though  $\theta_0$  is known.
8. Note that the assumption  $\beta_0 \neq 0$  is crucial for the theorem to hold. When  $\beta_0 = 0$ , the fBm does not influence the response at all and  $\hat{\theta}_n$  contains no information about  $\theta_0$ .

**3. Bootstrap confidence intervals.** In general, a valid Wald-type confidence interval for  $\theta_0$  would at least need a consistent estimator of the Hurst exponent  $H$ , which is a nuisance parameter in this problem. Unfortunately, however, accurate estimation of  $H$  is difficult and quite often unstable. Bootstrap methods have been widely applied to avoid issues of nuisance parameter estimation, and they work well in problems with  $\sqrt{n}$ -rates; see [3, 32, 33] and the references therein. In this section we study the consistency properties of two bootstrap methods that arise naturally in our setting. One of these methods leads to a valid confidence interval for  $\theta_0$  without requiring any knowledge of  $H$ .

3.1. *Preliminaries.* We start with a brief review of the bootstrap. Given a sample  $\mathbf{Z}_n = \{Z_1, Z_2, \dots, Z_n\} \stackrel{\text{i.i.d.}}{\sim} L$  from an unknown distribution  $L$ , suppose that the distribution function,  $F_n$ , say, of some random variable  $R_n \equiv R_n(\mathbf{Z}_n, L)$ , is of interest;  $R_n$  is usually called a root and it can in general be any measurable function of the data and the distribution  $L$ . The bootstrap method can be broken into three simple steps:

- (i) Construct an estimator  $\hat{L}_n$  of  $L$  from  $\mathbf{Z}_n$ .
- (ii) Generate  $\mathbf{Z}_n^* = \{Z_1^*, \dots, Z_n^*\} \stackrel{\text{i.i.d.}}{\sim} \hat{L}_n$  given  $\mathbf{Z}_n$ .
- (iii) Estimate  $F_n$  by  $F_n^*$ , the conditional c.d.f. of  $R_n(\mathbf{Z}_n^*, \hat{L}_n)$  given  $\mathbf{Z}_n$ .

Let  $d$  denote the Lévy metric or any other metric metrizing weak convergence of distribution functions. We say that  $F_n^*$  is weakly consistent if  $d(F_n, F_n^*) \xrightarrow{P} 0$ ; if  $F_n$  has a weak limit  $F$ , this is equivalent to  $F_n^*$  converging weakly to  $F$  in probability.

The choice of  $\hat{L}_n$  mostly considered in the literature is the empirical distribution. Intuitively, an  $\hat{L}_n$  that mimics the essential properties (e.g., smoothness) of the underlying distribution  $L$  can be expected to perform well. In most situations, the empirical distribution of the data is a good estimator of  $L$ , but in some nonstandard situations it may fail to capture some of the important aspects of the problem, and the corresponding bootstrap method can be suspect. The following discussion illustrates this phenomenon (the inconsistency when bootstrapping from the empirical distribution of the data) when  $\Delta_n \equiv n^{1/(2H)}(\hat{\theta}_n - \theta_0)$  is the random variable of interest.

3.2. *Inconsistency of bootstrapping pairs.* In a regression setup there are two natural ways of bootstrapping: bootstrapping pairs (i.e., the nonparametric bootstrap) and bootstrapping residuals (while keeping the predictors fixed). We show that bootstrapping pairs (drawing  $n$  data points with replacement from the original data set) is inconsistent for  $\theta_0$ .

**THEOREM 3.1.** *Under conditions (A1)–(A3), the nonparametric bootstrap is inconsistent for estimating the distribution of  $\Delta_n$ , that is,  $\Delta_n^* \equiv n^{1/(2H)}(\hat{\theta}_n^* - \hat{\theta}_n)$ , conditional on the data, does not converge in distribution to  $\Delta$  in probability, where  $\Delta$  is defined by (6).*

3.3. *Consistency of bootstrapping residuals.* Another bootstrap procedure is to use the form of the assumed model more explicitly to draw the bootstrap samples: condition on the predictor  $X_i$  and generate its response as

$$(7) \quad Y_i^* = \hat{\alpha}_n + \hat{\beta}_n X_i(\hat{\theta}_n) + \varepsilon_i^*,$$

where the  $\varepsilon_i^*$  are conditionally i.i.d. under the empirical distribution of the centered residuals  $\hat{\varepsilon}_i - \bar{\varepsilon}_n$ , with  $\hat{\varepsilon}_i = Y_i - \hat{\alpha}_n - \hat{\beta}_n X_i(\hat{\theta}_n)$  and  $\bar{\varepsilon}_n = \sum_{i=1}^n \hat{\varepsilon}_i/n$ . Let

$\hat{\alpha}_n^*$ ,  $\hat{\beta}_n^*$  and  $\hat{\theta}_n^*$  be the estimates of the unknown parameters obtained from the bootstrap sample. We approximate the distribution of  $\zeta_n$  [see (5)] by the conditional distribution of

$$\zeta_n^* \equiv [\sqrt{n}(\hat{\alpha}_n^* - \hat{\alpha}_n), \sqrt{n}(\hat{\beta}_n^* - \hat{\beta}_n), n^{1/(2H)}(\hat{\theta}_n^* - \hat{\theta}_n)],$$

given the data.

**THEOREM 3.2.** *Under conditions (A1)–(A3), the above procedure of bootstrapping residuals is consistent for estimating the distribution of  $\zeta_n$ , that is,  $\zeta_n^* \xrightarrow{d} \zeta$ , in probability, conditional on the data.*

We now use the above theorem to construct a valid confidence interval (CI) for  $\theta_0$  that does not require any knowledge of  $H$ . Let  $q_\alpha^*$  be the  $\alpha$ -quantile of the conditional distribution of  $(\hat{\theta}_n^* - \hat{\theta}_n)$  given the data, which can be readily obtained via simulation and does not involve the knowledge of any distributional properties of  $X$ . The proposed approximate  $(1 - 2\alpha)$ -level bootstrap CI for  $\theta_0$  is then given by

$$C_n = [\hat{\theta}_n - q_{1-\alpha}^*, \hat{\theta}_n - q_\alpha^*].$$

Under the assumptions of Theorem 3.2, the coverage probability of this CI is

$$\begin{aligned} P\{\theta_0 \in C_n\} &= P\{n^{1/(2H)}q_\alpha^* \leq \Delta_n \leq n^{1/(2H)}q_{1-\alpha}^*\} \\ &\approx P^*\{n^{1/(2H)}q_\alpha^* \leq \Delta_n^* \leq n^{1/(2H)}q_{1-\alpha}^*\} \\ &= P^*\{q_\alpha^* \leq \hat{\theta}_n^* - \hat{\theta}_n \leq q_{1-\alpha}^*\} \\ &= 1 - 2\alpha, \end{aligned}$$

where  $P^*$  denotes the bootstrap distribution given the data, and we have used the fact that the supremum distance between the relevant distribution functions of  $\Delta_n$  and  $\Delta_n^*$  is asymptotically negligible. The key point of this argument is that  $\Delta_n$  and  $\Delta_n^*$  have the same normalization factor  $n^{1/(2H)}$  and, thus, it “cancels” out. CIs for  $\alpha_0$  and  $\beta_0$  can be constructed in a similar fashion.

**3.4. Discussion.** In nonparametric regression settings, dichotomies in the behavior of different bootstrap methods are well known, for example, when using the bootstrap to calibrate omnibus goodness-of-fit tests for parametric regression models; see [14, 25, 36] and references therein. A dichotomy in the behavior of the two bootstrap methods, however, is surprising in a linear regression model. This illustrates that in problems with nonstandard asymptotics, the usual nonparametric bootstrap might fail, whereas a resampling procedure that uses some particular structure of the model can perform well. The improved performance of bootstrapping residuals will be confirmed by our simulation results in Section 6.

The difference in the behavior of the two bootstrap methods can be explained as follows. As in any M-estimation problem, the standard approach is to study the criterion (objective) function being optimized, in a neighborhood of the target parameter, by splitting it into an empirical process and a drift term. The drift term has different behavior for the two bootstrap methods: while bootstrapping pairs, it does not converge, whereas the bootstrapped residuals are conditionally independent of the predictors, and the drift term converges. This highlights the importance of designing the bootstrap to accurately replicate the structure in the assumed model. A more technical explanation is provided in a remark following the proof of Theorem 3.2.

Other types of resampling (e.g., the  $m$ -out-of- $n$  bootstrap, or subsampling) could be applicable, but such methods require knowledge of the rate of convergence, which depends on the unknown  $H$ . Also, these methods require the choice of a tuning parameter, which is problematic in practice. However, the residual bootstrap is consistent, easy to implement, and does not require the knowledge of  $H$  and the estimation of a tuning parameter.

The inconsistency of the nonparametric bootstrap casts some doubt on its validity for checking the stability of variable selection results in high-dimensional regression problems (as is common practice). Indeed, it suggests that more care (in terms of more explicit use of the model) is needed in the choice of a bootstrap method in such settings.

**4. Misspecification by a functional linear model.** The point impact model cannot capture effects that are spread out over the domain of the trajectory, for example, gene expression profiles for which the effect on a clinical outcome involves complex interactions between numerous genes. Such effects, however, may be represented by a functional linear model, and we now examine how the limiting behavior of  $\hat{\theta}_n$  changes when the data arise in this way.

4.1. *Complete misspecification.* In this case we treat (1) as the working model (for fitting the data), but view this model as being completely misspecified in the sense that the data are generated from the functional linear model (3). For simplicity, we set  $\alpha = 0$  and  $\beta = 1$  in the working model, and set  $\alpha = 0$  in the true functional linear model. The least squares estimator  $\hat{\theta}_n$  now estimates the minimizer  $\theta_0$  of

$$\mathbb{M}(\theta) \equiv E[Y - X(\theta)]^2 = \sigma^2 + E\left[\int_0^1 f(t)X(t) dt - X(\theta)\right]^2$$

and the following result gives its asymptotic distribution.

**THEOREM 4.1.** *Suppose that (A1) and (A3) hold, and that  $\mathbb{M}(\theta)$  has a unique minimizer and is twice-differentiable at  $0 < \theta_0 < 1$ . Then, in the misspecified case,*

$$n^{1/(4-2H)}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \arg \min_{t \in \mathbb{R}} (2aB_H(t) + bt^2),$$

where  $a^2 = \mathbb{M}(\theta_0)$  and  $b = \mathbb{M}''(\theta_0)/2$ .

*Remarks.*

1. Here the rate of convergence reverses itself from the correctly specified case: the convergence rate now decreases as  $H$  decreases, going from a parametric rate of  $n^{1/2}$  when  $H \rightarrow 1$ , to as slow as  $n^{1/4}$  as  $H \rightarrow 0$ . A heuristic explanation is that roughness in  $X$  now amounts to measurement error (which results in a slower rate) as the fluctuations of  $X$  are smoothed out in the true model.
2. In the case of Brownian motion trajectories ( $H = 1/2$ ), note that  $\mathbb{M}(\theta) = \theta - 2 \int_0^1 f(t) \min(t, \theta) dt + \text{const}$ , the normal equation is

$$(8) \quad \mathbb{M}'(\theta) = 1 - 2 \int_{\theta}^1 f(t) dt = 0$$

and  $\mathbb{M}''(\theta) = 2f(\theta)$ .

3. Also in the case  $H = 1/2$ , the limiting distribution is given in terms of two-sided Brownian motion with a parabolic drift, and was investigated originally by Chernoff [6] in connection with the estimation of the mode of a distribution, and shown to have a density (as the solution of a heat equation). The Chernoff distribution arises frequently in monotone function estimation settings; Groeneboom and Wellner [12] introduced various algorithms for computation of its distribution function and quantiles.

4.2. *Partial misspecification.* The nonparametric functional linear model (3) can be combined with (1) to give the semiparametric model

$$(9) \quad Y = \alpha + \beta X(\theta) + \int_0^1 f(t)X(t) dt + \varepsilon,$$

which allows  $X$  to have both a point impact and an influence that is spread out continuously in time. When  $f = 0$ , this model reduces to the point impact model; when  $\beta = 0$ , to the functional linear model. In this section we examine the behavior of  $\hat{\theta}_n$  when the working model is (1), as before, but the data are now generated from (9).

For simplicity, suppose that  $\alpha = 0$  and  $\beta = 1$  in both the working point impact model and in the true model (9). Denote the true value of  $\theta$  by  $\theta_0 \in (0, 1)$ . It can then be shown that  $\hat{\theta}_n$  is robust to small levels of misspecification, that is, it consistently estimates  $\theta_0$  with the same rate of convergence as in the correctly specified case. Indeed,  $\hat{\theta}_n$  targets the minimizer of the criterion function

$$\mathbb{M}(\theta) = E[Y - X(\theta)]^2 = |\theta - \theta_0|^{2H} - \int_0^1 f(t)[t^{2H} + \theta^{2H} - |\theta - t|^{2H}] dt + \text{const}.$$

Provided  $\int |f|$  is sufficiently small, the derivative of  $\mathbb{M}$  will be negative over the interval  $(0, \theta_0)$  and positive over  $(\theta_0, 1)$ , so  $\mathbb{M}$  is minimized at  $\theta_0$ . It is then possible

to extend Theorem 2.1 to give

$$(10) \quad n^{1/(2H)}(\hat{\theta}_n - \theta_0) \xrightarrow{d} a^{1/H} \arg \min_{t \in \mathbb{R}} (B_H(t) + |t|^{2H}/2),$$

where  $a \geq \sigma$  is defined in the statement of Theorem 4.1. This shows that the effect of partial misspecification is a simple inflation of the variance [cf. (6)], without any change in the form of the limit distribution.

It is also of interest to estimate  $\theta_0$  in a way that adapts to any function  $f$  (i.e., sufficiently smooth) in this semiparametric setting. This could be done, for example, by approximating  $f$  by a finite B-spline basis expansion of the form  $f_m(t) = \sum_{j=1}^m \beta_j \phi_j(t)$ , and fitting the working model

$$(11) \quad Y = \alpha + \beta X(\theta) + \sum_{j=1}^m \beta_j Z_j + \varepsilon,$$

where  $Z_j = \int_0^1 \phi_j(t) X(t) dt$  are additional covariates with regression coefficients  $\beta_j$ ; the resulting least squares estimator  $\tilde{\theta}_n$  can then be used as an estimate of  $\theta_0$  of  $\theta$ . For the working model (11), the misspecification is  $f - f_m$ , which will be small if  $m$  is sufficiently large. Therefore, based on our previous discussion,  $\tilde{\theta}_n$  will satisfy a result of the form (10); in particular,  $\tilde{\theta}_n$  will exhibit the fast  $n^{1/(2H)}$ -rate of convergence. Note that for this result to hold,  $m$  can be fixed and does not need to tend to infinity with the sample size.

**5. Two-sample problem.** In this section we discuss a variation of the point impact regression model in which the response takes just two values (say  $\pm 1$ ). This is of interest, for example, in case-control studies in which gene-expression data are available for a sample of cancer patients and a sample of healthy controls, and the target parameter is the locus of a differentially expressed gene.

Suppose we have two independent samples of trajectories  $X$ , with  $n_1$  trajectories from class 1, and  $n_2$  trajectories from class  $-1$ , for a total sample size of  $n = n_1 + n_2$ . It is assumed that  $\rho = n_1/n_2 > 0$  remains fixed, and the  $j$ th sample satisfies the model

$$X_{ij}(t) = \mu_j(t) + \varepsilon_{ij}(t), \quad j = 1, 2,$$

where  $\varepsilon_{ij}, i = 1, \dots, n_j$  are i.i.d. fBMs with Hurst exponent  $H \in (0, 1)$ , and  $\mu_j(t)$  is an unknown mean function, assumed to be continuous. The treatment effect  $\mathbb{M}(t) = \mu_1(t) - \mu_2(t)$  is taken to have a point impact in the sense of having a unique maximum at  $\theta_0 \in (0, 1)$ ; minima can of course be treated in a similar fashion. The least squares estimator of the sensitive time point now becomes

$$(12) \quad \hat{\theta}_n = \arg \max_{\theta} \{\bar{X}_1(\theta) - \bar{X}_2(\theta)\},$$

where  $\bar{X}_j(\theta) = \sum_{i=1}^{n_j} X_{ij}(\theta)/n_j$  is the sample mean for class  $j$ . Although a studentized version (normalizing the the difference of the sample means by a standard

error estimate) might be preferable in some cases, with small or unbalanced samples, say, to keep the discussion simple, we restrict attention to  $\hat{\theta}_n$ . The empirical criterion function  $\mathbb{M}_n(\theta) = \bar{X}_1(\theta) - \bar{X}_2(\theta)$  converges uniformly to  $\mathbb{M}(\theta)$  a.s. (by the Glivenko–Cantelli theorem), so  $\hat{\theta}_n$  is a consistent estimator of  $\theta_0$ .

As before, our objective is to find a confidence interval for  $\theta_0$  based on  $\hat{\theta}_n$  under appropriate conditions on the treatment effect. Toward this end, we need an assumption on the degree of smoothness of the treatment effect at  $\theta_0$  in terms of an exponent  $0 < S \leq 1$ :

$$\mathbb{M}(\theta) = \mathbb{M}(\theta_0) - c|\theta - \theta_0|^{2S} + o(|\theta - \theta_0|^{2S})$$

as  $\theta \rightarrow \theta_0$ , where  $c > 0$ . If  $\mathbb{M}$  is twice-differentiable at  $\theta_0$ , then this assumption holds only with  $S = 1$ ; for it to hold for some  $S < 1$ , a cusp is needed. When the smoothness of the treatment effect and the fBm match, that is,  $S = H$ , the rate of convergence of  $\hat{\theta}_n$  is  $n^{1/(2H)}$ , as before, and  $\hat{\theta}_n$  has a nondegenerate limit distribution of the same form as in Theorem 2.1:

$$(13) \quad n_1^{1/(2H)}(\hat{\theta}_n - \theta_0) \xrightarrow{d} \arg \min_{t \in \mathbb{R}} \{(1 + \sqrt{\rho})B_H(t) + c|t|^{2H}\}.$$

The key step in the proof (which is simpler than in the regression case) is given at the end of Section 8.

**6. Numerical examples.** In this section we report some numerical results based on trajectories from fBm simulations and from gene expression data.

We first consider a correctly specified example as in Section 2 and study the behavior of CIs for the sensitive time-point  $\theta_0$  using the two bootstrap based methods, and compare them with the  $100(1 - \alpha)\%$  Wald-type CI

$$(14) \quad \hat{\theta}_n \pm \left( \frac{\hat{\sigma}_n}{|\hat{\beta}_n| \sqrt{n}} \right)^{1/H} z_{H, \alpha/2}$$

with  $H$  assumed to be known. Here  $\hat{\sigma}_n$  is the sample standard deviation of the residuals, and  $z_{H, \alpha}$  is the upper  $\alpha$ -quantile of  $\arg \min_{t \in \mathbb{R}} (B_H(t) + |t|^{2H}/2)$ . In practice,  $H$  needs to be estimated to apply (14). Numerous estimators of  $H$  based on a single realization of  $X$  have been proposed in the literature [1, 7], although observation at fine time scales is required for such estimators to work well, and it is not clear that direct plug-in would be satisfactory. The quantiles  $z_{H, \alpha/2}$  needed to compute the Wald-type CIs were extracted from an extensive simulation of the limit distribution, as no closed form expression is available.

Table 1 reports the estimated coverage probabilities and average lengths of nominal 95% confidence intervals for  $\theta_0$  calculated using 500 independent samples. The data were generated from the model (1), for  $\alpha_0 = 0$ ,  $\beta_0 = 1$ ,  $\theta_0 = 1/2$ ,  $\varepsilon \sim N(0, \sigma^2)$  where  $\sigma = 0.3$  and  $0.5$ , the Hurst exponent  $H = 0.3, 0.5, 0.7$  and

TABLE 1

Monte Carlo results for coverage probabilities and average widths of nominal 95% confidence intervals for  $\theta_0$ ; data simulated from the linear model with  $\theta_0 = 1/2$ ,  $\alpha_0 = 0$  and  $\beta_0 = 1$

$n$	$\sigma$	$H$	Wald- $H$		R bootstrap		NP bootstrap	
			Cover	Width	Cover	Width	Cover	Width
20	0.3	0.3	0.874	0.023	0.924	0.044	1.000	0.174
		0.5	0.880	0.088	0.946	0.119	0.992	0.220
		0.7	0.822	0.170	0.912	0.249	0.970	0.360
	0.5	0.3	0.806	0.129	0.912	0.211	0.998	0.410
		0.5	0.852	0.256	0.924	0.333	0.988	0.487
		0.7	0.834	0.352	0.938	0.510	0.962	0.591
40	0.3	0.3	0.984	0.007	0.986	0.002	1.000	0.022
		0.5	0.892	0.048	0.942	0.053	0.992	0.087
		0.7	0.898	0.108	0.930	0.138	0.976	0.182
	0.5	0.3	0.900	0.039	0.928	0.054	0.998	0.149
		0.5	0.908	0.134	0.950	0.165	0.990	0.251
		0.7	0.856	0.229	0.946	0.332	0.962	0.386

sample sizes  $n = 20$  and  $40$ . To calculate the least squares estimators (2), we restricted  $\theta$  to a uniform grid of 101 points in  $[0, 1]$ ; the fBm trajectories were generated over the same grid. The fBm simulations were carried out in R, using the function `fbmSim` from the `fArma` package, and via the Cholesky method of decomposing the covariance matrix of  $X$ . Histograms and scatterplots of  $\hat{\theta}_n$  and  $\hat{\beta}_n$  for  $H = 0.3, 0.5, 0.7$  when  $\sigma = 0.5$  are displayed in Figure 2.

In practice,  $X$  can only be observed at discrete time points, so restricting to a grid is the natural formulation for this example. Indeed, the resolution of the observation times in the neighborhood of  $\theta_0$  is a limiting factor for the accuracy of  $\hat{\theta}_n$ , so the grid resolution needs to be fine enough for the statistical behavior of  $\hat{\theta}_n$  to be apparent. For large sample sizes, a very fine grid would be needed in the case of a small Hurst exponent (cf. Theorem 2.1). Indeed, the histogram of  $\hat{\theta}_n$  in the case  $H = 0.3$  (the first plot in Figure 2) shows that the resolution of the grid is almost too coarse to see the statistical variation, as the bin centered on  $\theta_0 = 1/2$  contains almost 80% of the estimates. This phenomenon is also observed in Table 1 when  $n = 40$  and  $\sigma = H = 0.3$ . The average length of the CIs is smaller than the resolution of the grid and, thus, we observe an over-coverage. The two histograms of  $\hat{\theta}_n$  for  $H = 0.5$  and  $H = 0.7$ , however, show increasing dispersion and become closer to bell-shaped as  $H$  increases.

Recall that, for simplicity, we pretend as if we know  $H$ , which should be an advantage, yet the residual bootstrap has better performance based on the results in Table 1. We see that usually the Wald-type CIs have coverage less than the nominal 95%, whereas the inconsistent nonparametric bootstrap method over-covers with observed coverage probability close to 1. Accordingly, the average lengths of

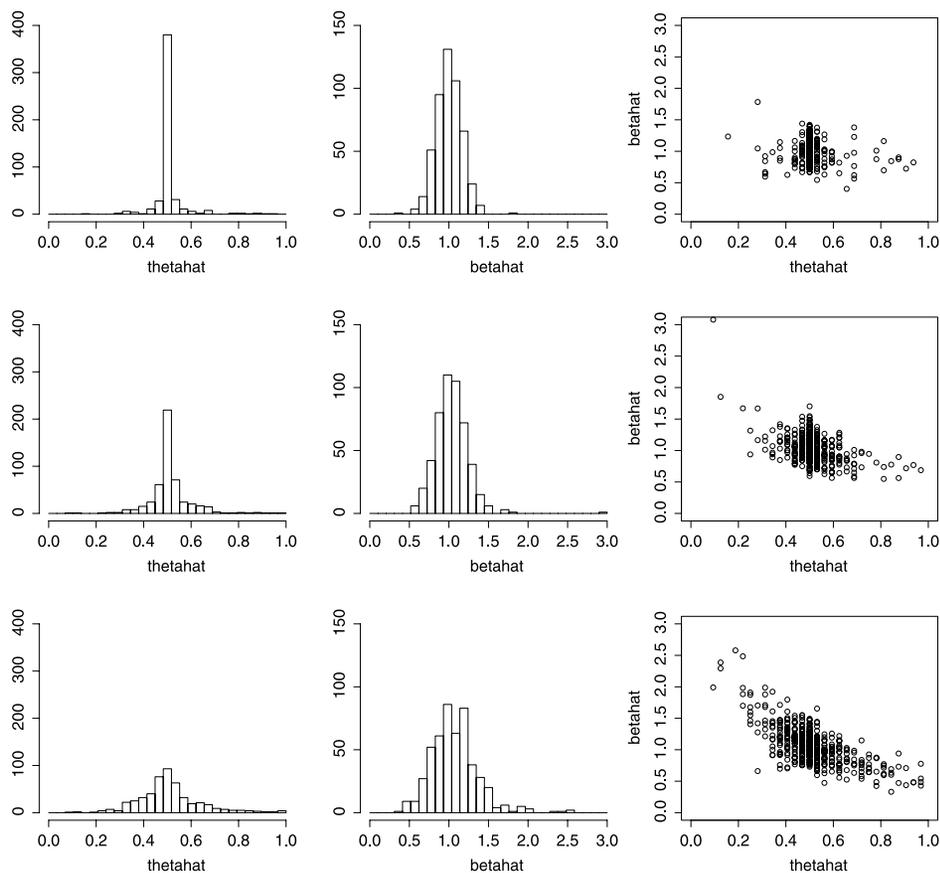


FIG. 2. Histograms and scatterplots of  $\hat{\theta}_n$  and  $\hat{\beta}_n$  in the correctly specified case for  $H = 0.3$  (top row),  $H = 0.5$  (middle row) and  $H = 0.7$  (bottom row), based on 500 samples of size  $n = 20$ .

the Wald-type CIs are the smallest, whereas those obtained from the nonparametric bootstrap method are the widest. The behavior of CIs obtained from the nonparametric bootstrap method also illustrates the inconsistency of this procedure. A similar phenomenon was also observed in [20] in connection with estimators that converge at  $n^{1/3}$ -rate.

Despite the asymptotic independence of  $\hat{\theta}_n$  and  $\hat{\beta}_n$ , considerable correlation is apparent in the scatterplots in Figure 2, with increasing negative correlation as  $H$  increases; note, however, that when  $H = 1$  there is a lack of identifiability of  $\theta$  and  $\beta$ , so the trend in the correlation as  $H$  approaches 1 is to be expected in small samples.

Next we consider a partially misspecified example, in which the data are now generated from (9) by setting  $f(t) = 1/2$  and  $\theta = \theta_* = 1/2$ , but the other ingredients are unchanged from the correctly specified example. The plots in Figure 2 correspond to those in Figure 3. The effect of misspecification on  $\hat{\theta}_n$  is a slight

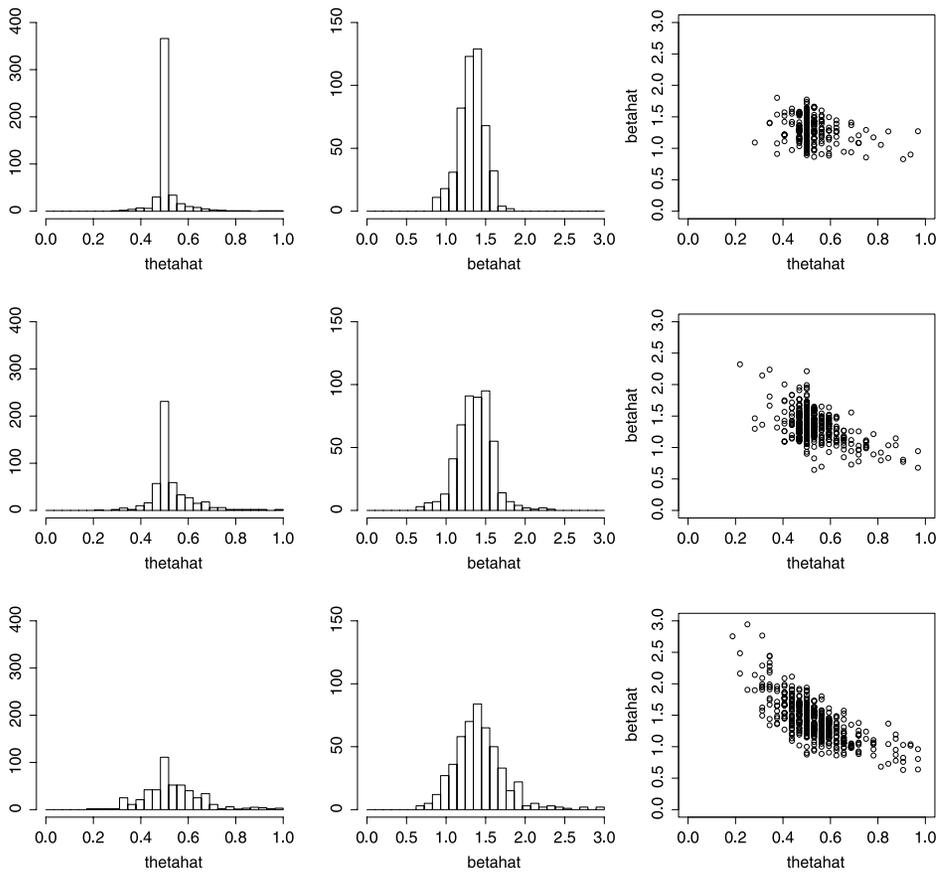


FIG. 3. Same as Figure 2 except in the partially misspecified case.

increase in dispersion but no change in mean; the effect on  $\hat{\beta}_n$  is a substantial shift in mean along with a slight increase in dispersion.

**6.1. Gene expression example.** Next we consider the gene expression data mentioned in connection with Figure 1, to see how the residual bootstrap performs with such trajectories. The trajectories consist of log gene expression levels from the breast tissue of  $n = 40$  breast cancer patients, along a sequence of 518 loci from chromosome 17. The complete gene expression data set is described in Richardson et al. [29]. Although a continuous response is not available for this particular data set, it is available in numerous other studies of this type; see the references mentioned in the [Introduction](#).

To construct a scalar response, we generated  $Y_i$  using the point impact model (1) with  $\alpha_0 = 0$  and  $\beta_0 = 1$ ,  $\theta_0 = 0.5$  (corresponding to the position of 259 base pairs along the chromosome) and  $\varepsilon \sim N(0, \sigma^2)$  for various values of  $\sigma$ . As previously noted, the trajectories are very rough in this example (with  $H$  estimated to

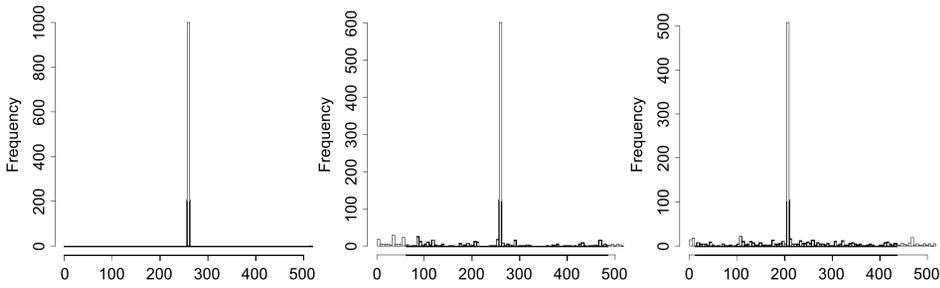


FIG. 4. Gene expression example: histograms of  $\hat{\theta}_n^*$  based on 1000 residual bootstrap samples and simulated responses with  $\sigma = 0.01$  (left),  $\sigma = 0.03$  (middle) and  $\sigma = 0.1$  (right).

be about 0.1), which implies a rapid rate of convergence for  $\hat{\theta}_n$ . We find that an abrupt transition in the behavior of the residual bootstrap occurs as  $\sigma$  increases: for small  $\sigma$ , the residual bootstrap estimates become degenerate at  $\theta_0$  due to the relatively coarse resolution; for moderately large  $\sigma$ , although a considerable portion of the estimates are concentrated at  $\theta_0$ , they become spread out over the 518 loci; for very large  $\sigma$ , the estimates are more or less uniformly scattered along the chromosome. Indeed, this is consistent with the behavior of the Wald-type CI (14) having width proportional to  $\sigma^{1/H}$ , which blows up dramatically as  $\sigma$  increases when  $H$  is small.

In Figure 4 we plot the bootstrap distribution of  $\hat{\theta}_n$  (obtained from 1000 residual bootstrap samples in each case) for  $\sigma = 0.01, 0.03$  and  $0.1$ . When  $\sigma = 0.01$ , the bootstrap distribution is degenerate at  $\theta_0$ ; the resolution of the grid is too coarse to see any statistical fluctuation in this case. When  $\sigma$  is moderate, namely,  $0.03$ , although the bootstrap distribution has a peak at  $\theta_0$ , the mass is widely scattered and the resulting CI now covers almost the entire chromosome. Further increasing the noise level causes the bootstrap distribution to become even more dispersed and its mode moves away from  $\theta_0$ ; the sample size of  $40$  is now too small for the method to locate the neighborhood of  $\theta_0$ .

**7. Concluding remarks.** In this paper we have developed a point impact functional linear regression model for use with trajectories as predictors of a continuous scalar response. It is expected that the proposed approach will be useful when there are sensitive time points at which the trajectory has an effect on the response. We have derived the rates of convergence and the explicit limiting distributions of the least squares estimator of such a parameter in terms of the Hurst exponent for fBm trajectories. We also established the validity of the residual bootstrap method for obtaining CIs for sensitive time points, avoiding the need to estimate the Hurst exponent. In addition, we have developed some results in the misspecified case in which the data are generated partially or completely from a standard functional linear model, and in the two-sample setting.

Although for simplicity of presentation we have assumed that the trajectories are fBm, it is clear from the proofs that it is only local properties of the trajectories in the neighborhood of the sensitive time point that drive the theory, and thus the validity of the confidence intervals. The consistency of the least squares estimator is of course needed, but this could be established under much weaker assumptions (namely, uniform convergence of the empirical criterion function and the existence of a well-separated minimum of the limiting criterion function; cf. [35], page 287).

Exploiting the fractal behavior of the trajectories plays a crucial role in developing confidence intervals based on the least squares estimator of the sensitive time point, in contrast to standard functional linear regression where it is customary to smooth the predictor trajectories prior to fitting the model ([27], Chapter 15). Our approach does not require any preprocessing of the trajectories involving a choice of smoothing parameters, nor any estimation of nuisance parameters (namely, the Hurst exponent). On the other hand, functional linear regression is designed with prediction in mind, rather than interpretability, so in a sense the two approaches are complimentary. The tendency of functional linear regression to over-smooth a point impact (see [21] for detailed discussion) is also due to the use of a roughness penalty on the regression function; the smoothing parameter is usually chosen by cross-validation, a criterion that optimizes for predictive performance.

Our model naturally extends to allow multiple sensitive time points, and any model selection procedure having the oracle property (such as the adaptive lasso) could be used to estimate the number of those sensitive time points. The bootstrap procedure for the (unregularized) least squares estimator can then be adapted to provide individual CIs around each time point, although developing theoretical justification would be challenging. Other challenging problems would be to develop bootstrap procedures that are suitable for the two-sample problem and for the misspecified model settings.

It should be feasible to carry through much of our program for certain types of diffusion processes driven by fBm, and also for processes having jumps. In the case of piecewise constant trajectories that have a single jump, the theory specializes to an existing type of change-point analysis [18]. Other possibilities include Lévy processes (which have stationary independent increments) and multi-parameter fBm. It should also be possible to develop versions of our results in the setting of censored survival data (e.g., Cox regression). Lindquist and McKeague [21] recently studied point impact generalized linear regression models in the case that  $X$  is standard Brownian motion and we expect that our approach can be extended to such models as well.

**8. Proofs.** To avoid measurability problems and for simplicity of notation, we will always use outer expectation/probability, and denote them by  $E$  and  $P$ ;  $E^*$  and  $P^*$  will denote bootstrap conditional expectation/probability given the data.

We begin with the proof of Theorem 2.1. The strategy is to establish (a) consistency, (b) the rate of convergence, (c) the weak convergence of a suitably localized

version of the criterion function, and (d) apply the argmax (or argmin) continuous mapping theorem.

8.1. *Consistency.* We start with some notation. Let  $m_\eta(Y, X) \equiv [Y - \alpha - \beta X(\theta)]^2$  and let  $\mathbb{M}_n(\eta) \equiv \mathbb{P}_n m_\eta = \frac{1}{n} \sum_{i=1}^n [Y_i - \alpha - \beta X_i(\theta)]^2$ , where  $\mathbb{P}_n$  denotes the expectation with respect to the empirical measure of the data. Let

$$\begin{aligned} \mathbb{M}(\eta) &\equiv P m_\eta = (\alpha_0 - \alpha)^2 + P[\{\beta_0 X(\theta_0) - \beta X(\theta)\}^2] + \sigma^2 \\ (15) \quad &= (\alpha_0 - \alpha)^2 + \sigma^2 + (\beta_0 - \beta)^2 P[X^2(\theta_0)] + \beta^2 P[X(\theta_0) - X(\theta)]^2 \\ &\quad + 2\beta(\beta_0 - \beta) P[X(\theta_0)\{X(\theta_0) - X(\theta)\}]. \end{aligned}$$

First observe that  $\mathbb{M}(\eta)$  has a unique minimizer at  $\eta_0$  as  $P[\beta X(\theta) \neq \beta_0 X(\theta_0)] > 0$ , for all  $(\beta, \theta) \in \mathbb{R} \times (0, 1)$  with  $(\beta, \theta) \neq (\beta_0, \theta_0)$ .

Using the fBm covariance formula (4),

$$\begin{aligned} \mathbb{M}(\eta) - \mathbb{M}(\eta_0) &= (\alpha_0 - \alpha)^2 + (\beta_0 - \beta)^2 |\theta_0|^{2H} + \beta^2 |\theta_0 - \theta|^{2H} \\ &\quad + \beta(\beta_0 - \beta)\{|\theta_0|^{2H} + |\theta_0 - \theta|^{2H} - |\theta|^{2H}\} \\ (16) \quad &= (\alpha_0 - \alpha)^2 + (\beta_0 - \beta)^2 |\theta_0|^{2H} + \beta\beta_0 |\theta_0 - \theta|^{2H} \\ &\quad + \beta(\beta_0 - \beta)\{|\theta_0|^{2H} - |\theta|^{2H}\}. \end{aligned}$$

To show that  $\hat{\eta}_n$  is a consistent estimator of  $\eta_0$ , first note that  $\hat{\eta}_n$  is uniformly tight. Also notice that  $\mathbb{M}(\eta)$  is continuous and has a unique minimum at  $\eta_0$ , and, thus, by Theorem 3.2.3(i) of [35], it is enough to show that  $\mathbb{M}_n \xrightarrow{P} \mathbb{M}$  uniformly on each compact subset  $K$  of  $\Xi = \mathbb{R}^2 \times [0, 1]$ , and that  $\mathbb{M}$  has a well-separated minimum in the sense that  $\mathbb{M}(\eta_0) < \inf_{\eta \notin G} \mathbb{M}(\eta)$  for every open set  $G$  that contains  $\eta_0$ . That  $\mathbb{M}$  has a well-separated minimum can be seen from the form of the expression in (16). For the uniform convergence, we need to show that the class  $\mathcal{F} = \{m_\eta : \eta \in K\}$  is  $P$ -Glivenko Cantelli ( $P$ -GC). Using GC preservation properties (see Corollary 9.27 of [17]), it is enough to show that  $\mathcal{G} = \{B_H(h) \equiv X(\theta_0 + h) - X(\theta_0) : h \in [-1, 1]\}$  is  $P$ -GC. Note that almost all trajectories of  $X$  are Lipschitz of any order strictly less than  $H$ , in the sense of (22) in Lemma 8.1 below. Thus, the bracketing number  $N_{[\cdot]}(\varepsilon, \mathcal{G}, L_1(Q)) < \infty$  and  $\mathcal{G}$  is  $P$ -GC, by Theorems 2.7.11 and 2.4.1 of [35].

8.2. *Rate of convergence.* We will apply a result of van der Vaart and Wellner ([35], Theorem 3.2.5) to obtain a lower bound on the rate of convergence of the  $\mathbb{M}$ -estimator  $\hat{\eta}_n$ . Setting  $\tilde{d}(\eta, \eta_0) = \max\{|\alpha - \alpha_0|, |\beta - \beta_0|, |\theta - \theta_0|^H\}$ , the first step is to show that

$$(17) \quad \mathbb{M}(\eta) - \mathbb{M}(\eta_0) \gtrsim \tilde{d}^2(\eta, \eta_0)$$

in a neighborhood of  $\eta_0$ . Here  $\gtrsim$  means that the right-hand side is bounded above by a (positive) constant times the left-hand side. Note that  $|\theta_0|^{2H} - |\theta|^{2H}$  has a bounded derivative in  $\theta \in [\delta, 1]$ , where  $\delta > 0$  is fixed, so for such  $\theta$  we have

$$\begin{aligned}
 & \beta(\beta - \beta_0)\{|\theta_0|^{2H} - |\theta|^{2H}\} \\
 & \geq -|\beta||\beta_0 - \beta|C|\theta_0 - \theta| \\
 (18) \quad & = -[|\beta|C|\theta_0 - \theta|^{1-H}]\beta_0 - \beta||\theta_0 - \theta|^H \\
 & \geq -c(\theta, \beta)\{(\beta_0 - \beta)^2 + |\theta_0 - \theta|^{2H}\},
 \end{aligned}$$

where  $C$  is the bound on the derivative,  $c(\theta, \beta) = |\beta|C|\theta_0 - \theta|^{1-H}/2$ , and we used the inequality  $|ab| \leq (a^2 + b^2)/2$ . As  $\beta_0 \neq 0$  and  $0 < \theta_0 < 1$ , by combining (16) and (18), suitably grouping terms, and noting that  $c(\theta, \beta)$  can be made arbitrarily small by restricting  $\eta$  to a sufficiently small neighborhood of  $\eta_0$ , there exist  $c_1 > 0$  and  $c_2 > 0$  such that

$$\mathbb{M}(\eta) - \mathbb{M}(\eta_0) \geq (\alpha_0 - \alpha)^2 + c_1(\beta_0 - \beta)^2 + c_2|\theta_0 - \theta|^{2H},$$

which shows that (17) holds.

Let  $\mathcal{M}_\delta \equiv \{m_\eta - m_{\eta_0} : \tilde{d}(\eta, \eta_0) < \delta\}$ , where  $\delta \in (0, 1]$ . Note that

$$\begin{aligned}
 m_\eta - m_{\eta_0} &= (\alpha^2 - \alpha_0^2) + \beta^2[X^2(\theta) - X^2(\theta_0)] + (\beta^2 - \beta_0^2)X^2(\theta_0) \\
 & \quad - 2Y(\alpha - \alpha_0) - 2\beta Y[X(\theta) - X(\theta_0)] - 2(\beta - \beta_0)YX(\theta_0) \\
 (19) \quad & \quad + 2\alpha\beta[X(\theta) - X(\theta_0)] + 2\alpha X(\theta_0)(\beta - \beta_0) \\
 & \quad + 2\beta_0 X(\theta_0)(\alpha - \alpha_0).
 \end{aligned}$$

This shows that  $\mathcal{M}_\delta$  has envelope

$$\begin{aligned}
 M_\delta(Y, X) &\equiv (2|\alpha_0| + \delta)\delta + (|\beta_0| + \delta)^2 \sup_{|\theta - \theta_0|^H < \delta} |X^2(\theta) - X^2(\theta_0)| \\
 & \quad + X^2(\theta_0)\delta(2|\beta_0| + \delta) + 2|Y|\delta \\
 (20) \quad & \quad + 2|Y|(|\beta_0| + \delta) \sup_{|\theta - \theta_0|^H < \delta} |X(\theta) - X(\theta_0)| \\
 & \quad + 2|X(\theta_0)||Y|\delta + 2(|\alpha_0| + \delta)(|\beta_0| + \delta) \sup_{|\theta - \theta_0|^H < \delta} |X(\theta) - X(\theta_0)| \\
 & \quad + 2(|\alpha_0| + \delta)|X(\theta_0)|\delta + 2|\beta_0||X(\theta_0)|\delta.
 \end{aligned}$$

Using a maximal inequality for fBm (Theorem 1.1 of [26]), we have

$$(21) \quad E \left[ \sup_{|\theta - \theta_0|^H < \delta} |X(\theta) - X(\theta_0)|^q \right] \lesssim \delta^q$$

for any  $q > 0$ . Then, using (A3) in conjunction with Hölder’s inequality (cf. the proof of Lemma 8.1), all nine terms in (20) can be shown to have second moments bounded by  $\delta^2$  (up to a constant) and, thus,  $EM_\delta^2 \lesssim \delta^2$ .

The following lemma shows that  $m_\eta$  is “Lipschitz in parameter” and, consequently, that the bracketing entropy integral  $J_{[\cdot]}(1, \mathcal{M}_\delta, L^2(P))$  is uniformly bounded as a function of  $\delta \in (0, 1]$ ; see [35], page 294. Without loss of generality, to simplify notation, we assume that  $\alpha = 0$  and  $\beta = 1$ , and state the lemma with  $\theta$  as the only parameter.

LEMMA 8.1. *If (A1) and (A3) hold and  $0 < \alpha < H$ , there is a random variable  $L$  with finite second moment such that*

$$(22) \quad |m_{\theta_1} - m_{\theta_2}| \leq L|\theta_1 - \theta_2|^\alpha$$

for all  $\theta_1, \theta_2 \in [0, 1]$  almost surely.

PROOF. The trajectories of fBm are Lipschitz of any order  $\alpha < H$  in the sense that

$$(23) \quad |X(t) - X(s)| \leq \xi|t - s|^\alpha \quad \forall t, s \in [0, 1]$$

almost surely, where  $\xi$  has moments of all orders; this is a consequence of the proof of Kolmogorov’s continuity theorem; see Theorem 2.2 of Revuz and Yor [28]. Noting that  $m_\theta(X, Y) = (Y - X(\theta))^2$ , we then have

$$|m_{\theta_1} - m_{\theta_2}| \leq C|X(\theta_1) - X(\theta_2)| \leq L|\theta_1 - \theta_2|^\alpha,$$

where  $C = 2(\sup_\theta |X(\theta)| + |Y|)$  and  $L = C\xi$ . Here  $L$  has a finite second moment:

$$EL^2 \leq \{EC^{2p}\}^{1/p} \{E\xi^{2q}\}^{1/q} < \infty$$

by Hölder’s inequality for  $1/p + 1/q = 1$  with  $p = 1 + \delta/2$  and  $\delta > 0$  comes from the moment condition (A3).  $\square$

Using a maximal inequality from [35] (see page 291), we then have

$$E_P \|\mathbb{G}_n\|_{\mathcal{M}_\delta} \lesssim J_{[\cdot]}(1, \mathcal{M}_\delta, L_2(P))(EM_\delta^2)^{1/2} \lesssim \delta$$

for all  $\delta \in (0, 1]$ , where  $\mathbb{G}_n = \sqrt{n}(\mathbb{P}_n - P)$ , and it follows that  $\tilde{d}(\hat{\eta}_n, \eta_0) = O_P(1/\sqrt{n})$  by Theorem 3.2.5 of [35].

8.3. *Localizing the criterion function.* To simplify notation, let  $r_n^{-1}\mathbf{h} \equiv (h_1/\sqrt{n}, h_2/\sqrt{n}, n^{-1/(2H)}h_3)$ , for  $\mathbf{h} = (h_1, h_2, h_3) \in \mathbb{R}^3$ . Then

$$(24) \quad \zeta_n = \arg \min_{\mathbf{h}} [\mathbb{M}_n(\eta_0 + r_n^{-1}\mathbf{h}) - \mathbb{M}_n(\eta_0)]$$

and we can write the expression in the square brackets after multiplication by  $n$  as the sum of an empirical process and a drift term:

$$(25) \quad \mathbb{G}_n[\sqrt{n}(m_{\eta_0+r_n^{-1}\mathbf{h}} - m_{\eta_0})] + n[\mathbb{M}(\eta_0 + r_n^{-1}\mathbf{h}) - \mathbb{M}(\eta_0)].$$

First consider the empirical process term, and note that

$$\begin{aligned}
 m_{\eta_0+r_n^{-1}\mathbf{h}} &= [Y - (\alpha_0 + n^{-1/2}h_1) - (\beta_0 + n^{-1/2}h_2)X(\theta_0 + n^{-1/(2H)}h_3)]^2 \\
 &= \left[ \varepsilon - \left\{ \frac{h_1}{\sqrt{n}} + \left( \beta_0 + \frac{h_2}{\sqrt{n}} \right) X(\theta_0 + n^{-1/(2H)}h_3) - \beta_0 X(\theta_0) \right\} \right]^2,
 \end{aligned}$$

so we obtain

$$\begin{aligned}
 \sqrt{n}[m_{\eta_0+r_n^{-1}\mathbf{h}} - m_{\eta_0}] &= \sqrt{n} \left[ \frac{h_1}{\sqrt{n}} + \left( \beta_0 + \frac{h_2}{\sqrt{n}} \right) \frac{\mathbb{B}(h_3)}{\sqrt{n}} + \frac{h_2}{\sqrt{n}} X(\theta_0) \right]^2 \\
 (26) \qquad \qquad \qquad &\quad - 2\varepsilon \left[ h_1 + \left( \beta_0 + \frac{h_2}{\sqrt{n}} \right) \mathbb{B}(h_3) + h_2 X(\theta_0) \right],
 \end{aligned}$$

where  $\mathbb{B}(h_3) \equiv \sqrt{n}[X(\theta_0 + n^{-1/(2H)}h_3) - X(\theta_0)] \stackrel{d}{=} B_H(h_3)$  (as a process in  $h_3$ ).

The result of applying  $\mathbb{G}_n$  to the first term on the right-hand side of the above display gives a term of order  $o_P(1)$  uniformly in  $\mathbf{h} \in [-K, K]^3$ , for each  $K > 0$ . This is seen by applying the maximal inequality from [35], page 291, as used above; here the class of functions  $\mathcal{F}_n$  in question is bounded by the envelope function

$$F_n = 3\sqrt{n} \left\{ \frac{K^2}{n} + \left( \beta_0 + \frac{K}{\sqrt{n}} \right)^2 \sup_{|h_3| \leq K} \frac{\mathbb{B}^2(h_3)}{n} + \frac{K^2}{n} X^2(\theta_0) \right\},$$

for which  $PF_n^2 = o(1)$  and  $J_{[\cdot]}(1, \mathcal{F}_n, L_2(P)) < \infty$ ; cf. the proof of Lemma 8.1. Hence, we just need to consider the second term. To determine the limit distribution of the empirical process term in (25), it thus suffices to show that

$$(27) \qquad \mathbb{G}_n[(\varepsilon, \varepsilon\mathbb{B}(h_3), \varepsilon X(\theta_0))] \xrightarrow{d} (\sigma Z_1, \sigma B_H(h_3), \sigma Z_2)$$

in  $\mathbb{R} \times C[-K, K] \times \mathbb{R}$ , where  $Z_1, Z_2$  are i.i.d.  $N(0, 1)$  and independent of the fBm  $B_H$ . For the second component above, notice that since  $\varepsilon$  is independent of  $\mathbb{B}$ ,

$$(28) \qquad \mathbb{G}_n[\varepsilon\mathbb{B}(h_3)] \stackrel{d}{=} B_H(h_3) \left( \frac{1}{n} \sum_{i=1}^n \varepsilon_i^2 \right)^{1/2} \xrightarrow{d} \sigma B_H(h_3)$$

in  $C[-K, K]$ . The asymptotic independence of the three components of (27) is a consequence of

$$\text{Cov}(\varepsilon, \varepsilon\mathbb{B}(h_3)) = \sigma^2 E[\mathbb{B}(h_3)] = 0,$$

$$\text{Cov}(\varepsilon, \varepsilon X(\theta_0)) = \sigma^2 E[X(\theta_0)] = 0,$$

$$\text{Cov}(\varepsilon\mathbb{B}(h_3), \varepsilon X(\theta_0)) = \sigma^2 \left[ \frac{\sqrt{n}}{2} (|\theta_0 + n^{-1/2H}h_3|^{2H} - |\theta_0|^{2H}) - \frac{h_3}{2\sqrt{n}} \right],$$

which tends to zero uniformly in  $h_3 \in [-K, K]$ , using the assumption  $H < 1$ .

It just remains to find the limit of the drift term in (25). Using (16), it is given by

$$\begin{aligned} & h_1^2 + h_2^2|\theta_0|^{2H} + (\beta_0 + n^{-1/2}h_2)\beta_0|h_3|^{2H} \\ & + h_2(\beta_0 + n^{-1/2}h_2)[\sqrt{n}\{|\theta_0|^{2H} - |\theta_0 + n^{-1/2}h_3|^{2H}\}] \\ & \rightarrow h_1^2 + h_2^2|\theta_0|^{2H} + \beta_0^2|h_3|^{2H} \end{aligned}$$

uniformly in  $\mathbf{h} \in [-K, K]^3$ . Combining this with the limit distribution of the first term in (25), we get from (24) and the argmin continuous mapping theorem that

$$\begin{aligned} \zeta_n & \xrightarrow{d} \arg \min_{\mathbf{h}} [-2\sigma(Z_1h_1 + \beta_0B_H(h_3) + h_2|\theta_0|^H Z_2) \\ & + (h_1^2 + h_2^2|\theta_0|^{2H} + \beta_0^2|h_3|^{2H})] \\ & \stackrel{d}{=} \left[ \sigma Z_1, |\theta_0|^{-H} \sigma Z_2, \arg \min_{h_3} \left\{ 2 \frac{\sigma}{|\beta_0|} B_H(h_3) + |h_3|^{2H} \right\} \right]. \end{aligned}$$

This completes the proof of Theorem 2.1.

8.4. *Proof of Theorem 3.1.* We prove the result by the method of contradiction. Before giving the proof, we state a general lemma that can be useful in studying bootstrap validity. The lemma can be proved easily using characteristic functions; see also Sethuraman [31] and Theorem 2.2 of Kosorok [16].

LEMMA 8.2. *Let  $W_n$  and  $W_n^*$  be random vectors in  $\mathbb{R}^l$  and  $\mathbb{R}^k$ , respectively; let  $Q$  and  $Q^*$  be distributions on the Borel sets of  $\mathbb{R}^l$  and  $\mathbb{R}^k$ , and let  $\mathcal{F}_n$  be  $\sigma$ -fields for which  $W_n$  is  $\mathcal{F}_n$ -measurable. If  $W_n$  converges in distribution to  $Q$  and the conditional distribution of  $W_n^*$  given  $\mathcal{F}_n$  converges (in distribution) in probability to  $Q^*$ , then  $(W_n, W_n^*)$  converges in distribution to  $Q \times Q^*$ .*

The basic idea of the proof of the theorem now is to assume that  $\Delta_n^* \xrightarrow{d} \Delta^*$  in probability, where  $\Delta^*$  has the same distribution as  $\Delta$ . Therefore,  $\Delta_n^* \xrightarrow{d} \Delta^*$  unconditionally also. We already know that  $\Delta_n \xrightarrow{d} \Delta$  from Theorem 2.1. By Lemma 8.2 applied with  $W_n = \Delta_n$ ,  $W_n^* = \Delta_n^*$  and  $\mathcal{F}_n = \sigma((Y_1, X_1), (Y_2, X_2), \dots, (Y_n, X_n))$ , we can show that  $(\Delta_n, \Delta_n^*)$  converges unconditionally to a product measure and, thus,  $\Delta_n + \Delta_n^* \xrightarrow{d} \Delta + \Delta^*$ . Thus,  $n^{1/(2H)}(\hat{\theta}_n^* - \theta_0) \equiv \Delta_n + \Delta_n^*$  converges unconditionally to a tight limiting distribution which has twice the variance of  $\Delta$ .

Using arguments along the lines of those used in the proof of Theorem 2.1, we can show that

$$n^{1/(2H)}(\hat{\theta}_n^* - \theta_0) \xrightarrow{d} \arg \min_{t \in \mathbb{R}} \{ 2\sigma\beta_0(B_H(t) + B_H^*(t)) + \beta_0^2|t|^{2H} \} \equiv \Delta^{**},$$

where  $B_H^*$  is another independent fBm with Hurst exponent  $H$ . Using properties of fBm, we see that

$$\Delta^{**} \stackrel{d}{=} \left( \sqrt{2} \frac{\sigma}{|\beta_0|} \right)^{1/H} \arg \min_{t \in \mathbb{R}} \{ B_H(t) + |t|^{2H}/2 \} \stackrel{d}{=} 2^{1/(2H)} \Delta.$$

Thus, the variance of the limiting distribution of  $n^{1/(2H)}(\hat{\theta}_n^* - \theta_0)$  is  $2^{1/H} > 2$  times the variance of  $\Delta$ , which is a contradiction.

8.5. *Proof of Theorem 3.2.* The bootstrap sample is  $\{(Y_i^*, X_i), i = 1, \dots, n\}$ , where the  $Y_i^*$  are defined in (7). Letting  $\mathbb{M}_n^*(\eta) \equiv \mathbb{P}_n^* m_\eta = \frac{1}{n} \sum_{i=1}^n [Y_i^* - \alpha - \beta X_i(\theta)]^2$ , the bootstrap estimates are

$$(29) \quad \hat{\eta}_n^* = (\hat{\alpha}_n^*, \hat{\beta}_n^*, \hat{\theta}_n^*) \equiv \arg \min_{\eta \in \Xi} \mathbb{M}_n^*(\eta).$$

We omit the rate of convergence part of the proof, and concentrate on establishing the limit distribution. Also, to keep the argument simple, we will assume that  $\hat{\eta}_n \rightarrow \eta_0$  a.s., but a subsequence argument can be used to bypass this assumption. Note that

$$(30) \quad \zeta_n^* = \arg \min_{\mathbf{h} \in \mathbb{R}^3} \{ n(\mathbb{P}_n^* - P_n)[m_{\hat{\eta}_n + r_n^{-1}\mathbf{h}} - m_{\hat{\eta}_n}] + nP_n[m_{\hat{\eta}_n + r_n^{-1}\mathbf{h}} - m_{\hat{\eta}_n}] \},$$

where  $P_n$  is the probability measure generating the bootstrap sample. Consider the first term within the curly brackets. Using a similar calculation as in (26),

$$(31) \quad \sqrt{n}(m_{\hat{\eta}_n + r_n^{-1}\mathbf{h}} - m_{\hat{\eta}_n}) = -2\varepsilon^* [h_1 + \hat{\beta}_n \hat{\mathbb{B}}(\hat{\theta}_n, h_3) + h_2 X(\hat{\theta}_n)] + A_n,$$

where  $\hat{\mathbb{B}}(\theta, t) \equiv \sqrt{n}[X(\theta + n^{-1/(2H)}t) - X(\theta)]$ , with the dependence on  $n$  suppressed for notational convenience, and  $a_n \equiv \sqrt{n}(\mathbb{P}_n^* - P_n)A_n = o_P(1)$  uniformly in  $\mathbf{h} \in [-K, K]^3$ . Then, using (31),

$$(32) \quad \begin{aligned} & \sqrt{n}(\mathbb{P}_n^* - P_n)[\sqrt{n}(m_{\hat{\eta}_n + r_n^{-1}\mathbf{h}} - m_{\hat{\eta}_n})] \\ &= -\sqrt{n}(\mathbb{P}_n^* - P_n)[\varepsilon^* \{h_1 + \hat{\beta}_n \hat{\mathbb{B}}(\hat{\theta}_n, h_3) + h_2 X(\hat{\theta}_n)\}] + a_n \\ &\stackrel{d}{\rightarrow} -2\sigma(Z_1 h_1 + \beta_0 B_H(h_3) + h_2 |\theta_0|^H Z_2) \end{aligned}$$

in  $C[-K, K]$ , a.s., where  $Z_1, Z_2$  are i.i.d.  $N(0, 1)$  that are independent of  $B_H$ .

To prove (32), first note that  $P_n[\varepsilon^* \{h_1 + \hat{\beta}_n \hat{\mathbb{B}}(\hat{\theta}_n, h_3) + h_2 X(\hat{\theta}_n)\}] = 0$ , as the  $X_i$  are fixed and the  $\varepsilon_i^*$  have mean zero under  $P_n$ . We will need the following properties of  $\hat{\mathbb{B}}(\hat{\theta}_n, t)$ , proved at the end:

$$(33) \quad \begin{aligned} & \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, t) \xrightarrow{P} 0, \quad \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, t) X_i(\hat{\theta}_n) \xrightarrow{P} 0, \\ & \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, s) \hat{\mathbb{B}}_i(\hat{\theta}_n, t) \xrightarrow{P} C_H(s, t), \end{aligned}$$

uniformly for  $|s|, |t| < K$ , where  $C_H(s, t)$  is the covariance function (4) of fBm. Now considering (32), by simple application of the Lindeberg–Feller theorem, it follows that

$$\sqrt{n}\mathbb{P}_n^*[\varepsilon^* h_1] \xrightarrow{d} h_1 N(0, \sigma^2), \quad \sqrt{n}\mathbb{P}_n^*[\varepsilon^* h_2 X(\hat{\theta}_n)] \xrightarrow{d} h_2 N(0, |\theta_0|^{2H} \sigma^2),$$

a.s. in  $C[-K, K]$ . Next consider  $\sqrt{n}\mathbb{P}_n^*[\varepsilon^* \hat{\mathbb{B}}(\hat{\theta}_n, t)]$ . The finite-dimensional convergence and tightness of this process follow from Theorems 1.5.4 and 1.5.7 in [35] using the properties of  $\hat{\mathbb{B}}(\hat{\theta}_n, t)$  stated in (33). The asymptotic independence of the terms under consideration also follows using (33) via a similar calculation as in (29).

To study the drift term in (30), note that

$$\begin{aligned} P_n m_\eta &= \frac{1}{n} \sum_{i=1}^n P_n [Y_i^* - \alpha - \beta X_i(\theta)]^2 \\ &= \frac{1}{n} \sum_{i=1}^n \frac{1}{n} \sum_{j=1}^n [\hat{\alpha}_n + \hat{\beta}_n X_i(\hat{\theta}_n) + (\hat{\varepsilon}_j - \bar{\varepsilon}_n) - \alpha - \beta X_i(\theta)]^2 \\ (34) \quad &= \frac{1}{n} \sum_{i=1}^n [(\hat{\alpha}_n - \alpha) + (\hat{\beta}_n - \beta) X_i(\hat{\theta}_n) + \beta \{X_i(\hat{\theta}_n) - X_i(\theta)\}]^2 \\ &\quad + \frac{1}{n} \sum_{j=1}^n (\hat{\varepsilon}_j - \bar{\varepsilon}_n)^2. \end{aligned}$$

Simple algebra then simplifies the drift term to

$$\begin{aligned} &\sum_{i=1}^n \left\{ \frac{h_1}{\sqrt{n}} + \frac{h_2}{\sqrt{n}} X_i(\hat{\theta}_n) + \frac{\hat{\mathbb{B}}_i(\hat{\theta}_n, h_3)}{\sqrt{n}} \left( \hat{\beta}_n + \frac{h_2}{\sqrt{n}} \right) \right\}^2 \\ &= h_1^2 + \frac{h_2^2}{n} \sum_{i=1}^n X_i^2(\hat{\theta}_n) + \left( \hat{\beta}_n + \frac{h_2}{\sqrt{n}} \right)^2 \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, h_3)^2 \\ (35) \quad &+ 2 \frac{h_1 h_2}{n} \sum_{i=1}^n X_i(\hat{\theta}_n) + 2 h_1 \left( \hat{\beta}_n + \frac{h_2}{\sqrt{n}} \right) \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, h_3) \\ &+ 2 h_2 \left( \hat{\beta}_n + \frac{h_2}{\sqrt{n}} \right) \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, h_3) X_i(\hat{\theta}_n) \\ &\xrightarrow{P} h_1^2 + h_2^2 |\theta_0|^{2H} + \beta_0^2 |h_3|^{2H} \end{aligned}$$

uniformly on  $[-K, K]$ , where we have used the properties of  $\hat{\mathbb{B}}(\hat{\theta}_n, h_3)$  in (33) and

$$\left| \frac{1}{n} \sum_{i=1}^n X_i(\hat{\theta}_n) \right| \leq \sup_{\theta} |(\mathbb{P}_n - P)X(\theta)| \xrightarrow{P} 0.$$

Thus, combining (30), (32) and (35), we get  $\zeta_n^* \xrightarrow{d} \zeta$  in probability.

It remains to prove (33). We only prove the last part, the other parts being similar. For fixed  $K > 0$ , consider the function class

$$\mathcal{F}_n = \{\hat{\mathbb{B}}(\theta, s)\hat{\mathbb{B}}(\theta, t) : \theta \in [0, 1], |s| < K, |t| < K\},$$

which has a uniformly bounded bracketing entropy integral, and envelope

$$F_n = \sup_{\theta, |s| < K, |t| < K} |\hat{\mathbb{B}}(\theta, s)\hat{\mathbb{B}}(\theta, t)| \leq n^{\alpha'/H} K^{2(H-\alpha')} \xi^2$$

from the Lipschitz property (23) of order  $\alpha = H - \alpha'$ , where  $0 < \alpha' < H/2$  and  $\xi$  has finite moments of all orders. Then

$$\begin{aligned} P \left\{ \sup_{|s|, |t| < K} \left| \frac{1}{n} \sum_{i=1}^n \hat{\mathbb{B}}_i(\hat{\theta}_n, t)\hat{\mathbb{B}}_i(\hat{\theta}_n, s) - C_H(s, t) \right| > \varepsilon \right\} \\ \leq P \left\{ \sup_{f \in \mathcal{F}_n} |(\mathbb{P}_n - P)f| > \varepsilon \right\} \leq \frac{1}{\varepsilon} E \left[ \sup_{f \in \mathcal{F}_n} |(\mathbb{P}_n - P)f| \right] \\ \lesssim \frac{1}{\varepsilon \sqrt{n}} J_{[\cdot]}(1, \mathcal{F}_n, L_2(P))(EF_n^2)^{1/2} \lesssim n^{\alpha'/H-1/2} \rightarrow 0, \end{aligned}$$

where we use a maximal inequality in Theorem 2.14.2 of [35].

*Remark.* The failure of the nonparametric bootstrap can be explained from the behavior of the drift term in (30). In the nonparametric bootstrap, we need to find the conditional limit of  $n\mathbb{P}_n[m_{\hat{\eta}_n+r_n^{-1}\mathbf{h}} - m_{\hat{\eta}_n}]$  given the data, but observe that  $\sqrt{n}\mathbb{P}_n$  applied to the second term of (26) fails to converge in probability. However, when bootstrapping residuals, the drift term in (30) becomes  $nP_n[m_{\hat{\eta}_n+r_n\mathbf{h}} - m_{\hat{\eta}_n}]$ , and  $\sqrt{n}P_n$  applied to the second term in (26) vanishes, so the drift term now converges in probability, as seen in (35).

8.6. *Proof of Theorem 4.1.* The consistency of  $\hat{\theta}_n$  follows using a Glivenko–Cantelli argument for the function class  $\mathcal{F} \equiv \{m_\theta(X, Y) = [Y - X(\theta)]^2 : \theta \in [0, 1]\}$  and the existence of a well-separated minimum for  $\mathbb{M}$ ; cf. the proof of Theorem 2.1. Note that  $\theta_0$  is the unique solution of the normal equation  $\mathbb{M}'(\theta) = 0$  and  $\mathbb{M}''(\theta_0) > 0$ , so

$$(36) \quad \mathbb{M}(\theta) - \mathbb{M}(\theta_0) \gtrsim d^2(\theta, \theta_0)$$

for all  $\theta$  in a neighborhood of  $\theta_0$ , where  $d$  is the usual Euclidean distance. The envelope function  $M_\delta = \sup_{|\theta-\theta_0| < \delta} |m_\theta - m_{\theta_0}|$  for  $\mathcal{M}_\delta \equiv \{m_\theta - m_{\theta_0} : \theta \in [0, 1]\}$  has  $L^2$ -norm of order  $\delta^H$ , from (21), so Theorem 3.2.5 of [35] applied with  $\phi_n(\delta) = \delta^H$  gives rate  $r_n = n^{1/(4-2H)}$  with respect to Euclidean distance.

Now write  $\hat{h}_n \equiv r_n(\hat{\theta}_n - \theta_0) = \arg \min_{h \in \mathbb{R}} \tilde{\mathbb{M}}_n(h)$ , where

$$(37) \quad \tilde{\mathbb{M}}_n(h) = r_n^2[\mathbb{M}_n(\theta_0 + h/r_n) - \mathbb{M}_n(\theta_0)], \quad h \in \mathbb{R}.$$

This gives

$$(38) \quad \tilde{M}_n(h) = n^{-H/(4-2H)} \mathbb{G}_n[Z_n(h)^2] - 2\mathbb{G}_n[WZ_n(h)] + \frac{1}{2}M''(\theta_0)h^2 + A_n,$$

where  $A_n = o(1)$  uniformly in  $h \in [-K, K]$ , for any  $K > 0$ , and

$$W \equiv \int_0^1 f(t)X(t) dt - X(\theta_0) + \varepsilon,$$

$$Z_n(h) \equiv n^{H/(4-2H)}[X(\theta_0 + h/r_n) - X(\theta_0)].$$

Note that  $Z_n(h) \xrightarrow{d} B_H(h)$  as processes, so, by Donsker's theorem, the first term in (38) converges to zero in probability uniformly over  $[-K, K]$ . For the second term, we claim that

$$(39) \quad \mathbb{G}_n[WZ_n(h)] \xrightarrow{d} aB_H(h)$$

as processes in  $C[-K, K]$ , where  $a^2 = E(W^2)$ . Application of the argmin continuous mapping theorem will then complete the proof.

To prove (39), for simplicity, we just give the detailed argument in the Brownian motion case, with  $B = B_{1/2}$  denoting two-sided Brownian motion. Consider the decomposition

$$(40) \quad \mathbb{G}_n[WZ_n(h)] = \mathbb{G}_n[(W - W_\eta)Z_n(h)] + \mathbb{G}_n[W_\eta Z_n(h)],$$

where

$$(41) \quad W_\eta = \int_{\theta_0-\eta}^{\theta_0+\eta} f(t)X(t) dt + (X(\theta_0 + \eta) - X(\theta_0))(F(1) - F(\theta_0 + \eta)),$$

$F(\theta) = \int_0^\theta f(t) dt$ , and  $\eta > 0$  is sufficiently small so that  $|\theta_0 \pm \eta| < 1$ . Splitting the range of integration for the first term in  $W$  into three intervals, and using the integration by parts formula (for semimartingales) over the intervals  $[0, \theta_0 - \eta]$  and  $[\theta_0 + \eta, 1]$ , we get

$$W - W_\eta = \int_0^{\theta_0-\eta} (F(\theta_0 - \eta) - F(t)) dX(t) + \int_{\theta_0+\eta}^1 (F(1) - F(\theta_0 + \eta)) dX(t) + \varepsilon + X(\theta_0)(F(1) - F(\theta_0 + \eta) - 1),$$

which implies, by the independent increments property, that  $W - W_\eta$  is independent of  $Z_n(h)$  for  $|h| < \eta n^{1/3}$ . Using the same argument as in proving (28), it follows that

$$\mathbb{G}_n[(W - W_\eta)Z_n(h)] \xrightarrow{d} a_\eta B(h)$$

as processes in  $C[-K, K]$ , for each fixed  $\eta > 0$ , where

$$a_\eta^2 = E(W - W_\eta)^2 \rightarrow E(W^2) = E\left[\int_0^1 f(t)X(t) dt - X(\theta_0)\right]^2 + \sigma^2 \equiv a^2$$

as  $\eta \rightarrow 0$ . Clearly,  $a_\eta B(h) \xrightarrow{d} aB(h)$  in  $C[-K, K]$  as  $\eta \rightarrow 0$ . If we show that the last term in (40) is asymptotically negligible in the sense that, for every  $M > 0$  and  $\delta > 0$ ,

$$(42) \quad \lim_{\eta \rightarrow 0} \limsup_{n \rightarrow \infty} P\left(\sup_{|h| < M} |\mathbb{G}_n[W_\eta Z_n(h)]| > \delta\right) = 0,$$

this will complete the proof in view of Theorem 4.2 in [4]. Theorem 2.14.2 in [35] gives

$$E\left[\sup_{|h| < M} |\mathbb{G}_n[W_\eta Z_n(h)]|\right] \lesssim J_{[\cdot]}(1, \mathcal{F}, L^2(P))(EF^2)^{1/2},$$

where  $J_{[\cdot]}(1, \mathcal{F}, L^2(P))$  is the bracketing entropy integral of the class of functions  $\mathcal{F} = \mathcal{F}_{n,\eta} = \{W_\eta Z_n(h) : |h| < M\}$ , and  $F = F_{n,\eta}$  is an envelope function for  $\mathcal{F}$ . We can take  $F = |W_\eta| \sup_{|h| < M} |Z_n(h)|$ . By the Cauchy–Schwarz inequality,

$$E(F^2) \leq (EW_\eta^4)^{1/2} \left(E \sup_{|h| < M} |B(h)|^4\right)^{1/2} \lesssim \eta M,$$

where we have used (21). The bracketing entropy integral can be shown to be uniformly bounded (over all  $\eta > 0$  and  $n$ ) using the Lipschitz property (23). The previous two displays and Markov’s inequality then lead to

$$\limsup_{n \rightarrow \infty} P\left(\sup_{|h| < M} |\mathbb{G}_n[W_\eta Z_n(h)]| > \delta\right) \lesssim \sqrt{\eta M}/\delta,$$

which implies (42) and establishes (39).

To establish (39) for general fBm, we apply Theorem 2.11.23 of [35] to the class of measurable functions  $\mathcal{F}_n = \{f_{n,h} : |h| < M\}$ , where  $f_{n,h}(X, \varepsilon) = WZ_n(h)$  and  $M > 0$  is fixed. Direct computation using the covariance of fBm shows that the sequence of covariance functions of  $f_{n,h}$  converges pointwise to the covariance function of  $aB_H(h)$ , and the various other conditions can be shown to be satisfied using similar arguments to what we have seen already.

8.7. *Proof of (13).* The key step involving the localization of the criterion function again relies on the self-similarity of fBm  $B_H$ :

$$\begin{aligned} n_1^{1/(2H)}(\hat{\theta}_n - \theta_0) &= \arg \max_h (\mathbb{P}_n^1 - \mathbb{P}_n^2)[X(\theta_0 + n_1^{-1/(2H)}h) - X(\theta_0)] \\ &\stackrel{d}{=} \arg \max_h \{(\mathbb{G}_n^1 - \sqrt{\rho}\mathbb{G}_n^2)[B_H(h)] \\ &\quad + n_1(\mathbb{M}(\theta_0 + n_1^{-1/(2H)}h) - \mathbb{M}(\theta_0))\} \\ &\stackrel{d}{\rightarrow} \arg \max_h \{(1 + \sqrt{\rho})B_H(h) - c|h|^{2H}\}, \end{aligned}$$

where  $\mathbb{G}_n^j = \sqrt{n_j}(\mathbb{P}_n^j - P_j)$  is the empirical process for the  $j$ th sample.

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