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## Data-driven estimation of diurnal duration patterns

Yuanhua Feng

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University of Paderborn

#### Abstract

This paper proposes a local linear estimator for diurnal patterns of transaction durations under a special nonparametric regression model, whose asymptotics are different to any known results. An iterative plug-in algorithm is developed for selecting the bandwidth. The ACD model is then applied to analyze the standardized durations. Data examples show that the proposals work well in practice.

Keywords: Autoregressive conditional duration, diurnal duration patterns, local linear estimator, bandwidth selection, iterative plug-in.

JEL Codes: C14, C41

#### 1 Introduction

Let  $t_0 < t_1 < \ldots < t_N < t_{N+1} = T$  be the time points at which trades occur and  $x_i = t_i - t_{i-1}$  the duration between trades, where  $t_0 = 0$  and N is the (random) number of trades. Consider the model  $x_i = \phi_i \psi_i \varepsilon_i$ , where  $\phi_i$  is a (deterministic) diurnal pattern and  $\psi_i$  is the conditional mean after removing  $\phi_i$ . Estimation of  $\phi(t)$  is a necessary step for further econometric analysis of transaction durations using e.g. the ACD (autoregressive conditional duration) of Engle and Russell (1998). Different approaches for estimating  $\phi(t)$  are introduced in the literature. For instance, Engle and Russell (1998) propose to use a cubic spline and a nonparametric estimator was introduced by Veredas et al. (2002). For further ideas on the estimation of  $\phi$  see e.g. Bauwens and Giot (2000), Hautsch (2004) and references therein.

This paper focuses on developing a data-driven local linear estimator of  $\phi$ . For this purpose a nonparametric regression model with some special features is defined, where  $\phi$ is the mean function and the scale function at the same time, and is also proportional to the reciprocal of the design density. The asymptotic variance and asymptotically optimal bandwidth of  $\hat{\phi}$  are hence different to any known results. An iterative plug-in (IPI, Gasser et al., 1991) algorithm with some improvements is developed for selecting the bandwidth under the current model. Data examples show that the proposals work well in practice.

#### 2 Local linear estimation of the diurnal pattern

The model  $x_i = \phi_i \psi_i \varepsilon_i$  (Engle and Russell, 1998, 2010) can be rewritten as follows:

$$
x_i = \phi(t_i) + \phi(t_i)(y_i - 1), i = 1, ..., N,
$$
\n(1)

where  $\phi(t_i)$  is the local mean of  $x_i, y_i = \psi_i \varepsilon_i$  with  $E(y_i) = 1, \psi_i$  is the conditional mean of  $y_i$ , which can be modeled by a unit ACD with  $\psi_i = \omega + \sum_{j=1}^p \alpha_j y_{i-j} + \sum_{k=1}^q \beta_k \psi_{i-k}$ ,  $\omega > 0, \ \alpha_j, \beta_k \geq 0$  and  $\omega = 1 - \sum \alpha_j - \sum \beta_k$ , and  $\varepsilon_i$  are i.i.d. non-negative random variables with  $E(\varepsilon_i) = 1$ . Let  $\xi_i = y_i - 1$ . Model (1) is a special nonparametric regression with stationary errors  $\xi_i$ . 1:  $\phi(t)$  is its mean and scale function at the same time; 2.  $x_i = t_i - t_{i-1}$  is determined by the regressor and 3.  $\phi(t_i) \to 0$ , as  $N \to \infty$ . Moreover, let  $f(t) > 0$  be the design density of t and  $m(t) = [f(t)]^{-1}$ , we have  $N\phi(t_i) = m(t_i) + o(N^{-1})$ . These features will affect the asymptotic properties of  $\hat{\phi}(t)$  strongly. We see  $m(t)$  is a given function, but  $\phi(t)$  depends on N. Hence we will first estimate  $m(t)$  from  $z_i = Nx_i$ and then put  $\hat{\phi}(t) = \hat{m}(t)/N$ , since the discussion with  $\hat{m}(t)$  is more convenient.

The derivatives  $m^{(\nu)}(t)$  can be estimated by minimizing the weighted least squares

$$
Q = \sum_{i=1}^{N} \left\{ z_i - a_0(t) - a_1(t)(t_i - t) - \dots - a_p(t)(t_i - t)^p \right\}^2 K\left(\frac{t_i - t}{b}\right),\tag{2}
$$

where K is a kernel and b is the bandwidth. We have  $\hat{m}^{(\nu)}(t) = \nu! \hat{a}_{\nu}$  and  $\hat{\phi}^{(\nu)}(t) =$  $\nu^{\dagger}a_{\nu}/N$ . In the sequel, local linear estimators  $\hat{m}(t)$  and  $\hat{\phi}(t) = \hat{m}(t)/N$  will be used. Let  $\hat{y}_i = x_i / \hat{\phi}(t_i)$ . A suitable ACD model can be fitted to  $\hat{y}_i$  using the standard QML method.

Let var  $[\hat{m}(t)], B[\hat{m}(t)], \text{var}[\hat{\phi}(t)]$  and  $B[\hat{\phi}(t)]$  denote the variance and bias of  $\hat{m}(t)$ and  $\hat{\phi}(t)$ , respectively. We have var  $[\hat{\phi}(t)] = \text{var}[\hat{m}(t)]/N^2$  and  $B[\hat{\phi}(t)] \approx B[\hat{m}(t)]/N$ . Asymptotic properties of  $\hat{m}(t)$  can be derived under regularity conditions. The asymptotic bias of  $\hat{m}(t)$  is the same as for a common local linear estimator. Let  $\gamma(k) = \text{cov}(y_i, y_{i+k}),$  $S = \sum_{i} \gamma(k)$  and  $R(K) = \int K^2(u) du$ . By adapting known results in the literature, we can obtain the asymptotic variance of  $\hat{m}(t)$  at  $0 < t < T$ :

$$
\text{var}\left[\hat{m}(t)\right] \approx \frac{R(K)S}{Nbf(t)}m^2(t) = \frac{R(K)S}{Nb}m^3(t),\tag{3}
$$

which is proportional to  $m^3(t)$ . Furthermore, let  $I(K) = \int u^2K(u)du$ . The optimal bandwidth for estimating  $m(t)$  and  $\phi(t)$  on [0, T],  $b_{\text{opt}}$ , is the same and is asymptotically

$$
b_{\rm opt} \approx b_{\rm A} = \left(\frac{R(K)S}{I^2(K)} \frac{\int m^3(t)dt}{\int [m''(t)]^2 dt}\right)^{1/5} N^{-1/5}.
$$
 (4)

Let  $V = R(K)S \int m^3(t)dt$  and  $b = o(b_A)$ . At an interior point  $b < t < T - b$ , we have

$$
\sqrt{Nb}[\hat{m}(t) - m(t)] \stackrel{\mathcal{D}}{\longrightarrow} N(0, V). \tag{5}
$$

### 3 Bandwidth selection

An IPI algorithm based on (4) with a starting bandwidth  $b_0 = T/10$  is developed, which extends the idea of Gasser et al. (1991) to random design nonparametric regression with dependent errors, huge sample size and very large error variance, where  $S$  is estimated by a lag-window estimator with the maximal lag  $K \approx 4N^{1/3}$  (see Bühlmann, 1996 and Feng and Wang, 2011). For any reasonable  $b_0$ , the IPI bandwidth converges to the same fix-point. The above choice of  $b_0$  ensures that S can already be well estimated at the beginning. By an IPI algorithm,  $m''(t)$  in the jth iteration is estimated using a bandwidth  $b_{2j}$  calculated from  $b_{j-1}$ . Here, the formula  $b_{2j} = T(b_j/T)^{1/2}$  (Beran and Feng, 2002) is used, which works better than  $\tilde{b}_{2j} = b_{j-1} * N^{1/10}$  (Gasser et al., 1991) in the current case. The choice of  $b_0$  and  $b_{2j}$  also helps to reduce a few iterations. Starting with  $b_0$ , the algorithm reads as follows:

- i) In the jth iteration, obtain  $\hat{\phi}_j(t)$  with  $b_{j-1}$ . Let  $\hat{y}_{ji} = x_i/\hat{\phi}_j(t_i)$ . Calculate  $\hat{\gamma}_j(k)$  from  $\hat{y}_{ji}$  and let  $\hat{S}_j = \sum$  $|k|<\!K$  $w_k\hat{\gamma}_j(k)$ , where  $w_k$  are the Bartlett-weights and  $K \approx 4N^{1/3}$ .
- ii) Obtain  $\hat{m}_j(t_i)$  with  $b_{j-1}$  and  $\hat{m}_j''(t_i)$  using local cubic with  $b_{2j} = T(b_{j-1}/T)^{\alpha}$ , where  $\alpha = 1/2$  or  $\alpha = 5/7$ . Let  $\hat{I}_j(m^3) = \frac{1}{N} \sum_{n=1}^{N}$  $i=1$  $[\hat{m}_j(t_i)]^3$  and  $\hat{I}_j([m'']^2) = \frac{1}{N} \sum_{i=1}^{N}$  $i=1$  $[\hat{m}''_j(t_i)]^2$ .

iii) Improve  $b_{j-1}$  by  $b_j = \left(\frac{R(K)\hat{S}_j}{I^2(K)}\right)$  $\hat{I}_j(m^3)$  $\overline{\hat{I}_{j}([m'']^2)}$  $\int^{1/5} N^{-1/5}$  and increase j by one. iv) Repeatedly carry out i) to iii) until convergence is reached and put  $\hat{b}_A = b_j$ .

Under regularity assumptions, in particular that  $E(y_i^4) < \infty$ , the rate of convergence of  $\hat{b}_A$ is the same as for nonparametric regression with independent errors and is determined by  $\alpha$ . If  $\alpha = 1/2$ ,  $\hat{b}_A$  is most stable so that  $\hat{b}_A \approx b_{\text{opt}}[1 + O(N^{-1/5}) + O_p(N^{-1/2})]$ . For  $\alpha = 5/7$ ,  $\hat{b}_A$  achieves the highest rate of convergence with  $\hat{b}_A \approx b_{opt}[1 + O(N^{-2/7}) + O_p(N^{-2/7})]$  (see Lemma 1 of Beran and Feng, 2002 with  $\delta = 0$ ). Theoretically, the use of  $\alpha = 2/7$  is more preferable, but the error variance in the current case is very large and the stability of  $\hat{b}_A$ is more important. Hence  $\alpha = 1/2$  will be used in this paper. Furthermore, we propose to calculate the final estimates using the local bandwidths  $\hat{b}(t) = \hat{b}_A * \hat{m}(t)$ . This is a quasi k-NN method and leads to further improvement of the estimation quality.

#### 4 Practical implementation and applications

An R code is written by means of the "lm" function with proper weights, which is applied to stock durations of a few German firms ( $T = 8.5$  and  $b_0 = 0.85$  hours). It shows that the algorithm works well in practice. Bandwidths (in hours) selected with the bisquare kernel for BMW stock durations in the first two weeks in Aug 2011 are given in Table 1 as examples. Note that  $\hat{b}_A$  is jointly determined by N, S and the complexity of  $\phi(t)$ 

			1.8.11 <b>2.8.11</b> 3.8.11 4.8.11 5.8.11 <b>8.8.11</b> 9.8.11 10.8.11 11.8.11 12.8.11		
			N 9249 14527 12789 19477 22317 24377 34286 25995 19437 15404		
			$\hat{b}_A$ 1.0657 1.4086 0.9794 0.8611 1.0867 0.5565 1.3248 0.8810 0.8397 0.9602		

Table 1. Selected bandwidths (h) for BMW diurnal duration patterns in two weeks

and changes strongly from one day to another. The largest bandwidth is  $\hat{b}_A = 1.4086$ on Aug 2, and the smallest is  $\hat{b}_A = 0.5565$  on Aug 8, 2011. The former is much bigger and the latter is much smaller than  $b_0$ . The number of iterations required also varies from case to case. It is e.g. just 3 on Aug 1, but 15 on Aug 9, 2011. The observed durations, the estimated diurnal patterns,  $\hat{\phi}(t)$ , and the standardized durations,  $\hat{y}_i$ , on Aug 2 and 8, 2011, respectively, are shown in Figure 1. The diurnal pattern on Aug 2, 2011 has a typical inverse U-form except for a sub-peak at about one hour prior to the close. In this case the smoothing quality of  $\hat{\phi}(t)$  is very good. The diurnal pattern on Aug 8, 2011 looks very special with two peaks in the morning and in the afternoon and some minor structures. Hence  $\hat{b}_A$  is now very small. The bandwidths used around lunch time and prior to the close seem to be not large enough. This problem might be solved using a varying bandwidth taking  $\hat{m}''(t)$  into account. Discussion on this is beyond the aim of this paper. The standardized durations seem to be stationary with clear clusters, except for a few outliers. Two EACD $(1, 1)$  (exponential ACD) models are fitted to  $\hat{y}_i$  in Figures 1(c) and 1(f), respectively, using the "fACD" package in R (Perlin, 2009). The results are listed in Table 2. These models fit the data very well. The estimation quality

ننا			
		$.0362(.0030)$ $.1197(.0053)$ $.8552(.0067)$ $.0487(.0028)$ $.1120(.0039)$ $.8473(.0054)$	

**Table 2.** EACD parameters for the 1. (left) and 2. (right) examples with  $p$ -values

after removing  $\phi(t)$  is improved. For instance, the EACD model obtained from  $x_i$  on Aug 2, 2011, is non-stationary with  $\hat{\alpha} + \hat{\beta} \approx 1$ . However, the first model given in Table 2 estimated from  $\hat{y}_i$  does not share this problem.

### 5 Final remarks

A local linear estimator of diurnal duration patterns on financial markets with special asymptotics is proposed. An IPI bandwidth selector is developed. Applications show that the proposal works well in practice. To our knowledge this paper is the first effort to develop a data-driven estimator of diurnal duration patterns. There are still many open questions in this context, such as further improvements of the data-driven algorithm, the estimation of  $m(t)$  via  $\hat{f}(t)$  and the significance test of  $\hat{\phi}(t)$ . Furthermore, discussion on the application of the estimation results and detailed economic sources for a non-typical diurnal duration dynamics like those happened on Aug 8, 2011 is also of great interest.

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Figure 1: Observed durations (above), estimated diurnal patterns (middle) and standardized durations (bottom) of BMW stock on two days.

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Jinjun Xue



