

Bounds of the Normal Approximation for Linear Recursions with Two Effects

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Abstract: Let X_0 be a non-constant random variable with finite variance. Given an integer $k \geq 2$, define a sequence $\{X_n\}_{n=1}^{\infty}$ of approximately linear recursions with small perturbations $\{\Delta_n\}_{n=0}^{\infty}$ by

$$X_{n+1} = \sum_{i=1}^k a_{n,i} X_{n,i} + \Delta_n \quad \text{for all } n \geq 0$$

where $X_{n,1}, \dots, X_{n,k}$ are independent copies of the X_n and $a_{n,1}, \dots, a_{n,k}$ are real numbers. In 2004, Goldstein obtained bounds on the Wasserstein distance between the standard normal distribution and the law of X_n which is in the form $C\gamma^n$ for some constants $C > 0$ and $0 < \gamma < 1$.

In this article, we extend the results to the case of two effects by studying a linear model $Z_n = X_n + Y_n$ for all $n \geq 0$, where $\{Y_n\}_{n=1}^{\infty}$ is a sequence of approximately linear recursions with an initial random variable Y_0 and perturbations $\{\Lambda_n\}_{n=0}^{\infty}$, i.e., for some $\ell \geq 2$,

$$Y_{n+1} = \sum_{j=1}^{\ell} b_{n,j} Y_{n,j} + \Lambda_n \quad \text{for all } n \geq 0$$

where Y_n and $Y_{n,1}, \dots, Y_{n,\ell}$ are independent and identically distributed random variables and $b_{n,1}, \dots, b_{n,\ell}$ are real numbers. Applying the zero bias transformation in the Stein's equation, we also obtain the bound for Z_n . Adding further

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conditions that the two models (X_n, Δ_n) and (Y_n, Λ_n) are independent and that the difference between variance of X_n and Y_n is smaller than the sum of variances of their perturbation parts, our result is the same as previous work.

Keywords: Hierarchical sequence, Stein's method, Zero bias

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1 Introduction and Main Theorem

Let Z be a standard normally distributed random variable and X_0 a non-constant random variable with finite variance. For a positive integer $k \geq 2$, we consider a sequence $\{X_n\}_{n=1}^{\infty}$ of approximately linear recursions with perturbations $\{\Delta_n\}_{n=0}^{\infty}$,

$$X_{n+1} = \sum_{i=1}^k a_{n,i} X_{n,i} + \Delta_n \quad \text{for all } n \geq 0$$

where the X_n and $X_{n,1}, \dots, X_{n,k}$ are independent and identically distributed random variables and $a_{n,1}, \dots, a_{n,k}$ are real numbers. For all integers $n \geq 0$, we introduce some notation for the model (X_n, a_n, Δ_n) ,

$$\lambda_{a,n}^2 = \sum_{i=1}^k a_{n,i}^2, \quad \varphi_{a,n} = \sum_{i=1}^k \frac{|a_{n,i}|^3}{\lambda_{a,n}^3}, \quad \text{Var}(X_n) = \sigma_{X,n}^2$$

and

$$\tilde{X}_n = \frac{X_n - EX_n}{\sigma_{X,n}}.$$

Arising originally from statistical physics, the approximately linear recursions are special type of hierarchical structures and often applied to the conductivity of random mediums. A natural way in the classical probability theory is to study limit theorems for the distributions of these models. A strong law of large numbers for the hierarchical structure was obtained by [6, 4, 3]. The central limit theorem for recursions was first introduced by [7] and the bounds to normal approximation based on the Wasserstein distance were obtained by [2]. The following two conditions were used in the last work.

Condition 1.1. For each $i = 1, \dots, k$, the sequence $\{a_{n,i}\}_{n=0}^{\infty}$ converges to some real number a_i satisfying that at least two of the a_i 's are nonzero. Set $\lambda_a^2 =$

$\sum_{i=1}^k a_i^2$. There exist $0 < \delta_{X,2} < \delta_{\Delta,2} < 1$ and positive constants $C_{X,2}$, $C_{\Delta,2}$ such that for all $n \geq 0$,

$$\text{Var}(X_n) \geq C_{X,2}^2 \lambda_a^{2n} (1 - \delta_{X,2})^{2n},$$

$$\text{Var}(\Delta_n) \leq C_{\Delta,2}^2 \lambda_a^{2n} (1 - \delta_{\Delta,2})^{2n}.$$

Condition 1.2. With $\delta_{X,2}$, $\delta_{\Delta,2}$ and λ_a as in the Condition 1.1, there exists $\delta_{X,4} \geq 0$ and $\delta_{\Delta,4} \geq 0$ such that

$$\phi_{X,\Delta,2} = \frac{(1 - \delta_{\Delta,2})(1 + \delta_{X,4})^3}{(1 - \delta_{X,2})^4} < 1 \quad \text{and} \quad \phi_{X,\Delta,4} = \left(\frac{1 - \delta_{\Delta,4}}{1 - \delta_{X,2}} \right)^2 < 1$$

and positive constants $C_{X,4}$, $C_{\Delta,4}$ such that

$$E(X_n - EX_n)^4 \leq C_{X,4}^4 \lambda_a^{4n} (1 + \delta_{X,4})^{4n},$$

$$E(\Delta_n - E\Delta_n)^4 \leq C_{\Delta,4}^4 \lambda_a^{4n} (1 - \delta_{\Delta,4})^{4n}.$$

Recall that the Wasserstein distance or L^1 -distance between two laws F and G is given by

$$\|F - G\|_1 = \int_{-\infty}^{\infty} |F(t) - G(t)| dt.$$

For any random variable X , the law or cumulative distribution function of X is denoted by $\mathcal{L}(X)$.

Theorem 1.3. [2] Under Conditions 1.1 and 1.2, there exist constants $C > 0$ and $\gamma \in (0, 1)$ such that

$$\left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(Z) \right\|_1 \leq C\gamma^n.$$

In this article, we extend the bounds to the case of two effects. Let $\{Z_n\}_{n=0}^{\infty}$ be a sequence of linear model with two effects given by

$$Z_n = X_n + Y_n \quad \text{for all } n \geq 0$$

where Y_0 is a non-degenerated random and for some integer $\ell \geq 2$,

$$Y_{n+1} = \sum_{j=1}^{\ell} b_{n,j} Y_{n,j} + \Lambda_n \quad \text{for all } n \geq 0$$

where $b_{n,1}, \dots, b_{n,\ell}$ are real numbers, $Y_{n,1}, \dots, Y_{n,\ell}$ are independent copy of the Y_n and Λ_n is a small perturbation. Note that the perturbations Δ_n and Λ_n always depend on X_n and Y_n , respectively. From now on, we assume that random variables from two models of recursions (X_n, Δ_n) and (Y_n, Λ_n) are independent for all $n \geq 0$, and denote

$$\lambda_n^2 = \sum_{i=1}^k a_{n,i}^2 + \sum_{j=1}^{\ell} b_{n,j}^2, \quad \text{Var}(Z_n) = \sigma_{X,n}^2 + \sigma_{Y,n}^2 = \sigma_n^2$$

and

$$\tilde{Z}_n = \frac{Z_n - EZ_n}{\sigma_n}.$$

The bound for linear recursions with two effects is derived by adding further assumption that the difference between variances of two models (X_n, Δ_n) , (Y_n, Λ_n) , is smaller than variances of perturbations, the following is our main theorem.

Theorem 1.4. *With constants $\delta_{X,2}, \delta_{X,4}, \delta_{\Delta,2}$ and $\delta_{Y,2}, \delta_{Y,4}, \delta_{\Lambda,2}$ as in Condition 1.1 and 1.2 for the models (X_n, Δ_n) and (Y_n, Λ_n) , suppose that*

$$\psi_{X,Y,\Lambda} = \frac{(1 - \delta_{\Lambda,2})(1 + \delta_{X,4})^3}{(1 - \delta_{Y,2})(1 - \delta_{X,2})^3} < 1 \quad \text{and} \quad \psi_{Y,X,\Delta} = \frac{(1 - \delta_{\Delta,2})(1 + \delta_{Y,4})^3}{(1 - \delta_{X,2})(1 - \delta_{Y,2})^3} < 1$$

and that

$$|\text{Var}(X_n) - \text{Var}(Y_n)| \leq \frac{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)}{\max\{\lambda_{a,n}^2, \lambda_{b,n}^2\}},$$

then there exist constants $C > 0$ and $\gamma \in (0, 1)$ such that

$$\left\| \mathcal{L}(\tilde{Z}_n) - \mathcal{L}(Z) \right\|_1 \leq C\gamma^n.$$

2 Auxiliary Results

Before proving the main theorem, we present some results for the models (X_n, Δ_n) and (Y_n, Λ_n) . For all $n \geq 0$, let

$$r_{X,n} = \frac{\lambda_n \sigma_{X,n}}{\sigma_{n+1}}, \quad r_{Y,n} = \frac{\lambda_n \sigma_{Y,n}}{\sigma_{n+1}}.$$

We begin with the bounds of $r_{X,n}$ and $r_{Y,n}$.

Lemma 2.1. *With constants $\delta_{X,2}$, $\delta_{\Delta,2}$ and $\delta_{Y,2}$, $\delta_{\Lambda,2}$ as in Condition 1.1 for the models (X_n, Δ_n) and (Y_n, Λ_n) , and suppose that*

$$|\text{Var}(X_n) - \text{Var}(Y_n)| \leq \frac{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)}{\max\{\lambda_{a,n}^2, \lambda_{b,n}^2\}},$$

then for an integer $p \geq 1$, there exists a positive constant $C_{r,p}$ such that

$$|r_{X,n}^p - 1| \leq C_{r,p} \left\{ \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \right\}$$

and

$$|r_{Y,n}^p - 1| \leq C_{r,p} \left\{ \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \right\}.$$

Proof. Following the argument of [7, Lemma 6], we consider the variances of linear model of recursions

$$\begin{aligned} \sigma_{n+1}^2 &= \text{Var}(Z_{n+1}) \\ &= \lambda_{a,n}^2 \text{Var}(X_n) + \lambda_{b,n}^2 \text{Var}(Y_n) + \text{Var}(\Delta_n) + \text{Var}(\Lambda_n) \\ &= \lambda_n^2 \sigma_{X,n}^2 + \lambda_{b,n}^2 \{\text{Var}(Y_n) - \text{Var}(X_n)\} + \text{Var}(\Delta_n) + \text{Var}(\Lambda_n), \end{aligned}$$

The triangle inequality yields

$$\begin{aligned} \sigma_{n+1} &\leq \lambda_n \sigma_{X,n} + \sqrt{\lambda_{b,n}^2 |\text{Var}(Y_n) - \text{Var}(X_n)|} + \sqrt{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)} \\ &\leq \lambda_n \sigma_{X,n} + 2 \sqrt{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)}. \end{aligned}$$

Also, we note that

$$\begin{aligned} \lambda_{a,n}^2 \sigma_{X,n}^2 &= \sigma_{n+1}^2 - \lambda_{b,n}^2 \{\text{Var}(Y_n) - \text{Var}(X_n)\} - \text{Var}(\Delta_n) - \text{Var}(\Lambda_n) \\ &\leq \sigma_{n+1}^2 + \lambda_{b,n}^2 |\text{Var}(Y_n) - \text{Var}(X_n)| + \text{Var}(\Delta_n) + \text{Var}(\Lambda_n), \end{aligned}$$

which implies that

$$\begin{aligned} \lambda_n \sigma_{X,n} &\leq \sigma_{n+1} + \sqrt{\lambda_{b,n}^2 |\text{Var}(Y_n) - \text{Var}(X_n)|} + \sqrt{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)} \\ &\leq \lambda_n \sigma_{X,n} + 2 \sqrt{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)}. \end{aligned}$$

Then there exists a constant $C_{r,1}$ such that

$$\begin{aligned}
|r_{X,n} - 1| &= \frac{|\lambda_n \sigma_{X,n} - \sigma_{n+1}|}{\sigma_{n+1}} \\
&\leq \frac{2\sqrt{\text{Var}(\Delta_n) + \text{Var}(\Lambda_n)}}{\sigma_{n+1}} \\
&\leq 2\sqrt{\frac{\text{Var}(\Delta_n)}{\text{Var}(X_{n+1})}} + 2\sqrt{\frac{\text{Var}(\Lambda_n)}{\text{Var}(Y_{n+1})}} \\
&\leq \frac{2C_{\Delta,2}(1 - \delta_{\Delta,2})^n}{C_{X,2}\lambda_a(1 - \delta_{X,2})^{n+1}} + \frac{2C_{\Lambda,2}(1 - \delta_{\Lambda,2})^n}{C_{Y,2}\lambda_b(1 - \delta_{Y,2})^{n+1}} \\
&\leq C_{r,1} \left\{ \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \right\}.
\end{aligned}$$

Now, since

$$|r^p - 1| = |(r - 1 + 1)^p - 1| \leq \sum_{j=1}^p \binom{p}{j} |r - 1|^j$$

and the assumption that $0 < \delta_{X,2} < \delta_{\Delta,2} < 1$ and $0 < \delta_{Y,2} < \delta_{\Lambda,2} < 1$, there are constants $C_{r,p}$ such that

$$|r_{X,n}^p - 1| \leq C_{r,p} \left\{ \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \right\}$$

and similarly, we can see that

$$|r_{Y,n}^p - 1| \leq C_{r,p} \left\{ \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \right\}$$

for all $p = 1, 2, 3, \dots$. □

For all $n \geq 0$, let

$$U_n = U_{X,n} + U_{Y,n}$$

where

$$U_{X,n+1} = \sum_{i=1}^k \frac{a_{n,i}}{\lambda_n} \left(\frac{X_{n,i} - EX_{n,i}}{\sigma_{X,n}} \right) \quad \text{and} \quad U_{Y,n+1} = \sum_{j=1}^{\ell} \frac{b_{n,j}}{\lambda_n} \left(\frac{Y_{n,j} - EY_{n,j}}{\sigma_{Y,n}} \right).$$

Next, we follow the proof of [1, Lemma 4.1] to prepare an inequality for the Wasserstein distance between laws of U_n and its zero bias transformation.

Lemma 2.2. For all integers $n \geq 1$ and the zero bias transformation U_n^* , \tilde{X}_n^* , \tilde{Y}_n^* of the U_n , \tilde{X}_n , \tilde{Y}_n , respectively, we have

$$\|\mathcal{L}(U_n) - \mathcal{L}(U_n^*)\|_1 \leq \|\mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*)\|_1 + \|\mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*)\|_1.$$

Proof. Set $m = k + \ell$. Let

$$\xi_i = \begin{cases} (X_{n,i} - EX_{n,i}) / \sigma_{X,n} & \text{for } i = 1, \dots, k \\ (Y_{n,i-k} - EY_{n,i-k}) / \sigma_{Y,n} & \text{for } i = k + 1, \dots, m \end{cases}$$

and

$$\alpha_{n,i} = \begin{cases} a_{n,i} & \text{for } i = 1, \dots, k \\ b_{n,i-k} & \text{for } i = k + 1, \dots, m. \end{cases}$$

Note that U_{n+1} is a sum of independent random variables and can be written as

$$U_{n+1} = \sum_{i=1}^m \frac{\alpha_{n,i}}{\lambda_n} \xi_i.$$

Let I be a random index independent of all other variables and satisfying that

$$P(I = i) = \frac{\alpha_{n,i}^2}{\lambda_n^2} \quad \text{for } i = 1, \dots, m.$$

By the result of [1, Lemma 2.8], the random variable

$$U_{n+1}^* = U_{n+1} - \frac{\alpha_{n,I}}{\lambda_n} (\xi_I^* - \xi_I)$$

has the U_{n+1} -zero biased distribution. By taking the dual form of the L^1 -distance discussed in [5], we can see that

$$\|\mathcal{L}(U_{n+1}) - \mathcal{L}(U_{n+1}^*)\|_1 = \inf E |X - Y| \leq E |U_{n+1} - U_{n+1}^*|$$

where the infimum is taken over all coupling of X and Y having the joint distribution with $\mathcal{L}(U_{n+1})$ and its zero bias distribution.

Let V_1, \dots, V_m be independent uniformly distributed random variables on $[0, 1]$. For $i = 1, \dots, m$, let ξ_i^* be the zero bias transformation of ξ_i . Let F_ξ and F_{ξ^*} be the distribution functions of ξ and ξ^* , respectively. Set

$$(\xi_i, \xi_i^*) = (F_{\xi_i}^{-1}(V_i), F_{\xi_i^*}^{-1}(V_i)) \quad \text{for all } i = 1, \dots, m.$$

By the results of [5], we obtain that

$$E |\xi_i - \xi_i^*| = \begin{cases} \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 & \text{for } i = 1, \dots, k \\ \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1 & \text{for } i = k+1, \dots, m. \end{cases}$$

Now, we obtain

$$\begin{aligned} & \left\| \mathcal{L}(U_{n+1}) - \mathcal{L}(U_{n+1}^*) \right\|_1 \\ & \leq E |U_{n+1} - U_{n+1}^*| \\ & = E \sum_{i=1}^m \frac{|\alpha_{n,i}|}{\lambda_n} |\xi_i - \xi_i^*| \mathbf{1}(I=i) \\ & = \sum_{i=1}^m \frac{|\alpha_{n,i}|^3}{\lambda_n^3} E |\xi_i - \xi_i^*| \\ & = \sum_{i=1}^k \frac{|\alpha_{n,i}|^3}{\lambda_n^3} \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 + \sum_{j=1}^{\ell} \frac{|b_{n,j}|^3}{\lambda_n^3} \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1 \\ & = \frac{\lambda_{a,n}^3 \varphi_{a,n}}{\lambda_n^3} \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 + \frac{\lambda_{b,n}^3 \varphi_{b,n}}{\lambda_n^3} \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1 \\ & \leq \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 + \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1. \end{aligned}$$

□

3 Proof of Main Theorem

Proof of Theorem 1.4. By the results of [1, Theorem 4.1], we can calculate the bound on L^1 -distance by using the zero bias transformation as follows

$$\left\| \mathcal{L}(\tilde{Z}_n) - \mathcal{L}(Z) \right\|_1 \leq 2 \left\| \mathcal{L}(\tilde{Z}_n) - \mathcal{L}(\tilde{Z}_n^*) \right\|_1. \quad (3.1)$$

Moreover, we can use equivalent forms of the L^1 -distance found in [5] and given by

$$\left\| \mathcal{L}(\tilde{Z}_n) - \mathcal{L}(\tilde{Z}_n^*) \right\|_1 = \sup_{h \in \mathfrak{Lip}} |Eh(\tilde{Z}_n) - Eh(\tilde{Z}_n^*)| = \sup_{f \in \mathfrak{F}_{ac}} |Ef'(\tilde{Z}_n) - Ef'(\tilde{Z}_n^*)|$$

where $\mathfrak{Lip} = \{h: \mathbb{R} \rightarrow \mathbb{R} : |h(x) - h(y)| \leq |x - y| \text{ for all } x, y \in \mathbb{R}\}$

and $\mathfrak{F}_{ac} = \{f: \mathbb{R} \rightarrow \mathbb{R} : f \text{ is absolutely continuous, } f(0) = f'(0) = 0, f' \in \mathfrak{Lip}\}.$

Now, we present some facts about the Stein's method for normal approximation. For each $f \in \mathcal{F}$, define $h: \mathbb{R} \rightarrow \mathbb{R}$ by

$$h(w) = f'(w) - wf(w).$$

By the characterization of normal distribution, $Eh(Z) = 0$. Also, we observe that

$$|h'(w)| = |f''(w) - wf'(w) - f(w)| \leq 1 + w^2 + \frac{w^2}{2}$$

and hence

$$|h(w) - h(u)| = \left| \int_u^w h'(t) dt \right| \leq |w - u| + \frac{1}{2} |w^3 - u^3|.$$

From the definition of zero bias transformation and that $\text{Var}(\tilde{Z}_{n+1}) = 1$, we have

$$\begin{aligned} & \left| Ef'(\tilde{Z}_{n+1}) - Ef'(\tilde{Z}_{n+1}^*) \right| \\ &= \left| Ef'(\tilde{Z}_{n+1}) - E\tilde{Z}_{n+1}f(\tilde{Z}_{n+1}) \right| \\ &= \left| Eh(\tilde{Z}_{n+1}) \right| \\ &\leq \left| Eh(\tilde{Z}_{n+1}) - Eh(U_{n+1}) \right| + |Eh(U_{n+1})| \\ &\leq E \left| \tilde{Z}_{n+1} - U_{n+1} \right| + \frac{1}{2} E \left| \tilde{Z}_{n+1}^3 - U_{n+1}^3 \right| + |Eh(U_{n+1})| \\ &= \beta_n + \left| Ef'(U_{n+1}) - Ef'(U_{n+1}^*) \right| \\ &\leq \beta_n + \left\| \mathcal{L}(U_{n+1}) - \mathcal{L}(U_{n+1}^*) \right\|_1 \\ &\leq \beta_n + \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 + \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1 \end{aligned} \quad (3.2)$$

where we apply Lemma 2.2 in the last inequality and denote for all $n \geq 0$,

$$\beta_n = E \left| \tilde{Z}_{n+1} - U_{n+1} \right| + \frac{1}{2} E \left| \tilde{Z}_{n+1}^3 - U_{n+1}^3 \right|. \quad (3.3)$$

By (3.1) and taking the supremum of (3.2) over $f \in \mathfrak{F}_{ac}$, we obtain

$$\begin{aligned} \left\| \mathcal{L}(\tilde{Z}_{n+1}) - \mathcal{L}(Z) \right\|_1 &\leq 2 \left\| \mathcal{L}(\tilde{Z}_{n+1}) - \mathcal{L}(\tilde{Z}_{n+1}^*) \right\|_1 \\ &\leq 2\beta_n + 2 \left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 + 2 \left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1. \end{aligned}$$

Applying the Condition 1.1 and 1.2 for the models (X_n, Δ_n) and (Y_n, Λ_n) in Theorem 1.3, there exist positive constants $C_{X,a,\Delta}$, $C_{Y,b,\Lambda}$ and $\gamma_{X,a,\Delta} \in (0, 1)$, $\gamma_{Y,b,\Lambda} \in (0, 1)$ such that for all $n \geq 0$,

$$\left\| \mathcal{L}(\tilde{X}_n) - \mathcal{L}(\tilde{X}_n^*) \right\|_1 \leq C_{X,a,\Delta} (\gamma_{X,a,\Delta})^n$$

and

$$\left\| \mathcal{L}(\tilde{Y}_n) - \mathcal{L}(\tilde{Y}_n^*) \right\|_1 \leq C_{Y,b,\Lambda} (\gamma_{Y,b,\Lambda})^n.$$

We remain to show that $\beta_n \leq C_\beta \gamma_\beta^n$ for some $C_\beta > 0$ and $\gamma_\beta \in (0, 1)$ and the proof is completed by choosing $C = C_{X,a,\Delta} + C_{Y,b,\Lambda} + C_\beta$ and $\gamma = \max \{ \gamma_{X,a,\Delta}, \gamma_{Y,b,\Lambda}, \gamma_\beta \}$.

Recalling the definition of $r_{X,n}$, $r_{Y,n}$ and $U_{X,n}$, $U_{Y,n}$ in Lemma 2.1 and 2.2, respectively, the linear model of recursions can be written as

$$\begin{aligned} \tilde{Z}_{n+1} &= \frac{Z_{n+1} - EZ_{n+1}}{\sigma_{n+1}} \\ &= \frac{X_{n+1} - EX_{n+1}}{\sigma_{n+1}} + \frac{Y_{n+1} - EY_{n+1}}{\sigma_{n+1}} \\ &= \frac{\sigma_{X,n}}{\sigma_{n+1}} \left\{ \sum_{i=1}^k a_{n,i} \left(\frac{X_{n,i} - EX_{n,i}}{\sigma_{X,n}} \right) + \frac{\Delta_n - E\Delta_n}{\sigma_{X,n}} \right\} \\ &\quad + \frac{\sigma_{Y,n}}{\sigma_{n+1}} \left\{ \sum_{j=1}^\ell b_{n,j} \left(\frac{Y_{n,j} - EY_{n,j}}{\sigma_{Y,n}} \right) + \frac{\Lambda_n - E\Lambda_n}{\sigma_{Y,n}} \right\} \\ &= r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1} + \Gamma_n \end{aligned}$$

where $\Gamma_n = \Gamma_{X,\Delta,n} + \Gamma_{Y,\Lambda,n}$,

$$\Gamma_{X,\Delta,n} = \frac{\sigma_{X,n}}{\sigma_{n+1}} \left(\frac{\Delta_n - E\Delta_n}{\sigma_{X,n}} \right) \quad \text{and} \quad \Gamma_{Y,\Lambda,n} = \frac{\sigma_{Y,n}}{\sigma_{n+1}} \left(\frac{\Lambda_n - E\Lambda_n}{\sigma_{Y,n}} \right).$$

Using Conditions 1.1 and 1.2 for the models (X_n, Δ_n) and (Y_n, Λ_n) , the result of [7, Lemma 6] gives that the limits

$$\lim_{n \rightarrow \infty} \frac{\sigma_{X,n}}{\lambda_{a,0} \dots \lambda_{a,n-1}} \quad \text{and} \quad \lim_{n \rightarrow \infty} \frac{\sigma_{Y,n}}{\lambda_{b,0} \dots \lambda_{b,n-1}}$$

exist in $(0, 1)$, so we have

$$\lim_{n \rightarrow \infty} \frac{\sigma_{X,n+1}}{\sigma_{X,n}} = \lambda_a \quad \text{and} \quad \lim_{n \rightarrow \infty} \frac{\sigma_{Y,n+1}}{\sigma_{Y,n}} = \lambda_b.$$

Therefore, there exist positive constants $C_{\Gamma,X,\Delta,2}$ and $C_{\Gamma,Y,\Lambda,2}$ such that

$$\begin{aligned} E\Gamma_{X,\Delta,n}^2 &\leq \left(\frac{\sigma_{X,n}}{\sigma_{X,n+1}} \right)^2 \frac{\text{Var}(\Delta_n)}{\text{Var}(X_n)} \leq C_{\Gamma,X,\Delta,2}^2 \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^{2n} \\ E\Gamma_{Y,\Lambda,n}^2 &\leq \left(\frac{\sigma_{Y,n}}{\sigma_{Y,n+1}} \right)^2 \frac{\text{Var}(\Lambda_n)}{\text{Var}(Y_n)} \leq C_{\Gamma,Y,\Lambda,2}^2 \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^{2n}. \end{aligned}$$

Moreover, there exist positive constants $C_{\Gamma,X,\Delta,4}$ and $C_{\Gamma,Y,\Lambda,4}$ such that

$$E\Gamma_{X,\Delta,n}^4 \leq \left(\frac{\sigma_{X,n}}{\sigma_{X,n+1}} \right)^4 E \left(\frac{\Delta_n - E\Delta_n}{\sigma_{X,n}} \right)^4 \leq C_{\Gamma,X,\Delta,4}^4 \left(\frac{1 - \delta_{\Delta,4}}{1 - \delta_{X,2}} \right)^{4n}$$

$$E\Gamma_{Y,\Lambda,n}^4 \leq \left(\frac{\sigma_{Y,n}}{\sigma_{Y,n+1}} \right)^4 E \left(\frac{\Lambda_n - E\Lambda_n}{\sigma_{Y,n}} \right)^4 \leq C_{\Gamma,Y,\Lambda,4}^4 \left(\frac{1 - \delta_{\Lambda,4}}{1 - \delta_{Y,2}} \right)^{4n}.$$

By independence for $X_{n,i}$'s and $Y_{n,j}$'s, there exist positive constants $C_{U,X}$ and $C_{U,Y}$ such that

$$\begin{aligned} EU_{X,n+1}^2 &= \frac{\lambda_{a,n}^2}{\lambda_n^2} E \left(\frac{X_n - EX_n}{\sigma_{X,n}} \right)^2 \leq 1 \\ EU_{Y,n+1}^2 &= \frac{\lambda_{b,n}^2}{\lambda_n^2} E \left(\frac{Y_n - EY_n}{\sigma_{Y,n}} \right)^2 \leq 1 \\ EU_{X,n+1}^4 &\leq 8 \sum_{i=1}^k \frac{a_{n,i}^4}{\lambda_n^4} E \left(\frac{X_n - EX_n}{\sigma_{X,n}} \right)^4 \leq C_{U,X}^4 \left(\frac{1 + \delta_{X,4}}{1 - \delta_{X,2}} \right)^{4n} \\ EU_{Y,n+1}^4 &\leq 8 \sum_{j=1}^{\ell} \frac{b_{n,j}^4}{\lambda_n^4} E \left(\frac{Y_n - EY_n}{\sigma_{Y,n}} \right)^4 \leq C_{U,Y}^4 \left(\frac{1 + \delta_{Y,4}}{1 - \delta_{Y,2}} \right)^{4n}. \end{aligned}$$

From Lemma 2.1 and Condition 1.1 and 1.2, the following results will be often used for all $n \geq 0$ and $p = 1, 2, 3$,

$$|r_{X,n}^p - 1| \leq C_{r,p} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) \quad (3.4)$$

$$|r_{Y,n}^p - 1| \leq C_{r,p} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n). \quad (3.5)$$

Now, considering the first term of β_n in (3.3),

$$\begin{aligned} &E |\tilde{Z}_{n+1} - U_{n+1}| \\ &= E |(r_{X,n} - 1) U_{X,n+1} + (r_{Y,n} - 1) U_{Y,n+1} + \Gamma_{X,\Delta,n} + \Gamma_{Y,\Lambda,n}| \\ &\leq |r_{X,n} - 1| \sqrt{EU_{X,n+1}^2} + |r_{Y,n} - 1| \sqrt{EU_{Y,n+1}^2} + \sqrt{E\Gamma_{X,\Delta,n}^2} + \sqrt{E\Gamma_{Y,\Lambda,n}^2} \\ &\leq 2C_{r,1} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) + C_{\Gamma,X,\Delta,2} \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + C_{\Gamma,Y,\Lambda,2} \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \\ &\leq C_0 (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n). \end{aligned}$$

For the second term of β_n ,

$$\begin{aligned}
& E \left| \tilde{Z}_{n+1}^3 - U_{n+1}^3 \right| \\
&= E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1} + \Gamma_n)^3 - U_{n+1}^3 \right| \\
&= E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1})^3 + 3(r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1})^2 \Gamma_n \right. \\
&\quad \left. + 3(r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1}) \Gamma_n^2 + \Gamma_n^3 - U_{n+1}^3 \right| \\
&\leq E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1})^3 - U_{n+1}^3 \right| + 3E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1})^2 \Gamma_n \right| \\
&\quad + 3E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1}) \Gamma_n^2 \right| + E \left| \Gamma_n \right|^3 \\
&:= A_1 + A_2 + A_3 + A_4.
\end{aligned}$$

Notice that

$$\begin{aligned}
A_1 &= E \left| (r_{X,n} U_{X,n+1} + r_{Y,n} U_{Y,n+1})^3 - (U_{X,n+1} + U_{Y,n+1})^3 \right| \\
&= E \left| (r_{X,n}^3 - 1) U_{X,n+1}^3 + 3(r_{X,n}^2 r_{Y,n} - 1) U_{X,n+1}^2 U_{Y,n+1} \right. \\
&\quad \left. + 3(r_{X,n} r_{Y,n}^2 - 1) U_{X,n+1} U_{Y,n+1}^2 + (r_{Y,n}^3 - 1) U_{Y,n+1}^3 \right| \\
&\leq E \left| (r_{X,n}^3 - 1) U_{X,n+1}^3 \right| + 3E \left| (r_{X,n}^2 r_{Y,n} - r_{Y,n} + r_{Y,n} - 1) U_{X,n+1}^2 U_{Y,n+1} \right| \\
&\quad + 3E \left| (r_{X,n} r_{Y,n}^2 - r_{X,n} + r_{X,n} - 1) U_{X,n+1} U_{Y,n+1}^2 \right| + E \left| (r_{Y,n}^3 - 1) U_{Y,n+1}^3 \right| \\
&\leq E \left| (r_{X,n}^3 - 1) U_{X,n+1}^3 \right| + E \left| (r_{Y,n}^3 - 1) U_{Y,n+1}^3 \right| \\
&\quad + 3E \left| (r_{X,n}^2 - 1) r_{Y,n} U_{X,n+1}^2 U_{Y,n+1} \right| + 3E \left| (r_{Y,n} - 1) U_{X,n+1}^2 U_{Y,n+1} \right| \\
&\quad + 3E \left| (r_{Y,n}^2 - 1) r_{X,n} U_{X,n+1} U_{Y,n+1}^2 \right| + 3E \left| (r_{X,n} - 1) U_{X,n+1} U_{Y,n+1}^2 \right| \\
&\leq |r_{X,n}^3 - 1| (E U_{X,n}^4)^{3/4} + |r_{Y,n}^3 - 1| (E U_{Y,n}^4)^{3/4} \\
&\quad + 3|r_{X,n}^2 - 1| r_{Y,n} E U_{X,n}^2 \sqrt{E U_{Y,n}^2} + 3r_{X,n} |r_{Y,n}^2 - 1| \sqrt{E U_{X,n}^2} E U_{Y,n}^2 \\
&\quad + 3|r_{Y,n} - 1| E U_{X,n}^2 \sqrt{E U_{Y,n}^2} + 3|r_{X,n} - 1| \sqrt{E U_{X,n}^2} E U_{Y,n}^2 \\
&\leq 8^{3/4} C_{r,3} C_{X,4}^3 \left\{ \left(\frac{(1 - \delta_{\Delta,2})(1 + \delta_{X,4})^3}{(1 - \delta_{X,2})^4} \right)^n + \left(\frac{(1 - \delta_{\Lambda,2})(1 + \delta_{X,4})^3}{(1 - \delta_{Y,2})(1 - \delta_{X,2})^3} \right)^n \right\} \\
&\quad + 8^{3/4} C_{r,3} C_{Y,4}^3 \left\{ \left(\frac{(1 - \delta_{\Delta,2})(1 + \delta_{Y,4})^3}{(1 - \delta_{X,2})(1 - \delta_{Y,2})^3} \right)^n + \left(\frac{(1 - \delta_{\Lambda,2})(1 + \delta_{Y,4})^3}{(1 - \delta_{Y,2})^4} \right)^n \right\} \\
&\quad + 6C_{r,2} (1 + 2C_{r,1}) (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) + 6C_{r,1} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) \\
&\leq C_1 (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n + \psi_{X,Y,\Lambda}^n + \psi_{Y,X,\Delta}^n).
\end{aligned}$$

As a special case of (3.4) and (3.5) when $p = 1$, we can see that for all $n \geq 0$

$$r_{X,n} \leq 1 + C_{r,1} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) \leq 1 + 2C_{r,1}$$

$$r_{Y,n} \leq 1 + C_{r,1} (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) \leq 1 + 2C_{r,1}.$$

So, we have that

$$\begin{aligned} A_2 &= 3E \left| (r_{X,n}U_{X,n+1} + r_{Y,n}U_{Y,n+1})^2 (\Gamma_{X,\Delta,n} + \Gamma_{Y,\Lambda,n}) \right| \\ &\leq 6E \left| (r_{X,n}^2U_{X,n+1}^2 + r_{Y,n}^2U_{Y,n+1}^2) (\Gamma_{X,\Delta,n} + \Gamma_{Y,\Lambda,n}) \right| \\ &\leq 6r_{X,n}^2 \sqrt{EU_{X,n+1}^4 E\Gamma_{X,\Delta,n}^2} + 6r_{X,n}^2 EU_{X,n+1}^2 \sqrt{E\Gamma_{Y,\Lambda,n}^2} \\ &\quad + 6r_{Y,n}^2 EU_{Y,n+1}^2 \sqrt{E\Gamma_{X,\Delta,n}^2} + 6r_{Y,n}^2 \sqrt{EU_{Y,n+1}^4 E\Gamma_{Y,\Lambda,n}^2} \\ &\leq 12\sqrt{2} (1 + C_{r,1})^2 C_{U,X}^2 C_{\Gamma,X,\Delta,2} \left(\frac{(1 - \delta_{\Delta,2})(1 + \delta_{X,4})^3}{(1 - \delta_{X,2})^4} \right)^n \\ &\quad + 6(1 + C_{r,1})^2 C_{\Gamma,X,\Delta,2} \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^n + 6(1 + C_{r,1})^2 C_{\Gamma,Y,\Lambda,2} \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^n \\ &\quad + 12\sqrt{2} (1 + C_{r,1})^2 C_{U,Y}^2 C_{\Gamma,Y,\Lambda,2} \left(\frac{(1 - \delta_{\Lambda,2})(1 + \delta_{Y,4})^3}{(1 - \delta_{Y,2})^4} \right)^n \\ &\leq C_2 (\phi_{X,\Delta,2}^n + \phi_{Y,\Lambda,2}^n) \end{aligned}$$

and that

$$\begin{aligned} A_3 &= 3E \left| (r_{X,n}U_{X,n+1} + r_{Y,n}U_{Y,n+1}) (\Gamma_{X,\Delta,n} + \Gamma_{Y,\Lambda,n})^2 \right| \\ &\leq 6E \left| (r_{X,n}U_{X,n+1} + r_{Y,n}U_{Y,n+1}) (\Gamma_{X,\Delta,n}^2 + \Gamma_{Y,\Lambda,n}^2) \right| \\ &\leq 6r_{X,n} \sqrt{EU_{X,n+1}^2 E\Gamma_{X,\Delta,n}^4} + 6r_{X,n} \sqrt{EU_{X,n+1}^2 E\Gamma_{Y,\Lambda,n}^2} \\ &\quad + 6r_{Y,n} \sqrt{EU_{Y,n+1}^2 E\Gamma_{X,\Delta,n}^2} + 6r_{Y,n} \sqrt{EU_{Y,n+1}^2 E\Gamma_{Y,\Lambda,n}^4} \\ &\leq 6(1 + C_{r,1}) (C_{\Gamma,X,\Delta,4}^2 + C_{\Gamma,X,\Delta,2}^2) \left(\frac{1 - \delta_{\Delta,2}}{1 - \delta_{X,2}} \right)^{2n} \\ &\quad + 6(1 + C_{r,1}) (C_{\Gamma,Y,\Lambda,2}^2 + C_{\Gamma,Y,\Lambda,4}^2) \left(\frac{1 - \delta_{\Lambda,2}}{1 - \delta_{Y,2}} \right)^{2n} \\ &\leq C_3 (\phi_{X,\Delta,2}^{2n} + \phi_{Y,\Lambda,2}^{2n}). \end{aligned}$$

Lastly,

$$\begin{aligned}
A_4 &\leq (E\Gamma_n^4)^{3/4} \\
&\leq 8^{3/4} (E\Gamma_{X,\Delta,n}^4 + E\Gamma_{Y,\Lambda,n}^4)^{3/4} \\
&\leq 8^{3/4} \left\{ C_{\Gamma,X,\Delta,4}^4 \left(\frac{1-\delta_{\Delta,4}}{1-\delta_{X,2}} \right)^{4n} + C_{\Gamma,Y,\Lambda,4}^4 \left(\frac{1-\delta_{\Lambda,4}}{1-\delta_{Y,2}} \right)^{4n} \right\}^{3/4} \\
&\leq C_4 (\phi_{X,\Delta,4}^{3n/2} + \phi_{Y,\Lambda,4}^{3n/2}).
\end{aligned}$$

Setting $\gamma_\beta = \max \{ \phi_{X,\Delta,2}, \phi_{Y,\Lambda,2}, \phi_{X,\Delta,4}^{3/2}, \phi_{Y,\Lambda,4}^{3/2}, \psi_{X,Y,\Lambda}, \phi_{Y,X,\Delta} \} \in (0, 1)$ and $C_\beta = 2C_0 + 4C_1 + 2C_2 + 2C_3 + 2C_4$, we obtain the claim for β_n . \square

References

- [1] L.H.Y. Chen, L. Goldstein, and Q-M. Shao, *Normal Approximation by Steins Method*, Springer Berlin Heidelberg, 2010.
- [2] L. Goldstein, Normal approximation for hierarchical structures, *Ann. Appl. Probab.*, **14**(2004), 1950–1969.
- [3] J. Jordan, Almost sure convergence for iterated functions of independent random variables, *Ann. Appl. Probab.*, **12**(2002), 985–1000.
- [4] D.L. Li and T.D. Rogers, Asymptotic behavior for iterated functions of random variables, *Ann. Appl. Probab.*, **9**(1999), 1175–1201.
- [5] S. Rachev, The Monge-Kantorovich mass transference problem and its stochastic applications. *Theory Probab. Appl.*, **29**(1984), 647–676.
- [6] J. Wehr, A strong law of large numbers for iterated functions of independent random variables, *J. Stat. Phys.*, **86**(1997), 1373–1384.
- [7] J. Wehr and J.M. Woo, Central limit theorems for nonlinear hierarchical sequences of random variables, *J. Stat. Phys.*, *Journal of Statistical Physics*, **104**(2001), 777–797.

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