

# Online Supplementary Material to “Trend Extraction from Economic Time Series with Missing Observations by Generalized Hodrick–Prescott Filters”<sup>\*</sup>

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## B.1 Introduction

This document provides online supplementary material to Yamada (2021). In Section B.2, the Matlab user-defined functions referred to in Yamada (2021) are provided. Section B.3 presents the figures referred to in Section 5 of Yamada (2021). Note that the equation numbers referred to in this document are the same as those in Yamada (2021).

## B.2 Matlab functions

In this section, we provide five Matlab user-defined functions. We note that among such functions, `calcxhat_nast` requires CVX, a package for specifying and solving convex programs (CVX Research, Inc., 2011; Grant and Boyd, 2008).

### B.2.1 A function to make $D_n$ in (6)

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```

1 function D_n=makeD_n(tau_n)
2     n=length(tau_n);
3     D1=diff(eye(n));
4     D2=D1(1:n-2,1:n-1);
5     invDelta=diag(ones(n-1,1)./diff(tau_n));
6     D_n=D2*invDelta*D1;
7 end

```

### B.2.2 A function to calculate $\hat{x}_n$ in (8)

```

1 function xhat_n=calcxhat_n(tau_n,y_n,lambda_n)
2     D_n=makeD_n(tau_n);
3     n=length(tau_n);
4     xhat_n=(eye(n)+lambda_n*D_n'*D_n)\y_n;
5 end

```

### B.2.3 A function to calculate the solution of the convex problem given by (26)–(27)

```

1 function xhat_nast=calcxhat_nast(tau_n,y_n,c)
2     D_n=makeD_n(tau_n);
3     n=length(tau_n);
4     cvx_clear
5     cvx_begin
6         variables xhat_nast(n)
7         minimize(sum((D_n*xhat_nast).^2))
8         subject to
9             sum((y_n-xhat_nast).^2)<=c
10    cvx_end
11 end

```

### B.2.4 A function to calculate $\hat{x}_T$ in (11) and $S\hat{x}_T$ in (12)

```

1 function [xhat_T,Sxhat_T]=calcxhat_T(tau_n,y_n,lambda_T)
2     T=tau_n(end);

```

```

3   I=eye(T);
4   D_T=diff(I,2);
5   S=I(tau_n,:);
6   xhat_T=(S'*S+lambda_T*D_T'*D_T)\(S'*y_n);
7   Sxhat_T=S*xhat_T;
8   end

```

### B.2.5 A function to calculate $\hat{\psi}$ in (A.38) and $\hat{\phi}$ in (A.42)

```

1   function [psihat,phihat]=calcxhat_T2(tau_n,y_n,lambda_T)
2   T=tau_n(end);
3   n=length(tau_n);
4   I_T=eye(T);
5   I_n=eye(n);
6   D_T=diff(I_T,2);
7   tau_n_c=setdiff((1:T)',tau_n);
8   S=I_T(tau_n,:);
9   S_p=I_T(tau_n_c,:);
10  R=eye(T-2)-D_T*S_p'*inv(S_p*D_T'*D_T*S_p')*S_p*D_T';
11  F=R*D_T*S';
12  psihat=(I_n+lambda_T*F'*F)\y_n;
13  phihat=-inv(S_p*D_T'*D_T*S_p')*S_p*D_T'*D_T*S'*psihat;
14  end

```

## B.3 Figures

In this section, we present the figures referred to in Section 5 of Yamada (2021). Figures B.1–B.5 correspond to the case where  $n = 90$ . Likewise, Figures B.6–B.10 (resp. Figures B.11–B.15) correspond to the case where  $n = 50$  (resp.  $n = 30$ ). Recall that Figures 5–9 in Yamada (2021) correspond to the case where  $n = 70$ .

From the figures in this material, we may confirm that the results shown in Yamada (2021) are also observable even for  $n = 90, 50, 30$ . For example, we may observe that  $\hat{\boldsymbol{x}}_n$  and  $\boldsymbol{S}\hat{\boldsymbol{x}}_T$  are almost the same. Nevertheless, we remark

that the deviations between the  $\text{gHP}_T$  filter and the HP filter increase as  $n/T$  decreases. See Figure 9 in Yamada (2021) and Figures B.5, B.10, and B.15 in this material.

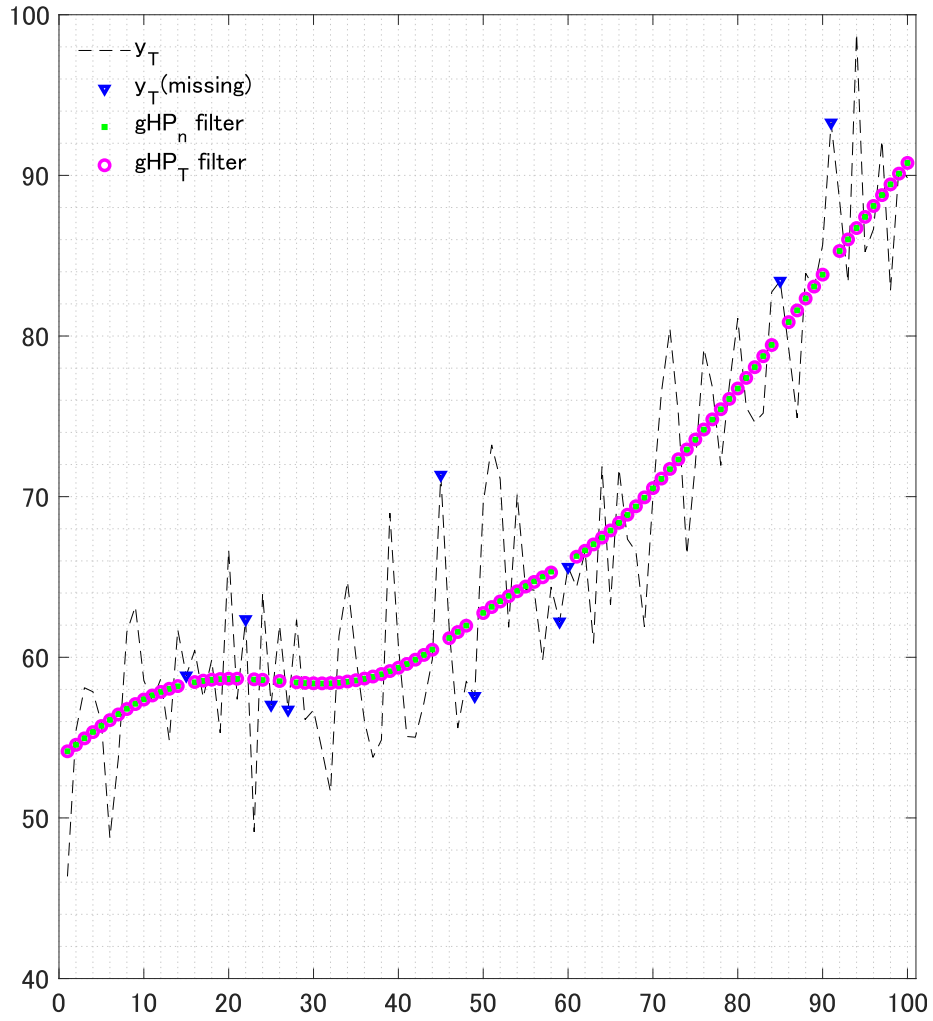


Figure B.1: For the explanation of  $y_T$ , see Figure 5 in Yamada (2021).  $y_T(\text{missing})$  denotes 10(= 100 - 90) missing observations selected randomly from  $\{y_2, \dots, y_{T-1}\}$ .  $\text{gHP}_n$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$ .  $\text{gHP}_T$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 1491.99$ , which is specified so that  $\|y_n - \hat{x}_n\|^2 = \|y_n - S\hat{x}_T\|^2$ .

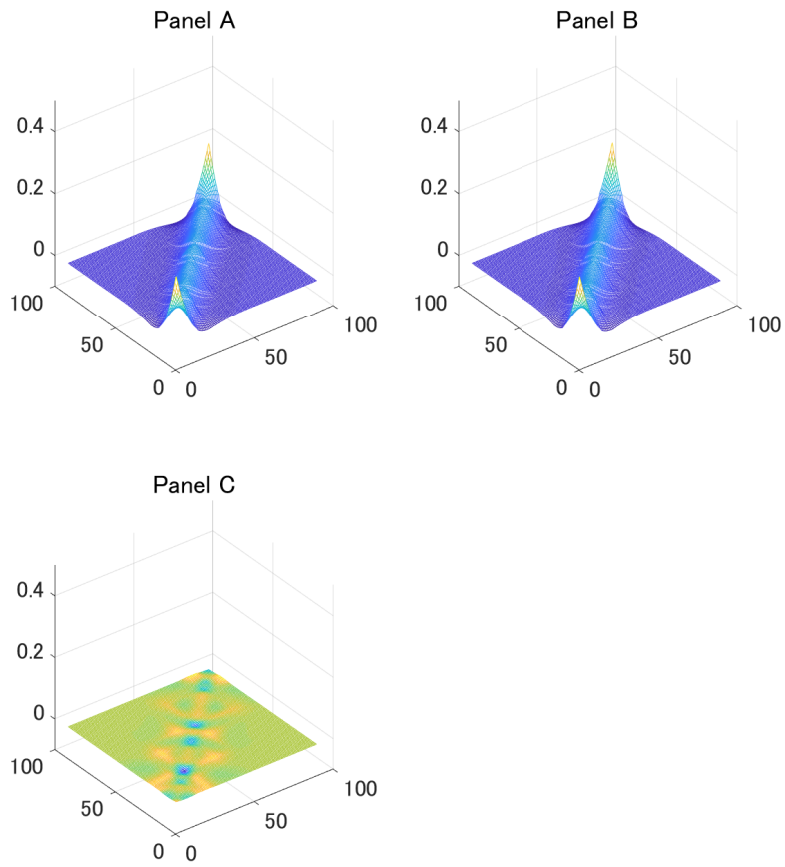


Figure B.2: Panel A (resp. Panel B) plots the smoother matrix corresponding to  $\hat{\mathbf{x}}_n$  (resp.  $\mathbf{S}\hat{\mathbf{x}}_T$ ) in Figure B.1. Panel C plots their difference.

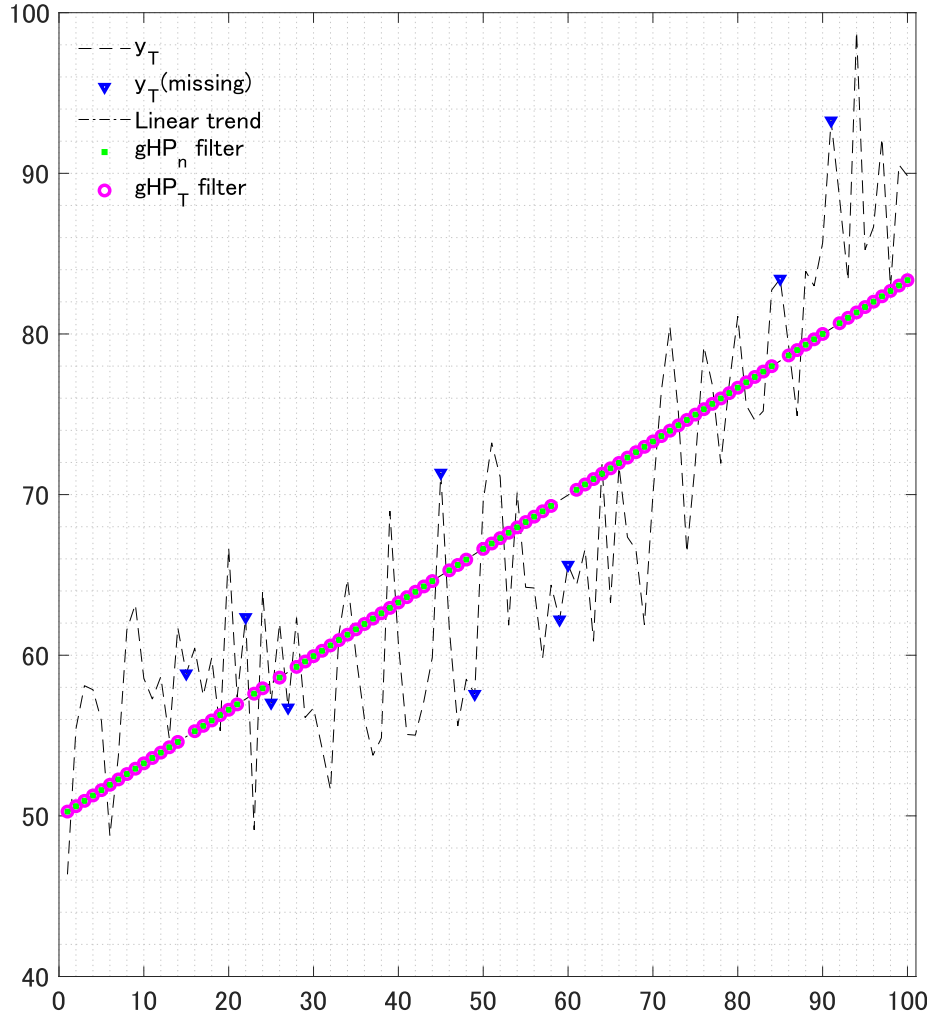


Figure B.3: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.1.  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^8$  and  $\text{gHP}_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^8$ . Linear trend denotes  $Py_n [= \Pi_n(\Pi_n' \Pi_n)^{-1} \Pi_n' y_n]$ .

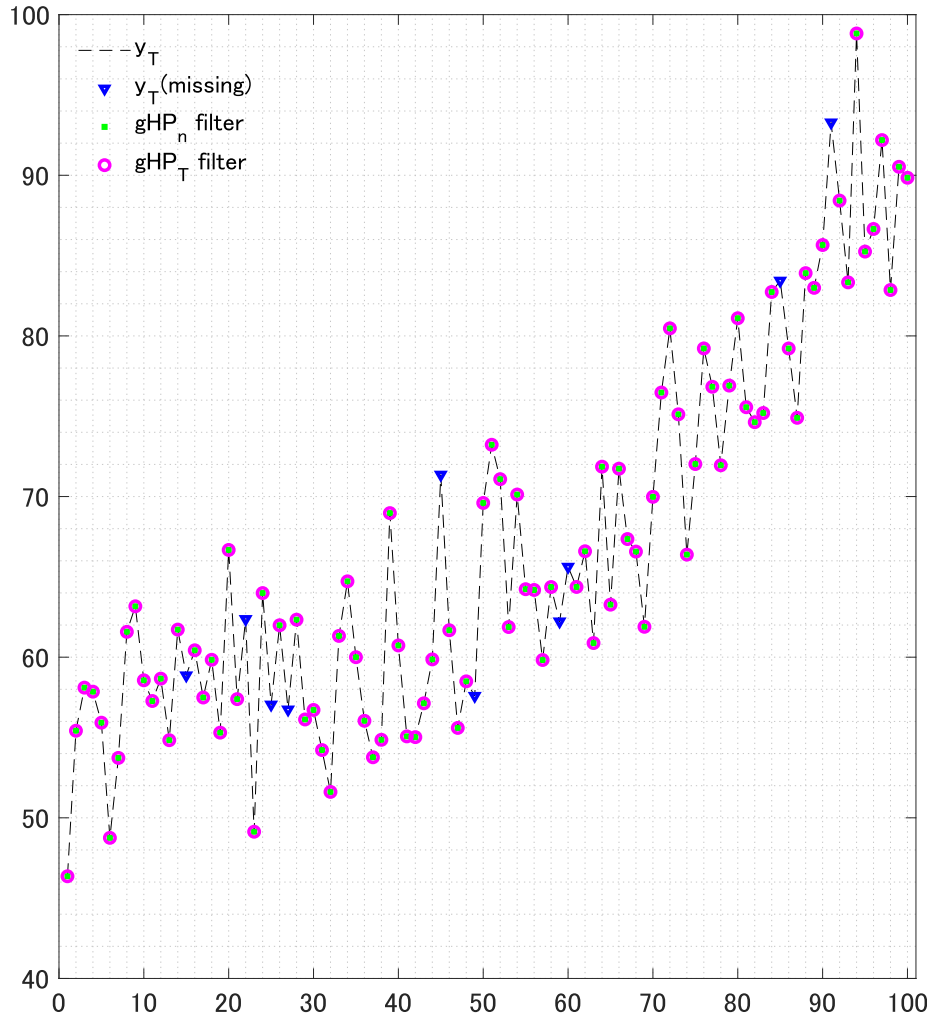


Figure B.4: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.1.  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^{-4}$  and  $\text{gHP}_T$  filter denotes  $\mathcal{S}\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^{-4}$ .



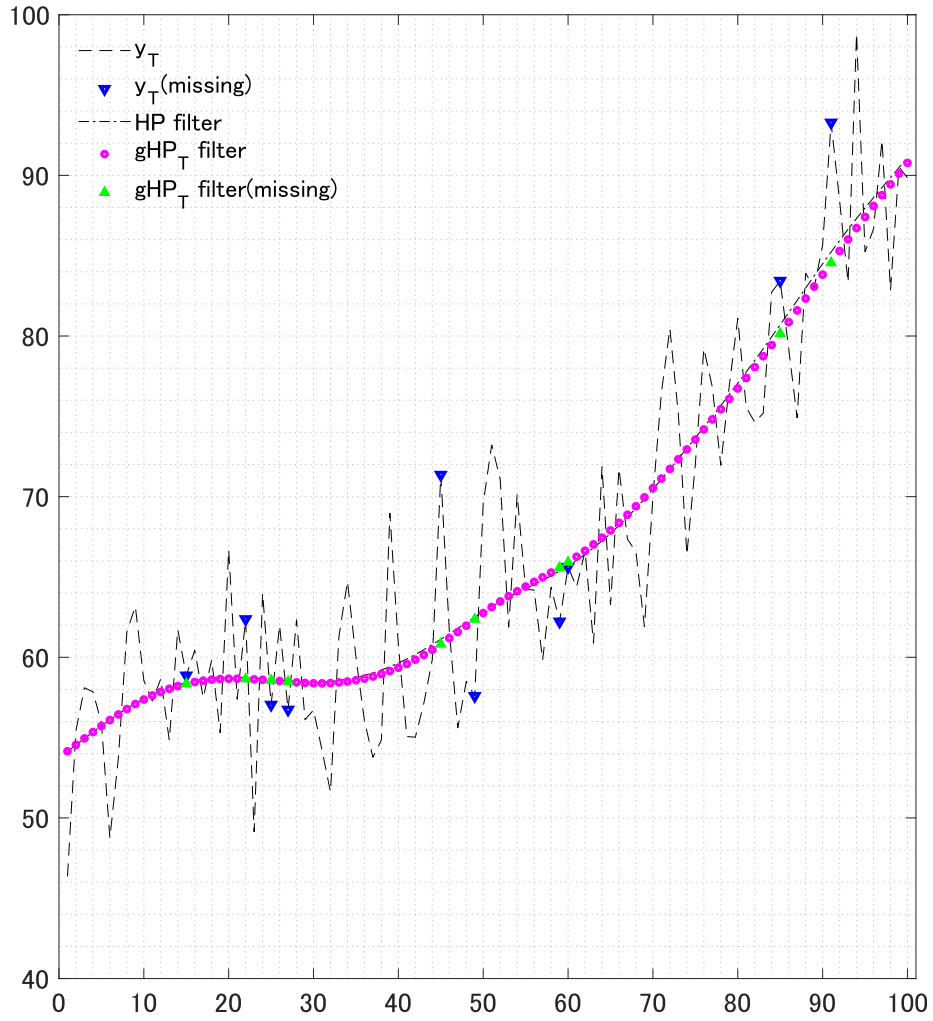


Figure B.5: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.1. HP filter denotes  $\hat{x}$  in (16), which is estimated with  $\lambda = 1600$  from not only available observations but also missing observations.  $gHP_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$  and  $gHP_T$  filter(missing) denotes  $S_{\perp}\hat{x}_T$  in (13) estimated with  $\lambda_T = 1600$ .

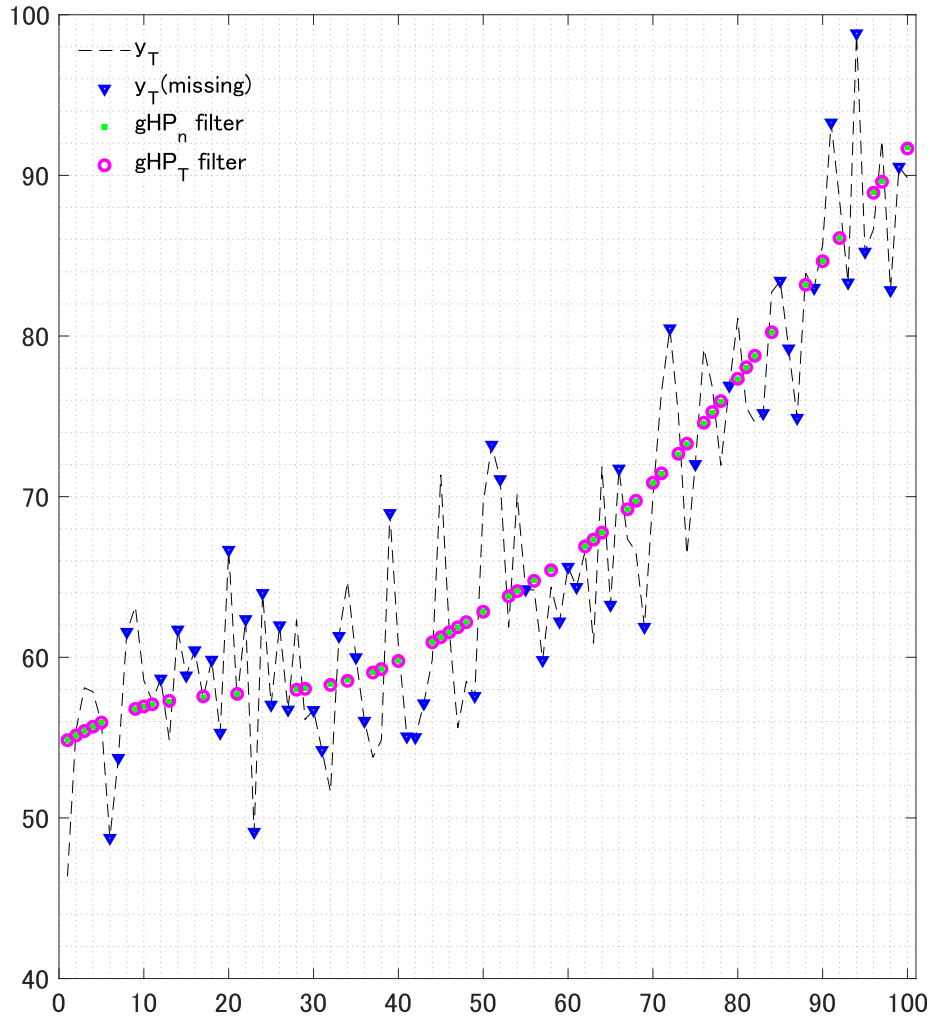


Figure B.6: For the explanation of  $y_T$ , see Figure 5 in Yamada (2021).  $y_T(\text{missing})$  denotes 50 (= 100 - 50) missing observations selected randomly from  $\{y_2, \dots, y_{T-1}\}$ .  $\text{gHP}_T$  filter denotes  $\mathcal{S}\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$ .  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 870.14$ , which is specified so that  $\|\mathbf{y}_n - \hat{x}_n\|^2 = \|\mathbf{y}_n - \mathcal{S}\hat{x}_T\|^2$ .

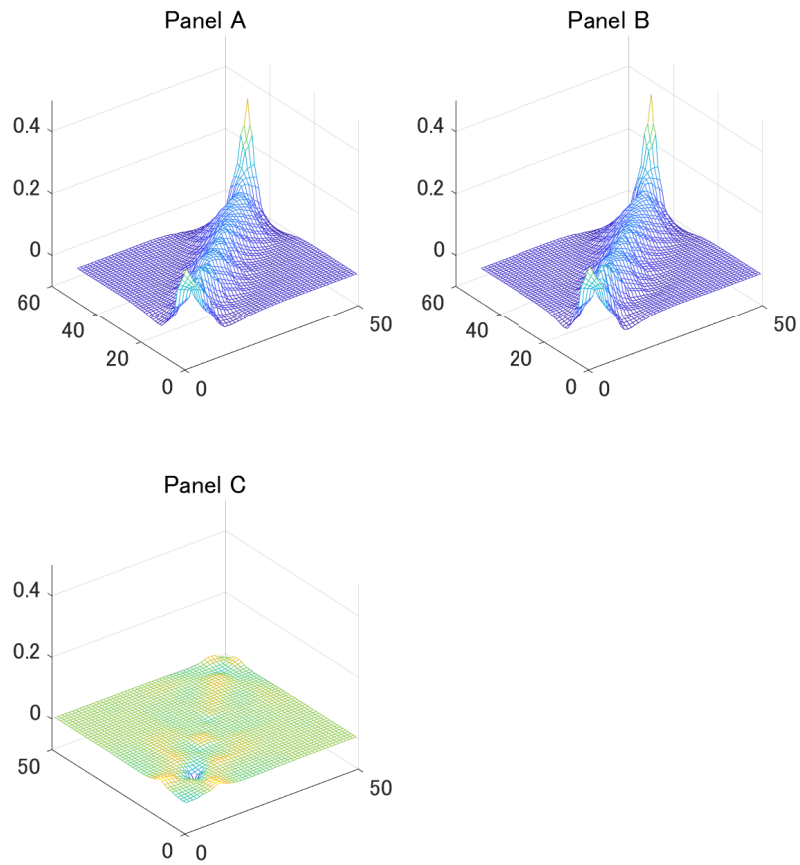


Figure B.7: Panel A (resp. Panel B) plots the smoother matrix corresponding to  $\hat{\mathbf{x}}_n$  (resp.  $\mathbf{S}\hat{\mathbf{x}}_T$ ) in Figure B.6. Panel C plots their difference.

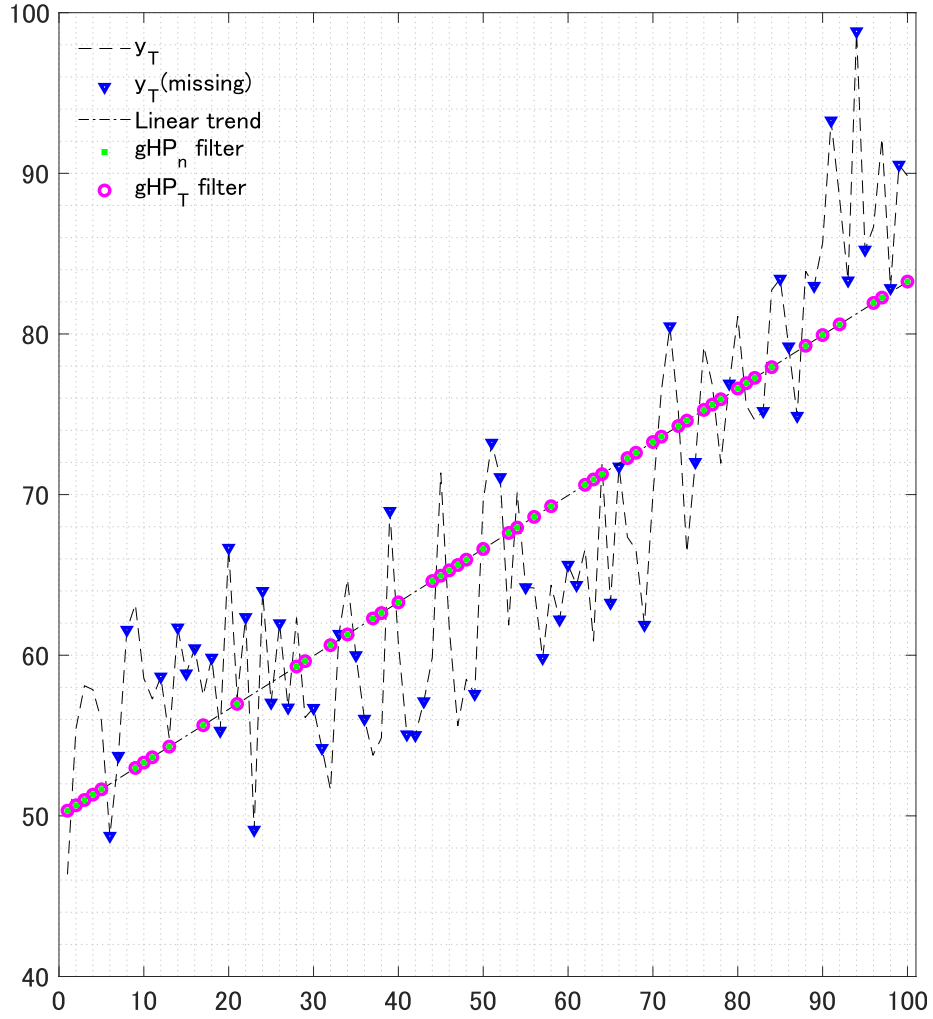


Figure B.8: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.6.  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^8$  and  $\text{gHP}_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^8$ . Linear trend denotes  $\mathbf{P}\mathbf{y}_n [= \mathbf{\Pi}_n(\mathbf{\Pi}'_n\mathbf{\Pi}_n)^{-1}\mathbf{\Pi}'_n\mathbf{y}_n]$ .

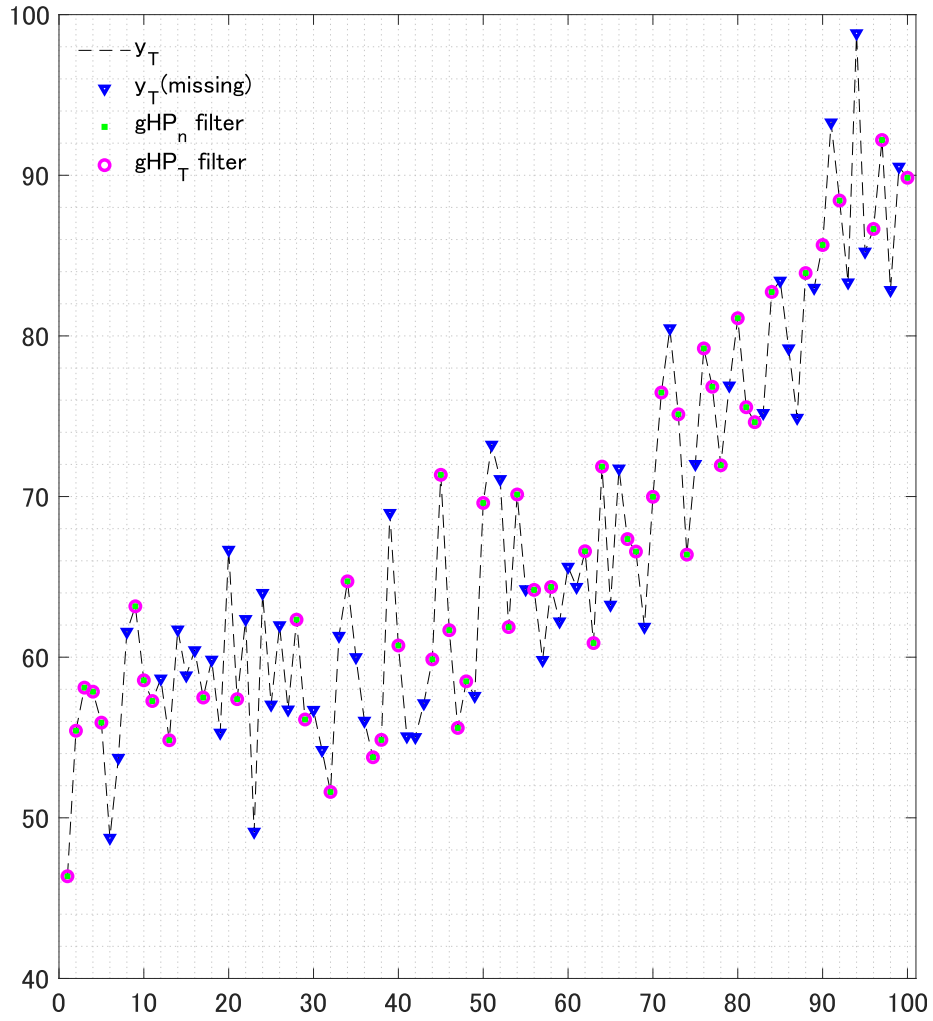


Figure B.9: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.6.  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^{-4}$  and  $\text{gHP}_T$  filter denotes  $\mathcal{S}\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^{-4}$ .

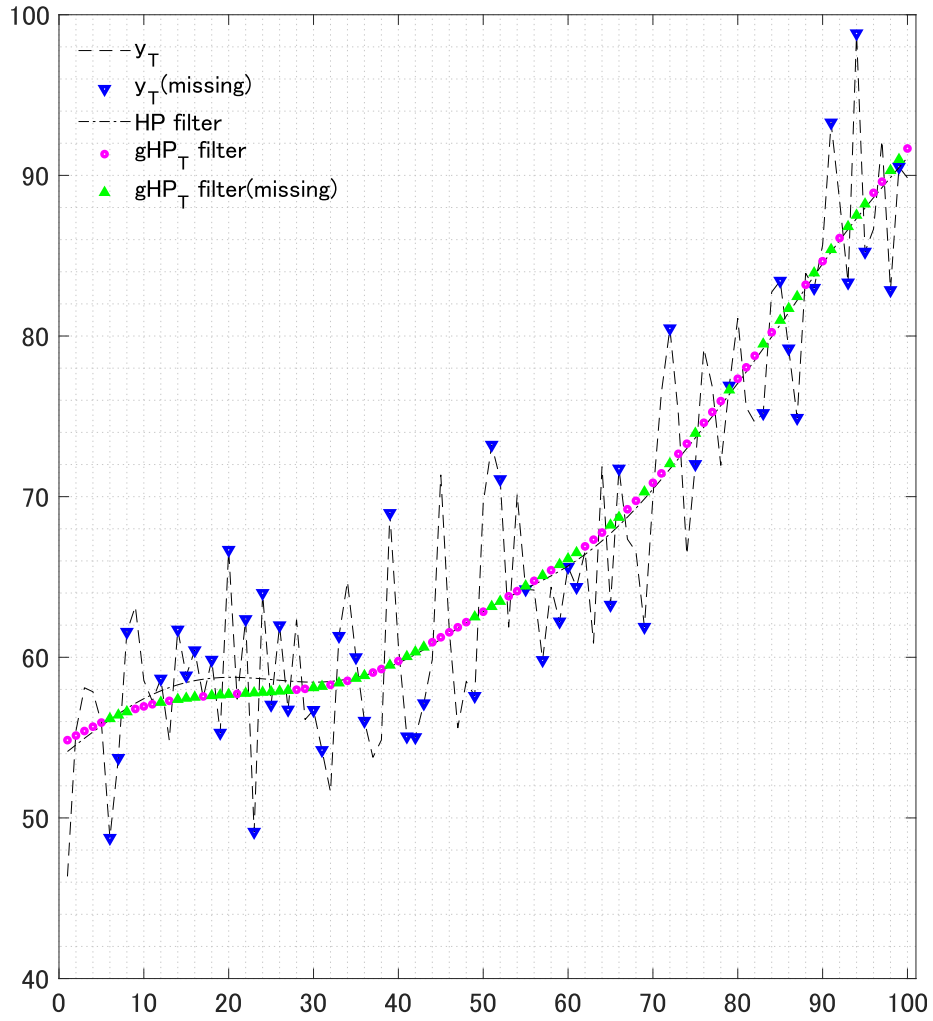


Figure B.10: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.6. HP filter denotes  $\hat{x}$  in (16), which is estimated with  $\lambda = 1600$  from not only available observations but also missing observations.  $gHP_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$  and  $gHP_T$  filter(missing) denotes  $S_{\perp}\hat{x}_T$  in (13) estimated with  $\lambda_T = 1600$ .

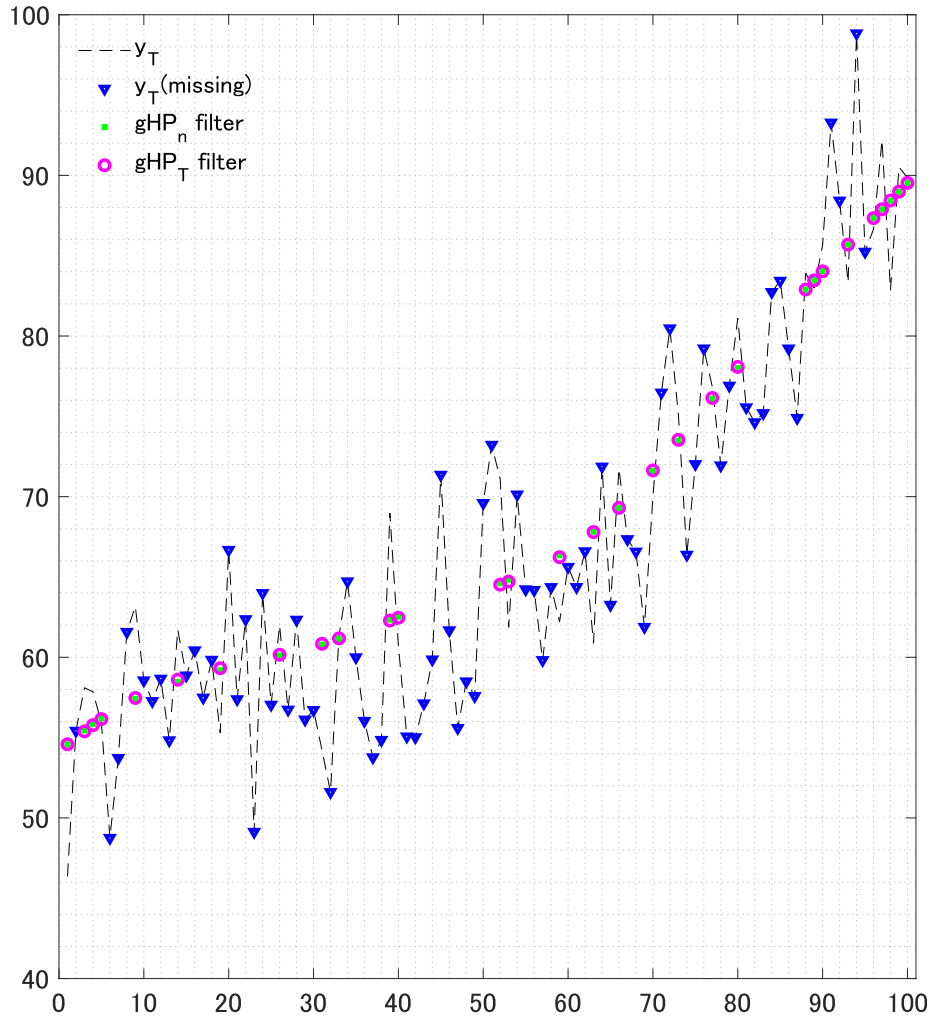


Figure B.11: For the explanation of  $y_T$ , see Figure 5 in Yamada (2021).  $y_T(\text{missing})$  denotes 70 (= 100 - 30) missing observations selected randomly from  $\{y_2, \dots, y_{T-1}\}$ .  $\text{gHP}_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$ .  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 464.34$ , which is specified so that  $\|y_n - \hat{x}_n\|^2 = \|y_n - S\hat{x}_T\|^2$ .

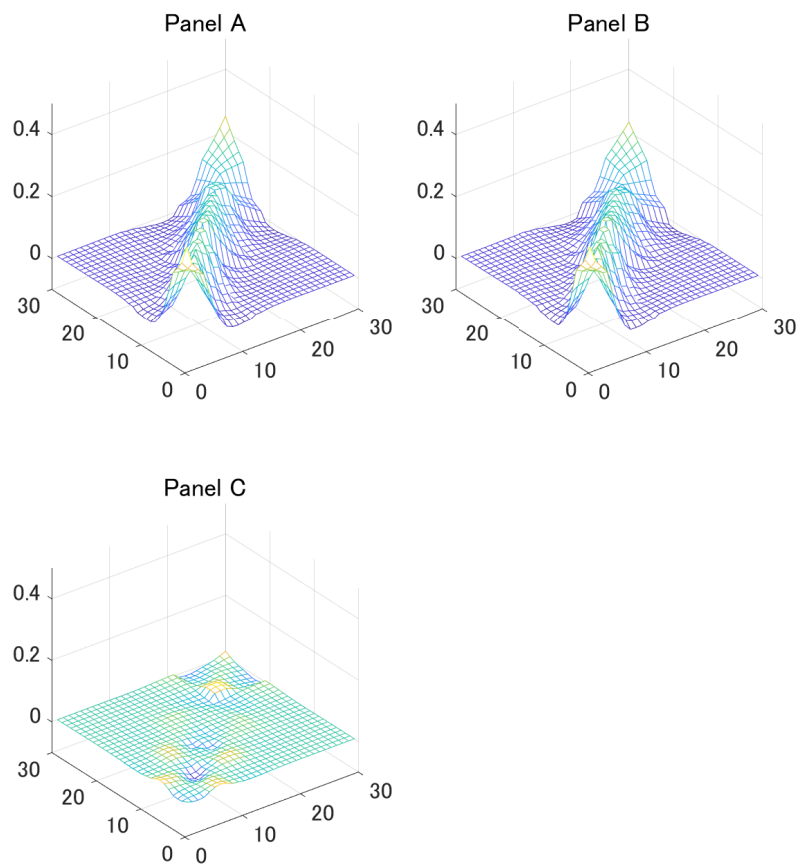


Figure B.12: Panel A (resp. Panel B) plots the smoother matrix corresponding to  $\hat{\mathbf{x}}_n$  (resp.  $\mathbf{S}\hat{\mathbf{x}}_T$ ) in Figure B.11. Panel C plots their difference.



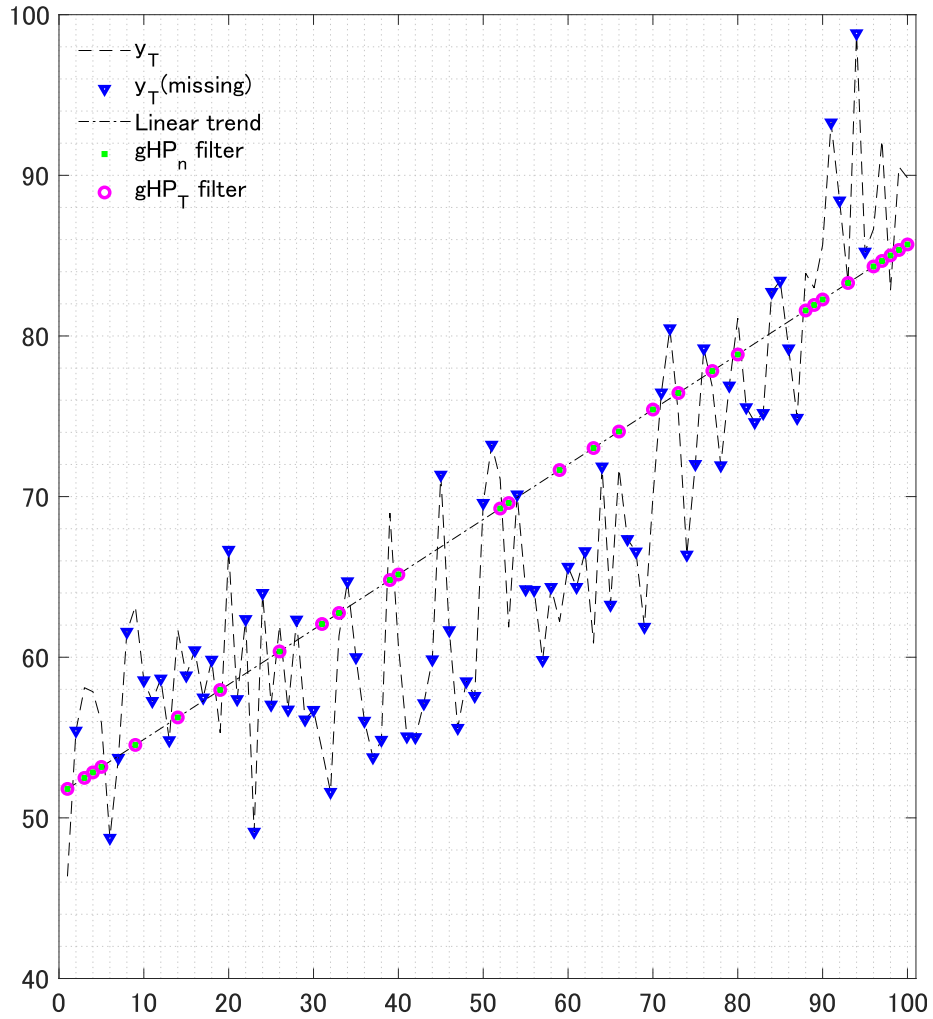


Figure B.13: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.11.  $\text{gHP}_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^8$  and  $\text{gHP}_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^8$ . Linear trend denotes  $P\mathbf{y}_n [= \Pi_n(\Pi_n' \Pi_n)^{-1} \Pi_n' \mathbf{y}_n]$ .

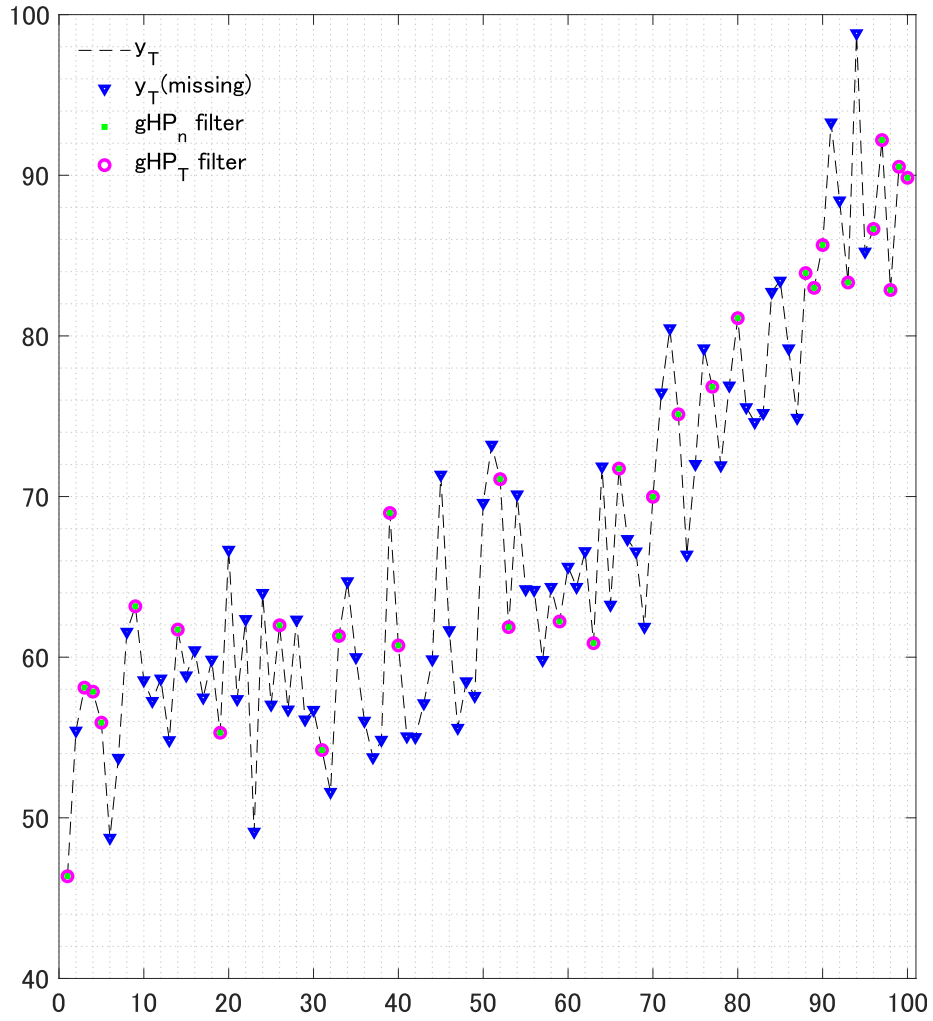


Figure B.14: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.11.  $gHP_n$  filter denotes  $\hat{x}_n$  in (8) estimated with  $\lambda_n = 10^{-4}$  and  $gHP_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 10^{-4}$ .

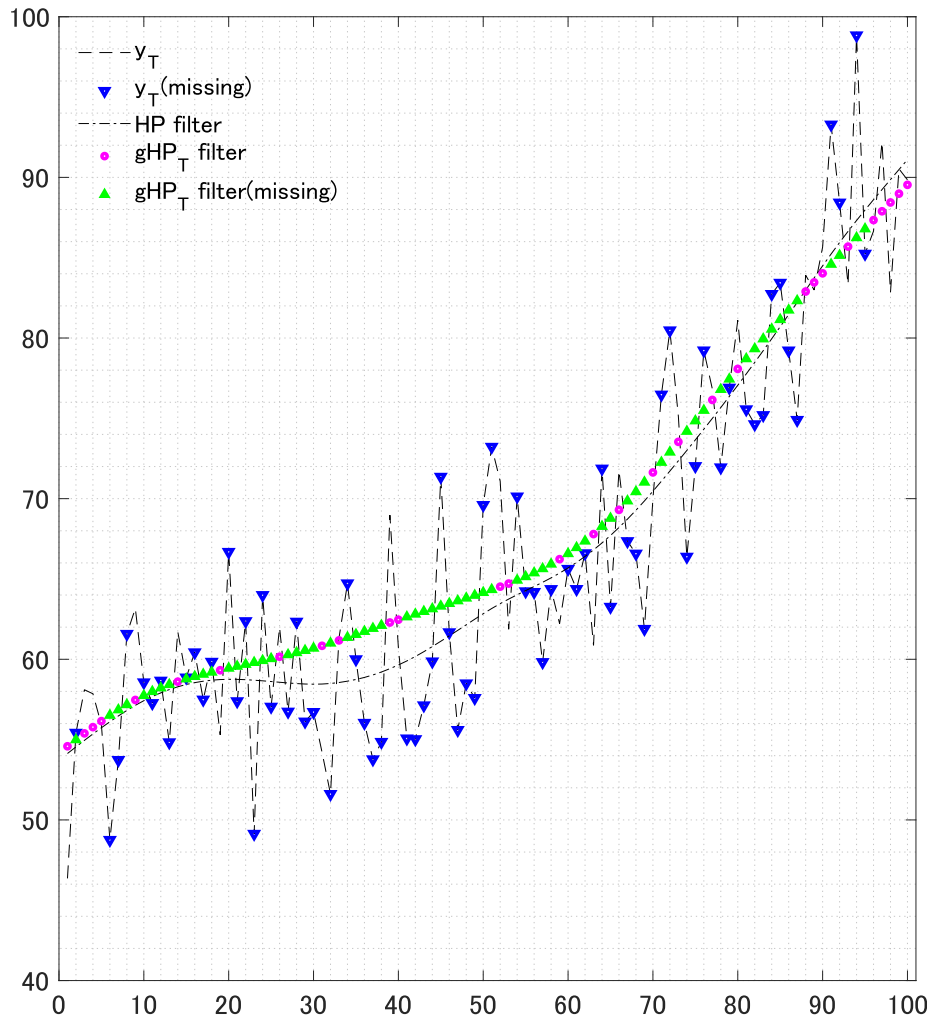


Figure B.15: For the explanation of  $y_T$  and  $y_T(\text{missing})$ , see Figure B.11. HP filter denotes  $\hat{x}$  in (16), which is estimated with  $\lambda = 1600$  from not only available observations but also missing observations.  $gHP_T$  filter denotes  $S\hat{x}_T$  in (12) estimated with  $\lambda_T = 1600$  and  $gHP_T$  filter(missing) denotes  $S_{\perp}\hat{x}_T$  in (13) estimated with  $\lambda_T = 1600$ .

## References

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2. Grant, M. and S. Boyd, 2008, Graph implementations for nonsmooth convex programs, in *Recent Advances in Learning and Control*, edited by V. Blondel, S. Boyd, and H. Kimura, 95–110, Springer, London.
3. Yamada, H., 2021, Trend extraction from economic time series with missing observations by generalized Hodrick–Prescott filters, *Econometric Theory*. [doi will be inserted here by typesetter].