

# 1 HP97

The Hodrick and Prescott (1997, HP) Filter can be expressed in State Space Form (SSF) using the following Unobserved Component (UC) model structure:

$$y_t = y_t^* + y_t^c \quad (1a)$$

$$\Delta^2 y_t^* = \varepsilon_{1t} \quad (1b)$$

$$y_t^c = \psi \varepsilon_{2t}, \quad (1c)$$

where  $y_t$  is (100 times) the log of GDP, and the shocks  $\{\varepsilon_{it}\}_{i=1}^2$  are mutually uncorrelated *i.i.d.*  $N(0,1)$ . The standard deviation  $\psi$  is the (square root of the) smoothing parameter, commonly set to 40 for quarterly macroeconomic data, implying a value of ' $\lambda$ ' of 1600.

The '*numbered shock*' to '*named shock*' mapping is:

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^* \\ \varepsilon_t^c \end{bmatrix}, \quad (2)$$

where  $\varepsilon_t^*$  is the trend (or permanent) shock and  $\varepsilon_t^c$  is the cycle (or transitory) shock.

## 2 Shock recovery

### 2.1 State Space Models with lagged states

Kurz (2018) adopts the following general SSF with lagged states in the measurement:

$$\text{Measurement : } Z_t = D_1 X_t + D_2 X_{t-1} + R \varepsilon_t \quad (3a)$$

$$\text{State : } X_t = \Phi X_{t-1} + Q \varepsilon_t, \quad (3b)$$

where  $\varepsilon_t \sim MN(0_m, I_m)$ ,  $D_1, D_2, \Phi, R$  are  $Q$  conformable system matrices,  $Z_t$  the observed variable and  $X_t$  the latent state variable, and  $m$  is the number of shocks  $\{\varepsilon_{it}\}_{i=1}^2$ .

### 2.2 HP97 in '*shock recovery*' SSF

To assess shock recovery, write the model in (1) in '*shock recovery*' SSF by collecting all observable variables in  $Z_t$  and all shocks (and other latent state variables) in  $X_t$ . Differencing  $y_t$  and  $y_t^c$  twice, and re-arranging the relations in (1) then yields:

$$\begin{aligned} \Delta^2 y_t &= \Delta^2 y_t^* + \Delta^2 y_t^c \\ &= \varepsilon_{1t} + \psi \Delta^2 \varepsilon_{2t} \\ &= \varepsilon_{1t} + \psi \varepsilon_{2t} - 2\psi \varepsilon_{2t-1} + \psi \varepsilon_{2t-2}, \end{aligned} \quad (4)$$

where  $\Delta^2 y_t$  is the only observed variable.

The Measurement and State equations of the ‘*shock recovery*’ SSF corresponding to the relations in (4) are then given by:

$$\begin{aligned} \text{Measurement : } Z_t &= D_1 X_t + D_2 X_{t-1} + R \varepsilon_t \\ \Leftrightarrow \Delta^2 y_t &= \varepsilon_{1t} + \psi \varepsilon_{2t} - 2\psi \varepsilon_{2t-1} + \psi \varepsilon_{2t-2} \end{aligned} \quad (5a)$$

$$Z_t = \underbrace{\begin{bmatrix} 1 & \psi & 0 \end{bmatrix}}_{D_1} \underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{2t-1} \end{bmatrix}}_{X_t} + \underbrace{\begin{bmatrix} 0 & -2\psi & \psi \end{bmatrix}}_{D_2} \underbrace{\begin{bmatrix} \varepsilon_{1t-1} \\ \varepsilon_{2t-1} \\ \varepsilon_{2t-2} \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} 0 & 0 \end{bmatrix}}_R \underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}}_{\varepsilon_t} \quad (5b)$$

$$\text{State : } X_t = \Phi X_{t-1} + Q \varepsilon_t,$$

$$\underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{2t-1} \end{bmatrix}}_{X_t} = \underbrace{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}}_{\Phi} \underbrace{\begin{bmatrix} \varepsilon_{1t-1} \\ \varepsilon_{2t-1} \\ \varepsilon_{2t-2} \end{bmatrix}}_{X_{t-1}} + \underbrace{\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}}_Q \underbrace{\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}}_{\varepsilon_t}. \quad (5c)$$

## 2.3 Shock recovery

The diagonal entries of the steady-state variance/covariance matrix of the smoothed and filtered states  $X_t$  denoted by  $P_{t|T}^*$  and  $P_{t|t}^*$ , respectively, are:

Shocks	$\text{diag}(P_{t T}^*)$	$\text{diag}(P_{t t}^*)$
$\varepsilon_{1t}$	0.9439	0.9995
$\varepsilon_{2t}$	0.0561	0.2006

(6)

indicating that the trend (or permanent) shock  $\varepsilon_{1t} = \varepsilon_t^*$  cannot be recovered ( $P^* \approx 1$ ), while the cycle shock  $\varepsilon_{2t} = \varepsilon_t^c$  appears to be recoverable ( $P^* \approx 0$ ). In [Figure 1](#), simulated states and estimated Kalman smoothed states are plotted for the two shocks of interest.

The correlation between the true (simulated) and estimated Kalman smoothed shocks can be analyzed by simply computing  $\text{Corr}(X_t, \hat{X}_{t|T})$ , where  $X_t = [\varepsilon_{1t} \ \varepsilon_{2t} \ \varepsilon_{2t-1}]'$  and  $\hat{X}_{t|T} = E_T X_t = E_T [\varepsilon_{1t} \ \varepsilon_{2t} \ \varepsilon_{2t-1}]'$ , yielding (for the first two elements of  $X_t$ ):

Shocks	$\text{Corr}(X_t, \hat{X}_{t T})$
$\varepsilon_{1t}$	0.2368
$\varepsilon_{2t}$	0.9713

(7)

As can be seen from (7), the estimated permanent shock  $\varepsilon_{1t}$  is only weakly correlated (0.2368) with the true value. The estimated cyclical shock  $\varepsilon_{2t}$ , on the other hand, is highly correlated (0.9713) with the true value. These facts can also be seen from [Figure 1](#) below.

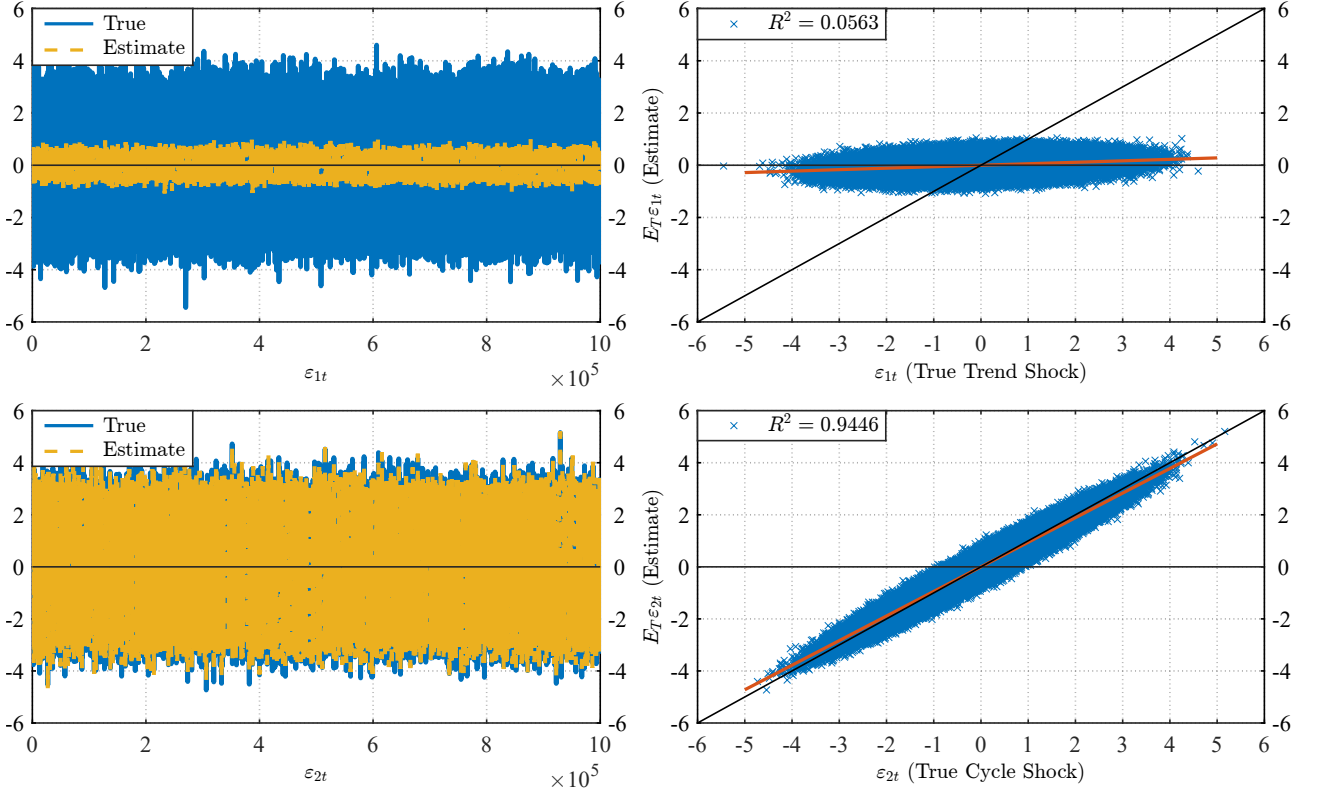


Figure 1: Comparison of true shocks and Kalman Smoothed estimates  $\varepsilon_{t|T}$ .

## 2.4 Shock Identities

Kalman Filter estimates of the permanent and transitory shocks  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  are linked by the identity:

$$E_t \varepsilon_{2t} = \psi E_t \varepsilon_{1t}, \quad (8)$$

and the corresponding Kalman Smoother estimates are linked by the *dynamic* identity:

$$\Delta^2 E_T \varepsilon_{1t} = \frac{1}{\psi} E_T \varepsilon_{2t-2}. \quad (9)$$

The filtered and smoothed estimates of the contemporaneous correlations are, respectively:

Corr( $\hat{X}_{t t}, \hat{X}_{t t}$ )			and	Corr( $\hat{X}_{t T}, \hat{X}_{t T}$ )		
Shocks	$\varepsilon_{1t}$	$\varepsilon_{2t}$		Shocks	$\varepsilon_{1t}$	$\varepsilon_{2t}$
$\varepsilon_{1t}$	1.0000	1.0000		$\varepsilon_{1t}$	1.0000	-0.1907
$\varepsilon_{2t}$	1.0000	1.0000		$\varepsilon_{2t}$	-0.1907	1.0000

Note that  $\varepsilon_{1t}$  and  $\varepsilon_{2t}$  were generated as *i.i.d.*  $N(0, 1)$  and mutually uncorrelated.

Running regressions corresponding to (8) and (9) obtained from the simulated data (without an intercept) yields regression coefficient of 40 and  $0.025 = 1/40$  when the smoothing parameter was set to  $\lambda = 1600 = 40^2$  in the simulation. The regression fit is perfect, yielding an  $R^2$  of 1 and a residual sum of squares of exactly 0 (see Panels (a) and (b) in Table 1, respectively). The file HP97.m replicates the output summarized here.

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Smoother Identity - Dependent variable: $\Delta^2 E\epsilon_1(t)$				
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NOTE: Identity should be: $\Delta^2 E\epsilon_1(t) = 1/40 E\epsilon_2(t-2)$ (and not $E\epsilon_2(t)$ as stated)				
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Variable	Estimate	stderr(HAC)	t-stat(HAC)	p-value
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$E\epsilon_2(t-2)$	0.025000	0.000000	86387073152284000.000000	0.000000
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R-squared	:		1.000000	No. of Regressors : 1.000000
Rbar-squared	:		1.000000	Plus Const.(if exist) : 1.000000
SE of regression	:		0.000000	Mean(y) : 0.000000
Sum Squared Errors	:		0.000000	Stdev(y) : 0.024297
Log-likelihood	:		34684702.107497	AIC : -72.207418
F-statistic	:	7462726407818066738958551098589184.000000		AICc : -72.207418
Pr(F-statistic)	:		0.000000	BIC : -72.207406
No. of observations	:		999998.000000	HQIC : -72.207415
Std.err.MLE (div by T)	:		0.000000	DW-stat. : 2.603240
Include Pre-whitening	:		0.000000	HAC Trunct.Lag. : 31.000000
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(a) Kalman Filter

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Filter Identity - Dependent variable: $E\epsilon_2(t)$				
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Variable	Estimate	stderr(HAC)	t-stat(HAC)	p-value
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$E\epsilon_1(t)$	40.000000	0.000000	2148831869013260288.000000	0.000000
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R-squared	:		1.000000	No. of Regressors : 1.000000
Rbar-squared	:		1.000000	Plus Const.(if exist) : 1.000000
SE of regression	:		0.000000	Mean(y) : 0.001377
Sum Squared Errors	:		0.000000	Stdev(y) : 0.894404
Log-likelihood	:		34359382.750073	AIC : -71.556641
F-statistic	:	4617478401287020629803264248150753280.000000		AICc : -71.556641
Pr(F-statistic)	:		0.000000	BIC : -71.556629
No. of observations	:		1000000.000000	HQIC : -71.556637
Std.err.MLE (div by T)	:		0.000000	DW-stat. : 1.999361
Include Pre-whitening	:		0.000000	HAC Trunct.Lag. : 31.000000
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(b) Kalman Smoother

Table 1: Shock identity regressions using Kalman filter and smoother estimates.

Since  $\epsilon_{1t} = \Delta^2 y_t^*$  and  $\epsilon_{2t} = \frac{1}{\psi} y_t^c$ , this implies that the output from the standard HP-Filter will give the corresponding identity to (9) as:

$$\begin{aligned}
\Delta^2 \underbrace{E_T \epsilon_{1t}}_{\Delta^2 y_t^*} &= \frac{1}{\psi} \underbrace{E_T \epsilon_{2t-2}}_{\frac{1}{\psi} y_{t-2}^c} \\
\Leftrightarrow \Delta^4 y_t^* &= \frac{1}{\psi^2} y_{t-2}^c, \\
\Leftrightarrow \Delta^4 \text{HP-trend}_t &= \frac{1}{\psi^2} \text{HP-cycle}_{t-2},
\end{aligned}$$

so that a regression of the fourth differenced HP-trend on a twice lagged HP-cycle will give a coefficient estimate of  $\frac{1}{40^2} = \frac{1}{1600} = 0.000625$ . The HP-Filter appears to be able to recover the transitory cyclical shock  $\epsilon_{2t} = \epsilon_t^c$ , but not the permanent shock. HP-Filter estimates of  $\epsilon_{1t}$  and  $\epsilon_{2t}$  induce a negative correlation between trend-cycle shocks, ie.,  $\text{Corr}(E_T \epsilon_{1t}, E_T \epsilon_{2t}) = -0.1907$ , despite being generated with zero correlation.