

Time-varying Minimum Variance Portfolio: A User's Manual

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Abstract

This document provides a detailed step-by-step implementation procedure for the paper “Time-varying Minimum Variance Portfolio” (Fan et al., 2022). We first introduce some main functions, including estimating time-varying factor loadings, time-varying covariance matrix (also the sparse residual covariance matrix estimation), the rolling window estimation procedure, and the two-step hypothesis test in the paper. Next, we also introduce some auxiliary functions, such as the tools for selecting values of various tuning parameters and functions used in the listed examples. Finally, we provide a comprehensive example to show how the codes work in real data scenarios. For users' convenience, all example codes can be found in the file *main_process.m* on GitHub <https://github.com/RuikeWu/TV-MVP>.

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1 Preliminary setting

Before running the provided code, some preliminary settings must be done locally to adapt to the suggested computing environment. We recommend the users put the provided folder ‘TV-MVP’ under the folder ‘bin’ in MATLAB.

- (1) Install CVX toolbox in MATLAB (the user needs to first download CVX toolbox named “cvx.rar”, and then unzip the file, and run *cvx_setup.m* in MATLAB command window).
- (2) Install packages ‘spcov’, ‘PDSCE’ and ‘R.matlab’ locally in R.
- (3) Open ‘Rspcov.bat’ in a text editor, edit the first path to the location of local ‘Rscript.exe’, e.g. $F : /R - 3.6.1/bin/Rscript.exe$, and the user need to replace $F : /R - 3.6.1/bin/$ by their local path. And further edit the second path to the location of ‘TV-MVP’ folder, e.g. $F : /matlab/bin/TV - MVP/spcov_test.R$, and the user needs to replace $F : /matlab/bin/TV - MVP$ by their local path. We suggest using ‘bat’ to run the code written by R and the ‘bat’ file called by MATLAB.
- (4) Open MATLAB, and change the working path to the current folder, e.g. $F : /matlab/bin/TV - MVP/$

2 Main Functions

2.1 *Timevarying_factor_model.m*

Description: This function compute the time-varying factor loading estimator and corresponding estimated factors discussed in Section 3.1 of Fan et al., 2022. There are some other outputs for this function, which are used by the hypothesis test function.

Usage:

$$[Factor_loadings, Factor_set] = Timevarying_factor_model(R, f_number, Kernel_set, h)$$

Input:

- (1) R is $N \times T$ excess return matrix, N is the dimension of the portfolio, T is the sample size.
- (2) f_number is an integer, the number of factors.
- (3) $Kernel_set$ is a pre-calculating kernel weighting matrix using bandwidth h , see the following example to learn how to calculate, and the details of the underlying kernel function can be found in function *Kernel2* in later “Other functions” section.
- (4) h is bandwidth used in calculating $Kernel_set$.

Output:

- (1) $Factor_loading$ is $T \times 1$ cell, each element of the cell is $f_number \times N$ estimated time-varying factor loadings at each time point.
- (2) $Factor_set$ is a $f_number \times T$ matrix, and each row is the estimated factor given in Section 3.1 in the main paper.

Example 1: In this example, we show how to use function *Timevarying_factor_model* to estimate factor loadings and factors nonparametrically. We generate virtual data using smooth time-varying factor loading and residuals from multivariate normal distribution with cross-correlation covariance matrix. Portfolio size, sample size and ρ (control the departure from constant factor loading) are set to be 50, 250 and 0.7, respectively. The number of factors is set to 2, with AR(1)-type factors whose unconditional variances are both 1. The number of factors is estimated by BIC-type information criterion introduced in B.3 of the paper Appendix of Fan et al. (2022), and rule of thumb bandwidth is used. Regarding the results, firstly, the estimated factor number K is exactly equal to 2. And the first estimated loading is shown in Figure 1, one can observe that a large variation is featured by the factor loading estimator.

```
% Basic setting
clear;clc;
rng(2);% set the random seed
d = 50; T = 250; % set the dimension and sample size
rho = 0.7; % set the departure from the null.
h = (2.35/sqrt(12)) * T^(-0.2) * d^(-0.1); % set rule of thumb bandwidth

% generate data using smooth time varying factor loading and cross-sectional dependence
% setting defined in Appendix C.2.1 of Fan et al. (2022).
[Y,~,s_cov] = data_generate(d,T,rho);

% Pre-calculating all kernel weights to increase computing speed.
Kernel_set = zeros(T,T); % Reserve space for storing kernel weights
for r = 1 : T
    for t = 1 : T
        % see an introduction for Function Kernel2 in the 'Other functions' section
        k = (h^-1) * Kernel2(T,t,r,h);
        Kernel_set(t,r) = k^0.5;
    end
end

% Using BIC-type information criterion to select the number of factors
% max number is set to 10, see more details of Function factor_number_selection in 'Other
functions' section
K = factor_number_selection(Y,10);

% Estimate factor loading and corresponding factors
[Factor_loadings,Factor] = Timevarying_factor_model(Y,K,Kernel_set,h);

% plot the loading for first common factor in time series.
Fir_loading = [];
for i = 1 : T
    loading_temp = Factor_loadings{i};
    Fir_loading(i,:) = loading_temp(1,:);
end
plot(Fir_loading)
```

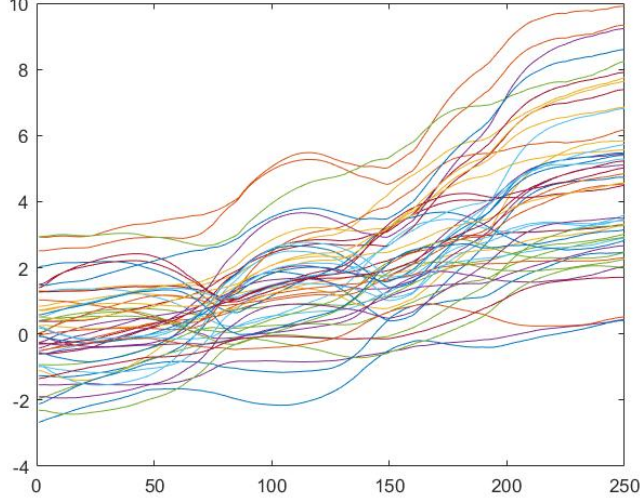


Figure 1: Time-varying factor loadings

2.2 *Time_cov.m*

Description: This function compute the proposed estimator for time-varying covariance matrix $\Sigma_{r,t}$ and the sparse estimator for residual covariance estimator Σ_e in Section 2 of the main article.

Usage:

$$[Sigma_r, Sigma_e, Residuals] = Time_COV(R, PCV, f_number, tau, h)$$

Input:

- (1) R is $N \times T$ excess return matrix, N is the dimension of the portfolio, T is sample size
- (2) PCV is the penalty (tuning) parameter λ for the residual sparse matrix
- (3) f_number is the number of factors
- (4) τ is a small and positive parameter in (B.6) for the positive-definite error covariance matrix
- (5) h is the bandwidth parameter, and the default is the rule of thumb $2.35/\sqrt{12}T^{-0.2}N^{-0.1}$

Output:

- (1) $Sigma_r$ is the proposed estimated time-varying covariance matrix.
- (2) $Sigma_e$ is the sparse residual covariance matrix estimator shown in (3.4).
- (3) $Residuals$ are the residuals after estimating time-varying factor loadings.

Example 2: Based on the same settings in Example 1, we further provide an example to show how to use Function *Time_cov*. In this example, we use the cross-validation method proposed in Appendix B.1 of the main paper to select the tuning parameter λ .

We show the visualization of residual covariance matrix and its sparse estimator in Figure 2. The left plot displays the true residual covariance matrix, and the right plot gives the

estimated residual sparse covariance matrix, the contrast of color reflects the magnitude of covariance elements. We can observe a similar pattern between these two figures.

```
% Continue to the example 1.
tau = 0.001; % set the value for positive definite matrix estimation.

% From example 1, obvious time-varying feature is shown in factor loadings
% Hence, we first get the estimated residual filtered by estimated time-varying factor loadings.
[~,~,Residuals] = Time_COV(Y,0,K,tau)

% We use the cross-validation method proposed in Appendix B.1 of the main paper for
tuning parameter  $\lambda$ 
% The folds is set to 3, see more details of Function CV_for_spcov in 'Other functions'
section
lambda = CV_for_spcov(Residuals,3,tau);

% Estimate covariance matrix and residual covariance matrix.
[Sigma_r,Sigma_e] = Time_COV(Y,lambda,K,tau)

% Visual sparse matrix estimator
map = [1,1,0;0,0.8,1;0,0.6,1;
       0,0.4,1;0,0.2,1;0,0,1]; % define color map
subplot(1,2,1); imagesc(s_cov); colormap(map);
subplot(1,2,2); imagesc(Sigma_e); colormap(map); colorbar
```

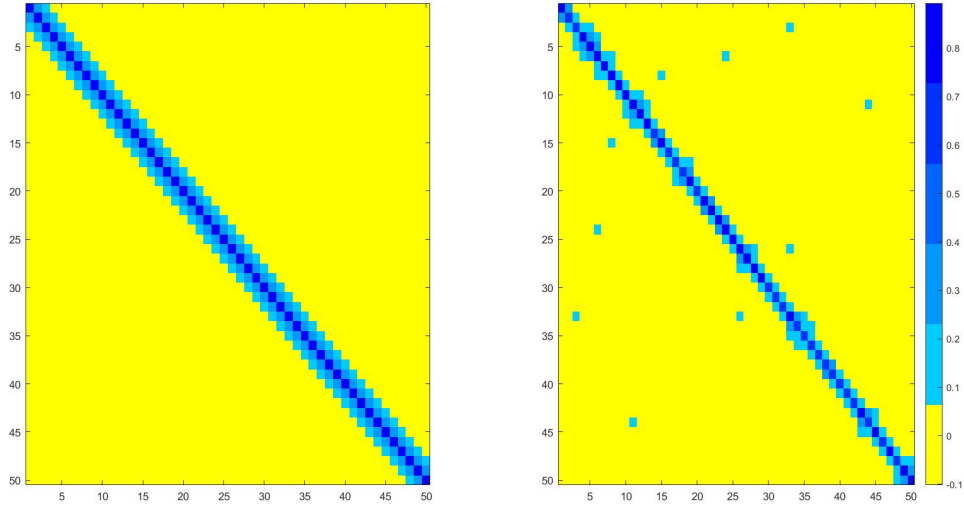


Figure 2: Spare residual covariance matrix(left) and its estimator(right)

2.3 Rolling_window.m

Description: The rolling window process is described in the empirical analysis for daily return data. One could use cross-validations for tuning parameter λ and kernel bandwidth in Appendix B.1 and B.2, respectively, and use BIC-type information criterion for the number of factors in B.3. The parameters are updated annually (or semi-annually, quarterly, etc.).

Usage:

$[info, Tv_return, eq_return] = Rolling_window(Data_matrix, history, persist, cur_pos, end_pos)$

Input:

- (1) *Data_matrix* is the whole excess return matrix with N rows, N is the number of assets, and the number of columns depends on the length of investment periods, e.g., length is 10340 for daily data from 01/1980 to 12/2019.
- (2) *history* is the length of the time window.
- (3) *persist* is the holding periods after each rebalancing.
- (4) *cur_pos* is the position of the start time point in *Data_matrix*.
- (5) *end_pos* is the position of the end time point in *Data_matrix*.

Output:

- (1) *info* is a 1×6 row vector containing the Sharpe ratio, mean return and standard deviation of out of sample portfolios from 'TV-MVP' and '1/N', the information from left to right is Sharpe ratio of 'TV-MVP' and '1/N', mean excess return of 'TV-MVP' and '1/N', and standard deviation of 'TV-MVP' and '1/N'.
- (2) *Tv_return* contains all out of sample realized excess returns of constructed portfolio based on 'TV-MVP'.
- (3) *eq_return* contains all out of sample realized excess returns of constructed portfolio based on '1/N'.

Example 3: In this example, we conduct the rolling window procedure using provided data *R0*, which is a 50×500 excess return matrix. We set the length of window to be 250, the holding period of portfolio is 5, that is, we conduct weekly rebalancing. The rolling window procedure continues to run until the end of the sample. The data is the largest 50 stocks in S&P index on 01/04/2010, the positions from 251-500 correspond to nearly one year's return data from 01/2010 to 12/2010. We plot the cumulative excess return of two strategies in Figure 3, one can observe that 'TV-MVP' strategy obtains a higher cumulative return than the '1/N' strategy. And the output $info = [0.0865, 0.0488, 0.0006, 0.0005, 0.0075, 0.0105]$.

```
clear; clc;
load('example_data.mat'); % load provided data
[info, Tv_return, eq_return] = Rolling_window(R0, 250, 5, 251, 500)
% plot the cumulative excess return of TV-MVP portfolio and '1/N' strategy.
plot(cumsum(Tv_return))
hold on;
plot(cumsum(eq_return), '--')
legend('Tv\_return', 'Equal\_return', 'Location', 'northwest', 'NumColumns', 2)
```

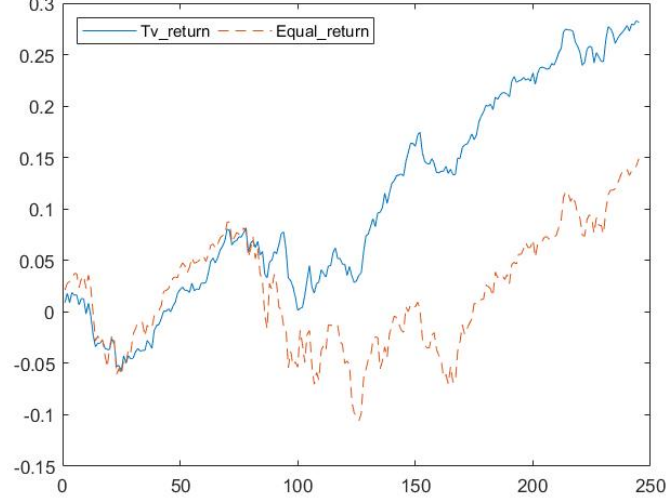


Figure 3: Cumulative excess return

2.4 *FWYZtest_step1_bt.m*

Description: Hypothesis test for checking the constancy of factor loading using our bootstrap procedure. The bandwidth used in the hypothesis test is set to be rule of thumb $2.35/\sqrt{12}T^{-0.2}N^{-0.1}$, and the loop for bootstrap is set to 199 for time efficiency. The p-value of step 1 test is given by the code $\text{sum}(J_pT < J_pT_{set})/199$.

Usage:

$$[J_pT_set, J_pT] = \text{FWYZtest_step1_bt}(R, K, \text{Kernel_set})$$

Input:

- (1) R is $N \times T$ excess return matrix, N is the dimension of the portfolio, T is the sample size.
- (2) K is the number of factors
- (3) Kernel_set is a pre-calculating kernel weighting matrix using default bandwidth.

Output:

- (1) J_pT_set is the set that contains all bootstrap statistics values J_{pT}^* defined in Appendix C.2 of Fan et al. (2022).
- (2) J_pT is the test statistic value described in equation (5.5) of the main article.

Example 4: Continue with Example 2, the step 1 test should reject the constant factor loading null hypothesis since the smooth time-varying factor loading is used. The p_val calculated by this example is < 0.001 , that is to say, we have sufficient evidence to reject the constant factor loading null hypothesis.

```
[J_pT_set, J_pT] = FWYZtest_step1_bt(Y, K, Kernel_set);
p_val = sum(J_pT < J_pT_set)/199;
```


2.5 *FWYZtest_step2.m*

Description: Hypothesis test for checking the constancy of residual covariance matrix in step 2.

Usage:

$$[Ln, ifa] = FWYZtest_step2(R, alpha)$$

Input:

- (1) R is $N \times T$ residual return matrix, N is the dimension of the portfolio, T is sample size.
- (2) $alpha$ is significance level, e.g, $alpha = 0.05$.

Output:

- (1) Ln gives the value of statistic in (5.12) of the main paper.
- (2) ifa is a binary variable, it takes 1 if the result rejects the null hypothesis, and takes 0 if not.

Example 5: Continue with Example 4, the step 2 test can not reject the hypothesis that residual covariance matrix is time-invariant. The ifa computed by this example is 0, which gives us the evidence for constant residual covariance matrix.

```
% since we have already rejected the constant factor loading,  
% we get use the estimated residual in example 2  
  
% We set the significance level to be 0.05.  
[Ln, ifa] = FWYZtest_step2(Residuals, 0.05);
```

2.6 *size_test.m*

Description: This code offers another example of our two-step hypothesis test procedure, it calculates the size for each step test under “Size2” model set-up in Appendix C.2.1 of Fan et al. (2022). Note that in this procedure, for conservative, we give the significance level for each step of the test as half of the total level.

Usage:

$$level = size_test(d, T, loop, alpha1);$$

Input:

- (1) d is the dimension of the data.
- (2) T is the sample size of the data.
- (3) $loop$ is the replications for computing size.
- (4) $alpha1$ is the overall significant level, e.g, $alpha1 = 0.05$.

Output:

- (1) $level$ is a 3-dimensional vector, the first and second elements give the sizes of first step test and second step test under $alpha1/2$, respectively. And the third element is the size of the whole testing procedure under $alpha1$.

Example 6: We provide an example to illustrate the usage, we compute the size under the setting ‘Size2’ in Appendix C.2.1. The dimension, sample size and replications are 50, 300 and 500. The output $level = [0.028, 0.043, 0.07]$, which is exactly the same as the results in Table C.5 in Appendix of Fan et al. (2022).

```
clear; clc;
alpha1 = 0.05; d = 100; T = 300; % set value for significance level, dimension and sample size.
loop = 500;
level = size_test(d, T, loop, alpha1);
```

3 Other functions

3.1 *Kernel2.m*

Description: Calculate $k_{h,tx}^*$ in Section 3.1 of the main paper. In detail, the method of Hong and Li (2005), Su and Wang(2017) to use the boundary kernel to solve it, that is

$$k_{h,tx}^* = h^{-1} K_x^* \left(\frac{t-x}{Th} \right) = \begin{cases} h^{-1} K \left(\frac{t-x}{Th} \right) / \int_{-(x/Th)}^{\infty} K(u) du, & \text{if } x \in [0, \lfloor Th \rfloor] \\ h^{-1} K \left(\frac{t-x}{Th} \right), & \text{if } x \in [\lfloor Th \rfloor, T - \lfloor Th \rfloor] \\ h^{-1} K \left(\frac{t-x}{Th} \right) / \int_{-\infty}^{(1-x/T)/h} K(u) du, & \text{if } x \in (T - \lfloor Th \rfloor, T] \end{cases}$$

and we take Epanechnikov kernel $K(u) = \frac{3}{4}(1 - u^2)\mathbb{1}(|u| \leq 1)$.

Usage:

$$result = Kernel2(T, t, x, h)$$

Input:

- (1) T is sample size.
- (2) t is the time point around target.
- (3) x is the target point.
- (4) h is bandwidth.

Output:

- (1) $result$ gives the value of $k_{h,tx}^*$.

3.2 *factor_number_selection.m*

Description: Estimate the number of factors using BIC-type information criterion, that is

$$\hat{m} = \arg \min_m IC(m)$$

where $IC(m) = \log V(m, \{\check{B}_x(m)\}) + \frac{p+Th}{pTh} \log(\frac{pTh}{p+Th})m$, see more details in Appendix B.3 of Fan et al. (2022). Under some regularity conditions, it is shown that \hat{m} is consistent to the true number of factors m_0 .

Usage:

$$f_number = factor_number_selection(R, max_number)$$

Input:

- (1) R is $p \times T$ excess return matrix.
- (2) max_number is the pre-set maximum number of factors.

Output:

- (1) f_number gives the estimated number of common factors.

3.3 $CV_for_spcov.m$

Description: Using cross-validation method to choose the tuning parameter λ , that is

$$\hat{\lambda}_{CV} = \arg \max_{\lambda} k^{-1} \sum_{j=1}^k \{-\log \det(\hat{\Sigma}_e(A_j^c)) - \text{tr}(S_{A_j} \hat{\Sigma}_e^{-1}(A_j^c))\}$$

see more details in Appendix B.1 of the main article.

Usage:

$$lambda = CV_for_spcov(R, k, tau)$$

Input:

- (1) R is $p \times T$ residual matrix.
- (2) k is the fold of cross-validation.
- (3) tau is a small and positive parameter for the positive definiteness of the error covariance matrix estimate.

Output:

- (1) $lambda$ gives the selected value of tuning parameter.

3.4 $CV_for_h.m$

Description: Using cross-validation method to choose the bandwidth h , that is

$$h_{CV} = \arg \max_h \sum_{j=2}^k \{SR(\widehat{W}(\cup_{i=1}^{j-1} A_i, h), r_t(A_j))\}$$

see more details in Appendix B.2 of the main article.

Usage:

$$h_cv = CV_for_h(R, lambda, f_number, tau)$$

Input:

- (1) R is $p \times T$ excess return matrix.
- (2) $lambda$ is tuning parameter.
- (3) K is the number of factors.
- (4) tau is a small and positive parameter for the positive definiteness of the error covariance matrix estimate.

Output:

- (1) h_cv gives the selected bandwidth.

3.5 *data_generate*

Description: Generate data using smooth time-varying factor loadings $b_{it}^{(1)}, b_{it}^{(2)}$ and residuals from multivariate normal distribution $N(0, \Sigma_e)$ where $\Sigma_e = (a_{ij})_{i,j=1,\dots,p}$ and $a_{ij} = 0.5^{|i-j|}$.

$$b_{it}^{(1)} = \rho \left((3 + z_i^{(1)})t/T + z_i^{(2)} \sin(4\pi t/T) \right) + z_i^{(3)}$$
$$b_{it}^{(2)} = \rho \left((3 + v_i^{(1)})t/T + v_i^{(2)} \sin(4\pi t/T) + (v_i^{(4)}t/T)^2 \right) + v_i^{(3)}$$

where $z^{(j)}, j = 1, 2, 3$ and $v^{(j)}, j = 1, 2, 3, 4$ are standard normal variables.

Usage:

$$[Y, r_cov, s_cov] = data_generate(p, T, rho)$$

Input:

- (1) p is the dimension of the portfolio.
- (2) T is sample size.
- (3) rho controls the departure from constant factor loading.

Output:

- (1) Y is generated return data.
- (2) r_cov is population return covariance matrix.
- (3) s_cov is Σ_e .

3.6 *Markowitz_MVP*

Description: Obtain the minimum variance portfolio.

Usage:

$$W = Markowitz_MVP(r_cov);$$

Input:

- (1) r_cov is covariance matrix of excess return.

Output:

- (1) W is the optimal weight by solving the minimum variance problem.

4 Example

In this section, we provide a comprehensive example for providing a whole picture for the users. We first generate the virtual excess return data using Function *data_generate* with dimension $d = 50$, sample size $T = 200$ and $\rho = 1$.

```
clear; clc;
d = 50; T = 200; rho = 1;
h = (2.35/sqrt(12)) * T^(-0.2) * d^(-0.1);

rng(2);
% generate virtual excess return data
[Y, r_cov, s_cov] = data_generate(d, T, rho);
```

With this excess return data Y , we will show how to apply our codes to make analysis and get the time-varying minimum variance portfolio step by step. Firstly, we estimate the number of common factors using suggested BIC, and further test for time-varyingness of factor loading and residual covariance matrix as the following.

```
alpha1 = 0.05; % set the significant level
% pre-calculating all kernel weights.
Kernel_set = zeros(T,T);
for r = 1 : T
    for t = 1 : T
        k = (h^-1) * Kernel2(T,t,r,h);
        Kernel_set(t,r) = k^0.5;
    end
end

% Using BIC-type information criterion to estimate the number of factors
K = factor_number_selection(Y,10);

% Test for the constancy of factor loadings.
[J_pT_set, J_pT] = FWYZtest_step1_bt(Y, K, Kernel_set);
p_val = sum(J_pT < J_pT_set)/199;
```

After conducting the codes in above box, we can input K and p_val directly in command window, and the results are displayed in the following box. The estimated number of factors is exactly the same as the true number of common factors, and we can reject the hypothesis of the constancy of factor loadings at least under the significant level 0.05.

```
>> K
K = 2
>> p_val
p_val = 0
```

We next test for the constancy of residual covariance matrix. Since rejecting the constancy of factor loadings, we need to use estimated time varying factor loadings to estimate the residuals firstly.

```
% Obtain the estimated residuals using estimated time varying factor loadings with rule ob
thumb
% bandwidth.
[~,~,Residuals] = Time_COV(Y,0,K,0)
[Ln,ifa] = FWYZtest_step2(Residuals,alpha1);
```

Input ifa into the command window, we can get the results displayed below, $ifa = 0$ means we can not reject the constancy of residual covariance matrix under the significant level 0.05.

```
>> ifa
ifa =
logical
0
```

By now, we conducted basic analysis of the return data: the data Y has time varying factor loadings and constant residual covariance matrix (the same as the population settings), therefore, it is suitable to estimate the covariance matrix of excess return using our time-varying tools proposed in the main text. Next, we start constructing the minimum variance portfolio. In detail, we first select the values for tuning parameter by suggested three-fold cross-validation, and then estimate the time-varying covariance excess return matrix, finally, we get the minimum variance portfolio.

```

tau = 0.001;
% using three-fold corss-validation method
lambda = CV_for_spcov(Residuals, 3, tau);
% estimate return covariance matrix at the end point of sample and residual covariance matrix
[Sigma, RES_cov, Residuals] = Time_COV(Y, lambda, K, tau);

% estimate sample covariance matrix of return.
sample_cov = cov(Y');

wopt = Markowitz_MVP(r_cov); % theoretical minimum variance portfolio
wopt_tv = Markowitz_MVP(Sigma); % time-varying minimum variance portfolio
% minimum variance portfolio based on sample covariance
wopt_sam = Markowitz_MVP(sample_cov);

% We plot theoretical optimal weight and estimated weight by 'TV-MVP' of all dimension.
plot(wopt, 'xr-'); hold on; plot(wopt_tv, 'ob-');

```

The plots of oracle weight and its estimation from ‘TV-MVP’ are shown in Figure 4, it is clear that the weight allocation of ‘TV-MVP’ is quiet close to theoretical optimal level.

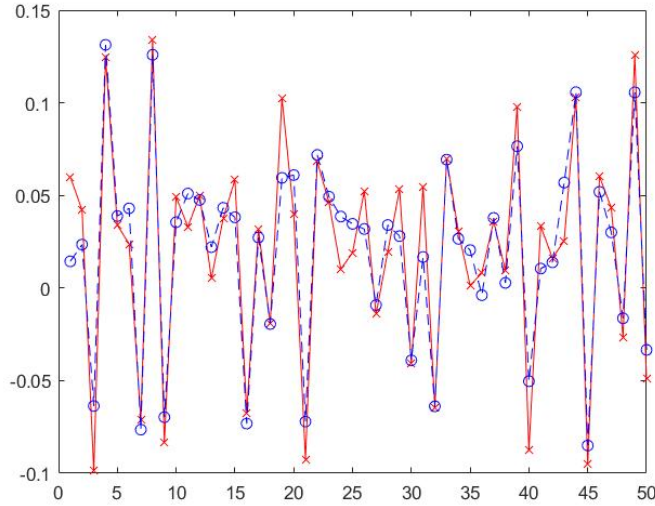


Figure 4: Theoretical optimal weight(red real line with 'x' at the nod) and estimated weight from ‘TV-MVP’(blue dotted line with 'o' at the nod).

To show the superiority of ‘TV-MVP’, we further plot the patterns of absolute deviation of weights between theoretical optimal weights and its estimation from ‘TV-MVP’ and sample covariance-based strategy.

```
% We plot the absolute deviation from theoretical weight.
devia_tv = abs(wopt - wopt_tv);
devia_sam = abs(wopt - wopt_sam);
plot(devia_tv,'r'); hold on; plot(devia_sam,'b--');
```

The plots are shown in Figure 5, it is easy to see that time-varying minimum variance portfolio is closer to theoretical version than sample covariance-based portfolio.

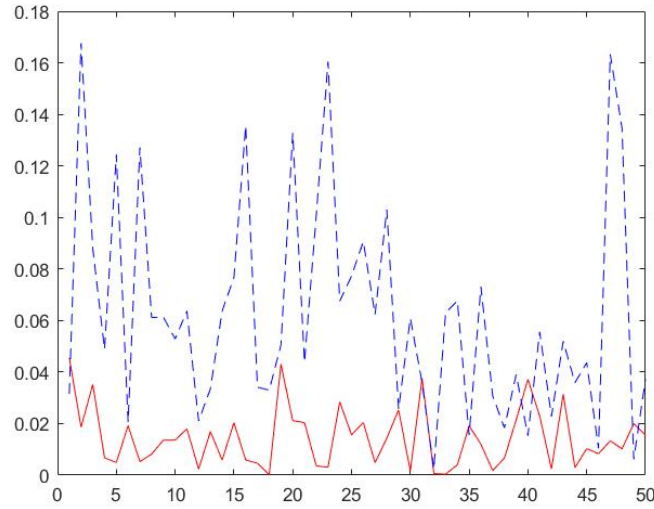


Figure 5: Absolute deviation of each dimension between theoretical minimum variance portfolio and time-varying minimum variance portfolio (red line), theoretical minimum variance portfolio and minimum variance portfolio based on sample covariance (dotted line)

Next, we calculate the optimal (theoretical) risk of the portfolio , TV-MVP and (time constant) minimum variance portfolio based on sample covariance matrix.

```
% Compute risk
risk = wopt' * r_cov * wopt;
risk_tv = wopt_tv' * Sigma * wopt_tv;
risk_sam = wopt_sam' * sample_cov * wopt_sam;
```

Similar with before, one can just input '*risk*', '*risk_tv*' and '*risk_sam*' into command window to see the final results as below.

```
>> risk
risk = 0.1373
>> risk_tv
risk_tv = 0.1000
>> risk_sam
risk_sam = 0.2117
```

It can be concluded that the estimated portfolio variance from TV-MVP is much closer to the theoretical level than that from sample covariance matrix.

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