ESRI Discussion Paper Series No.357

Economic Structural Change and Business Cycle Monitoring within the Framework of PCA-DFM

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October 2020

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Abstract

From a practical aspect, this paper is concerned about the general question of how economic structural changes matter in business cycle monitoring. Recent works provide a theoretical answer within the framework of a principal component estimation of dynamic factor model: the structural changes as parameter shifts in dynamic factor model do not affect the cyclical composite indicator as an estimated common component of a canonical time series. Not only is the effect of instability averaged out in a principal component estimation to some extent, but spurious factors absorb the effect if its magnitude is larger. Because this proposition relies on an asymptotics and some thought-to-be general but unverifiable conditions, this paper sees its validity using Japanese monthly 330 time series variables spanning Feb. 1983 to Oct. 2018. In addition, recently proposed tests for structural change are applied to this dataset.

1. Introduction

This paper provides the results of empirical research on a general question: How do economic structural changes affect business cycles? The two terms "economic structural change" and "business cycle" are highly conceptualistic. As an example of structural change, one might be able to point to changes in industrial structure, technological progress, demographic changes, sift of monetary policy, or even catastrophic events. However, its boundaries are ambiguous. Moreover, for business cycles, while Burns and Mitchell's (1946) adumbrative quasi-definition outlines the concept of business cycles, there are many ways to measure the amplitude or phase of those phenomenon (e.g. United Nations and Eurostat 2017).

To give an exact meaning to the general question, the framework of principal component analysis on dynamic factor models (PCA-DFM) is applicable. On the one hand, DFM is a statistical model, in which many time-series variables are commonly driven by much less unobserved factors. This data generating process is compatible to Burns and Mitchell's (1946) view of business cycles as the co-

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movements of a wide range of time series variables. Moreover, if one can see the space of the common factors as an appropriately rotated space of macro-shocks, the classical view that macroeconomic fluctuations are generated by successive shocks is captured by DFM in reduced form.

On the other hand, PCA is a general statistical tool to reduce the dimensions of information. DFM, including a large number of time series variables under realistic assumptions (approximate DFM), are suitably estimated by PCA (Stock and Watson 2002, Forni et al. 2000, 2005). In estimation of DFM by PCA, a large number of time series variables can be included in the model with a lighter computational burden.

In DFM, structural changes are represented as changes on factor loadings. For example, associated with a change in industrial structure, a factor that has been strongly driving the output of some industries may lose its influence on another variables. As mentioned later, although tests for structural change in empirical applications consider sudden, discontinuous or lumped changes of parameters rather than gradual changes as the alternative hypothesis, both sudden and gradual changes are captured within PCA-DFM in terms of its implications for business-cycle monitoring.

Business cycles can be measured by a cyclical composite indicator (CCI) in DFM. There are two straightforward ways to construct a business cycle index in DFM framework: one is interpreting the factor of the single-factor model as the business cycle (Stock and Watson 1989). The other is to use the estimated common component of a canonical variable, which is thought a priori to coincide with the reference cycle (e.g., Altissimo et al. 2001, 2010). If the number of factors in the DFM is exactly one, the former is a special case of the latter. In addition, CCI calculated by a simple cross-sectional averaging method (e.g., Conference Board CCI, Cabinet Office CCI) can be seen as a special case of CCI of the single-factor model (see, for example, Stock and Watson 2016, pp.429-430).

Under the framework of PCA-DFM, the question is concretized to: what effects does the instability of factor loading in DFM have on the CCI calculated in the PCA-DFM, ignoring for instability (the effect on now-casting or forecasting is beyond the scope of this paper)?

By virtue of the recent research, a theoretical answer is at hand: business cycle monitoring with CCI, based on components decomposition within PCA-DFM, is not confounded by structural change. Under thought-to-be mild conditions, if the magnitude of the change is small in a sense, PCA can consistently estimate the DFM (Stock and Watson 2002, Bates et al. 2013). Even if the change is not small, common components and idiosyncratic components are identified with PCA (Breitung and Eickmeier 2011, Chen et al. 2014). So, CCI as an estimated common component of a canonical variable is consistent in full-sample estimation.

The intuition behind the tolerance for the small instability in PCA-DFM is that, given limited dependence of factor-loading changes across a series, the changes are mutually offset by the effect of cross-sectional averaging. The effect of “small” break of loadings is entirely captured as additive $o_p(1)$ term in estimated factor. In the case of “large” break, the explanation of validity of the estimated common component as CCI is as follows: a sifting of factor loadings with sufficiently large magnitude is observationally equivalent to the introduction of additional factors into common components, with factor loading unchanged. This DFM with the spurious factor has constant factor loadings, and is equivalent to the original DFM with instable factor loadings. The inflated number of factors is consistently estimated by information criterion of Bai and Ng (2002). So, a common component of spurious factor representation is identified by PCA-DFM.

Because the theoretical answer relies on the asymptotics and general but unverifiable conditions, it makes sense to see empirically whether the CCI of PCA-DFM is robust toward potential structural changes. Using Japanese monthly 330 time series variables spanning Feb. 1983 to Oct. 2018, this paper calculates CCI in PCA-DFM famework, taking into consideration of the possibility of structural change (i.e. estimates based on the sub samples before and after every assumed break date), and compares it with CCI ignoring the possibility of structural change (i.e. based on the full sample). In addition, this paper presents some results of empirical application of recently proposed tests for structural change in the DFM.

The rest of this paper is organized as follows. Section 2 explains the analytical tools implemented in this paper. Section 3 describes the dataset. Section 4 shows the results of empirical analyses, and. Section 5 concludes.

2. Analytical framework

2.1. DFM

Suppose that we observe the data for N time-series variables over a period of Ttime units. Let $i = 1, \cdots, N$ indicate each time series variable, and $t = 1, \cdots, T$ for each time so that X_{it} denotes the value of the variable i at time t. DFM without structural break is written as:

$$X_{it} = \lambda_i' F_t + \varepsilon_{it} \quad , \tag{1}$$

where$(r \times 1)$ vector λ_i is factor loadings of variable i, $(r \times 1)$ vector F_t is common factors at time t, and variable ε_{it} is an idiosyncratic component. The term $\lambda_i' F_t$ is called the common component of variable i. All of factor loadings λ_i, common factors F_t, idiosyncratic components ε_{it}, and the number of common factors r are unobservable. The number of factors is far fewer than the number of time-series variables $(r \ll N)$. Although model (1) looks superficially static rather than dynamic because the relationship between the observables and the factors is contemporaneous (i.e., the common components of observables at time t are determined by common factors only at that time), redefinition of common factors $F_t \equiv (f_t', f_{t-1}', \cdots, f_{t-s}')'$ captures the dynamic relationship between the underlying dynamic factors f_t and the observables.

In DFM, each time series X_{it} is transformed appropriately so as to be stationary. In addition, it is usually assumed that the common component and idiosyncratic component are uncorrelated. See assumption (1-II) of Forni et al. (2000). As for exceptional example, moderate dependence between factors and idiosyncratic components is allowed for that the consistent estimation of the number of factors (Bai and Ng 2002), or of consistent estimation of factor space (Stock and Watson 1998, 2000) is achieved. Both cross-sectional correlation and serial correlation of idiosyncratic components are permissible to some extent.

2.2. Structural Break in DFM

In DFM, structural changes are defined as changes on factor loadings. For a given series i, the structural change for the series at break date T_i^* is expressed as the below equation.

$$X_{it} = \begin{cases} \lambda_i^{(1)\prime} F_t + \varepsilon_{it} & (t = 1, \cdots, T_i^*) \\ \lambda_i^{(2)\prime} F_t + \varepsilon_{it} & (t = T_i^* + 1, \cdots, T) \end{cases} \tag{2}$$

As is usually expressed, a middle point of time is represented by fraction $\pi \in (0,1)$ so that the integer $\lfloor \pi T \rfloor$ is that middle point. The point of time and the corresponding fraction are referred interchangeably: $\pi_i^* \in (0,1)$ such that $\lfloor \pi_i^* T \rfloor = T_i^*$ is the break date for series i in equation (2).

DFM with structural change has another representation in which the factor loadings are stable and the dimensions of factor space are expanded more than the original expression. That is, equation (2) can be rewritten as following:

$$X_{it} = \lambda_i^{(1)\prime} F_t + \left(\lambda_i^{(2)} - \lambda_i^{(1)}\right)' (F_t \otimes 1[t > T_i^*]) + \varepsilon_{it} = \tilde{\lambda}_i' \tilde{F}_t + \varepsilon_{it} \ , \tag{3}$$

where $\tilde{\lambda}_i \equiv \left(\lambda_i^{(1)\prime}, \lambda_i^{(2)\prime} - \lambda_i^{(1)\prime}\right)' Q^{-1}$ and $\tilde{F}_t \equiv \mathrm{Q}(F_t', F_t' \otimes 1[t > T_i^*])'$ with nonsingular $(2r \times 2r)$ matrix Q appropriately defined.

Note that the type of structural change in which some new factors emerge or some of original factors disappear is also included into the expression of equation (2) or (3). Emerging factors are corresponding to elements of factor loading switching from zeros to non-zeros, and disappearing factors to non-zeros-to-zeros.

2.3. CCI in DFM

To construct CCI by PCA-DFM, we exploit quarterly GDP as the reference cycle. In this paper, CCI is defined by the estimated and predicted-to-be-monthly common component of quarterly GDP. Following Stock and Watson (1998), we handle the data with mixed frequency and missing observations in PCA-DFM by solving the least square problem:

$$\left(\{\hat{F}_t\}_{t=1}^{T}, \{\hat{\lambda}_i\}_{i=1}^{N}\right) \equiv \underset{\substack{\{F_t\}_{t=1}^{T} \\ \{\lambda_i\}_{i=1}^{N}}}{\operatorname{argmin}} \sum_{i=1}^{N} \sum_{t=1}^{T} S_{it}(X_{it} - \lambda_i' F_t)^2 \ , \tag{4}$$

where S_{it} is a binary indicator equal to 1 whenever variable i is observed at time t, and 0 otherwise; $(N \times r)$ matrix $\Lambda \equiv (\lambda_1 \cdots \lambda_N)'$ is factor-loading matrix; $(T \times r)$ matrix $F \equiv (F_1' \cdots F_T')'$ is a common-factor matrix. The largest r eigenvalues of the covariance matrices of observed variables are the same as those of common components estimated by PCA. The number of factors are estimated by the information criterion of Bai and Ng (2002).

2.4. Structural break tests

In this paper, we apply two types of tests for structural break in DFM. The first is the test for change in the factor loadings of a given time series. Breitung and Eickmeier (2011) extend Andrew's (1993) structural break test to PCA-DFM situation. Yamamoto and Tanaka (2015) provide a modification of Breitung and Eickmeier (2011) as the latter is accompanied by non monotonicity power problem (i.e., the power of the test does not necessarily increase with the magnitude of break). Secondly, the test for the joint null hypothesis that factor loadings are time-invariant for all of the series is proposed by Chen t al. (2014) and Han and Inoue (2015). The idea of both tests is based on the fact that structural changes in factor loadings at a common date make second moment of PC estimator of common factors change at the break date. In the following, we explain the implementation of each tests.

2.4.1. Tests for individual instabilities

In Breitung and Eickmeier's (2011) test (BE test), the null hypothesis is that factor loadings of a given time series are stable: $\lambda_i^{(1)} = \lambda_i^{(2)}$ in equation (2). Consider the decomposition of time series i to common component and idiosyncratic term by principal component estimation using the full sample time period: $X_{it} = \hat{\lambda}_i' \hat{F}_t + \hat{u}_t$. The Lagrange multiplier type statistic of BE test for break date π is defined as below:

$$\xi_{LM}^{BE}(\pi) \equiv \frac{1}{\pi(1-\pi)} \left(\frac{1}{\sqrt{T}} \sum_{t=1}^{\lfloor \pi T \rfloor} \hat{u}_t \hat{F}_t\right)' \hat{V}^{-1} \left(\frac{1}{\sqrt{T}} \sum_{t=1}^{\lfloor \pi T \rfloor} \hat{u}_t \hat{F}_t\right) \ ,$$

where the matrix $\hat{V}$ is a heteroscedasticity and autocorrelation consistent (HAC) estimation of the covariance matrix of $\hat{u}_t \hat{F}_t$. In this paper, we use Newey-West statistic with Bartlett kernel:

$$\hat{V} = \frac{1}{T} \sum_{t=1}^{T} \hat{u}_t^2 \hat{F}_t \hat{F}_t' + \sum_{j=1}^{m} \left(1 - \frac{j}{m+1}\right) \frac{1}{T} \left(\sum_{t=j+1}^{T} \hat{u}_t \hat{u}_{t-j} \hat{F}_t \hat{F}_{t-j}' + \sum_{t=j+1}^{T} \hat{u}_{t-j} \hat{u}_t \hat{F}_{t-j} \hat{F}_t'\right) \ .$$

If the break date is unknown, we use the sup-LM test statistic:

$$\sup \xi_{LM}^{BE}(\pi_0) \equiv \sup_{\pi \in [\pi_0, 1-\pi_0]} \xi_{LM}^{BE}(\pi) \ ,$$

with predetermined truncation parameter $\pi_0 \in (0,1)$. Wald type statistics of BE test is:

$$\xi_{Wald}^{BE}(\pi) \equiv T\left(\hat{\lambda}_1(\pi) - \hat{\lambda}_2(\pi)\right)'\left(\frac{\hat{V}_1(\pi)}{\pi} + \frac{\hat{V}_2(\pi)}{1-\pi}\right)^{-1}\left(\hat{\lambda}_1(\pi) - \hat{\lambda}_2(\pi)\right) \ ,$$

where $\hat{V}_1(\pi)$ and $\hat{V}_2(\pi)$ are HAC estimates of covariance matrices of factor loading estimators for pre- and post-break-point subsample respectively.

$$\hat{V}_1(\pi) \equiv \frac{1}{T\pi}\left[\sum_{t=1}^{\lfloor T\pi \rfloor} \tilde{u}_t^2 \hat{F}_t \hat{F}_t' + \sum_{j=1}^{m}\left(1 - \frac{j}{m+1}\right)\left(\sum_{t=j+1}^{\lfloor T\pi \rfloor} \tilde{u}_t \tilde{u}_{t-j} \hat{F}_t \hat{F}_{t-j}' + \sum_{t=j+1}^{\lfloor T\pi \rfloor} \tilde{u}_{t-j} \tilde{u}_t \hat{F}_{t-j} \hat{F}_t'\right)\right]$$

$$\hat{V}_2(\pi) \equiv \frac{1}{T(1-\pi)}\left[\sum_{t=\lfloor T\pi \rfloor+1}^{T} \tilde{u}_t^2 \hat{F}_t \hat{F}_t' + \sum_{j=1}^{m}\left(1 - \frac{j}{m+1}\right)\left(\sum_{t=\lfloor T\pi \rfloor+j+2}^{T} \tilde{u}_t \tilde{u}_{t-j} \hat{F}_t \hat{F}_{t-j}' + \sum_{t=\lfloor T\pi \rfloor+j+2}^{T} \tilde{u}_{t-j} \tilde{u}_t \hat{F}_{t-j} \hat{F}_t'\right)\right]$$

$\{\tilde{u}_t\}_{t=1}^{T}$ are the residuals of the estimated model under the alternative $H_1(\pi)$. Sup-Wald is:

$$\sup \xi_{Wald}^{BE}(\pi_0) \equiv \sup_{\pi \in [\pi_0, 1-\pi_0]} \xi_{Wald}^{BE}(\pi) \ .$$

Asymptotically $\xi_{LM}^{BE}(\pi)$ or $\xi_{Wald}^{BE}(\pi)$ has chi-squared distribution with degrees of freedom of the number of factors, and the asymptotic critical value for $\sup \xi_{LM}^{BE}(\pi_0)$ or $\sup \xi_{Wald}^{BE}(\pi_0)$ is reported by Andrew (1993). In our empirical work, with the time dimension $T = 429$ and the truncation $\pi_0 = 0.15$, sup-Wald turns out to be unstable near the both sides of truncated period. So, we focus only on the test statistics LM or sup-LM for BE test in the sequel.

As the authors pointed out, BE test has the problem of losing power when the number of factors is overestimated. Because the DFM with structural break is observationally equivalent to the DFM with inflated number of factors and stable factor loadings (see equations (2) and (3)), overestimation of the number of factors makes BE test more likely give a decision in favor of the null hypothesis. This is a difficult dilemma because any consistent estimator of the number of factors tends to overestimate it under alternative hypothesis. To solve this problem, Yamamoto and Tanaka (2015) suggest the modification of BE test (YT test). YT test designs the statistics in such a way that the effects of inflated dimensions of factor space on a leaning toward null are suppressed:

$$W^{YT}(\pi_0, \bar{r}) \equiv \max_{1 \le q \le \bar{r}} \sup_{\pi \in [\pi_0, 1-\pi_0]} w(\pi, q) \ ,$$

where $w(\pi, q)$ is the Wald statistic for the structural break test of regression bellow at time $\lfloor T\pi \rfloor$:

$$X_{it} = \lambda_{i,q} \hat{F}_{q,t} + v_{iqt} \ ,$$

i.e., the regression of the variable X_{it} on the q-th factor estimates by principle components $\hat{F}_{q,t}$. The asymptotic critical values of $W^{YT}(\pi_0, \bar{r})$ are reported in Yamamoto and Tanaka (2015).

2.4.2. Tests for overall instabilities

While BE test and YT test are the tests for the factor loading stability of a particular variable, Chen, Dolado, and Gonzalo's (2014) test (CDG test) and Han and Inoue's (2015) test (HI test) are the tests for joint null hypothesis that all factor loadings are constant over time. The alternative hypothesis is that non-negligible fraction of or all variables have experienced big breaks in their loadings. Both of CDG and HI tests rely on the observational equivalence of the factor loading break and the instability of second moment of factors estimated by PCA. HI test exploits more information than CDG: the former directly compares the estimated covariance matrices of factors before and after the break date, and the latter focuses on the stability of regression of one of estimated factors on the others. In comparison, CDG test assumes only factor loading changes in the alternative but HI test has power also for the emerging or disappearing factors as a break, and their results of Monte Carlo simulation show that CDG test is more powerful than HI test for small sample size (not greater than N=100 and T=100).

CDG test implements Andrew's (1993) structural break test for the regression of an arbitrary chosen factor on the others:

$$\hat{F}_{1t} = \hat{\gamma}'\hat{F}_{-1t} + \hat{v}_t \ ,$$

where $\hat{F}_{1t}$ and $\hat{F}_{-1t} \equiv \left(\hat{F}_{2t}, \cdots, \hat{F}_{rt}\right)'$ are the factors estimated by PCA with full sample. By the definition of PCA estimation of factors, it holds that $\hat{v}_t = \hat{F}_{1t}$ for the full sample regression. Then, the LM statistic with permissible break fraction π is:

$$\xi_{LM}^{CDG}(\pi) \equiv \frac{1}{\pi(1-\pi)}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{\lfloor \pi T \rfloor}\hat{F}_{1t}\hat{F}_{-1t}\right)'\hat{S}^{-1}\left(\frac{1}{\sqrt{T}}\sum_{t=1}^{\lfloor \pi T \rfloor}\hat{F}_{1t}\hat{F}_{-1t}\right) \ ,$$

where $\hat{S}$ is heteroscedasticity and autocorrelation consistent (HAC) estimate of covariance matrix of $\hat{F}_{1t}\hat{F}_{-1t}$. In this paper, we use the Newey-West estimator and the Bartlett kernel with bandwidth $m = 10$.

$$\begin{aligned}\hat{S} \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{F}_{1t}\hat{F}_{1t}\hat{F}_{-1t}\hat{F}'_{-1t} \\ &+ \sum_{j=1}^{m}\left(1-\frac{j}{m+1}\right)\frac{1}{T}\left(\sum_{t=j+1}^{T}\hat{F}_{1t}\hat{F}_{1t-j}\hat{F}_{-1t}\hat{F}'_{-1t-j}\right. \\ &\left.+ \sum_{t=j+1}^{T}\hat{F}_{1t-j}\hat{F}_{1t}\hat{F}_{-1t-j}\hat{F}'_{-1t}\right) \ .\end{aligned}$$

If the break point is dealt as unknown, the sup-LM test is applied with symmetric truncation $\pi_0 = 0.15$:

$$\sup \xi_{LM}^{CDG}(\pi_0) \equiv \sup_{\pi\in[\pi_0, 1-\pi_0]} \xi_{LM}^{CDG}(\pi) \ .$$

The Wald statistic is calculate as follows:

$$\xi_{Wald}^{CDG}(\pi) \equiv T\big(\hat{\gamma}_1(\pi) - \hat{\gamma}_2(\pi)\big)' \left(\frac{\hat{S}_1(\pi)}{\pi} + \frac{\hat{S}_2(\pi)}{1-\pi}\right)^{-1} \big(\hat{\gamma}_1(\pi) - \hat{\gamma}_2(\pi)\big) \ ,$$

$$\sup \xi_{Wald}^{CDG}(\pi_0) \equiv \sup_{\pi \in [\pi_0, 1-\pi_0]} \xi_{Wald}^{CDG}(\pi) \ ,$$

where $\hat{S}_1(\pi)$ and $\hat{S}_2(\pi)$ are HAC estimates of covariance matrices of the coefficient estimators $\hat{\gamma}$ for pre- and post-break-point subsample respectively. Chen et al. (2014) recommend to use the Wald type test rather than the LM type test to avoid the suffering from the adequacy of the first factor as a regressand in the first step of their procedure.

HI test measures the difference of covariance matrices of factors for pre- and post-break.

$$\xi_{LM}^{HI}(\pi) \equiv \hat{A}(\pi)'\hat{B}(\pi)^{-1}\hat{A}(\pi) \ ,$$

where

$$\hat{A}(\pi) \equiv \mathrm{vech}\left(\sqrt{T}\left(\frac{1}{\lfloor \pi T \rfloor}\sum_{t=1}^{\lfloor \pi T \rfloor} \hat{F}_t\hat{F}_t' - \frac{1}{T - \lfloor \pi T \rfloor}\sum_{t=\lfloor \pi T \rfloor+1}^{T} \hat{F}_t\hat{F}_t'\right)\right) \ .$$

The matrix $\hat{B}(\pi)$ is HAC estimate (again, Newey-West and Bartlett) of covariance of $\hat{A}(\pi)$:

$$\hat{B}(\pi) \equiv \left(\frac{1}{\pi} + \frac{1}{1-\pi}\right)\left(\hat{\Gamma}_0 + \sum_{j=1}^{m}\left(1 - \frac{j}{m+1}\right)\left(\hat{\Gamma}_j + \hat{\Gamma}_j'\right)\right) \ ,$$

where

$$\hat{\Gamma}_j \equiv \frac{1}{T}\sum_{t=j+1}^{T} \mathrm{vech}\big(\hat{F}_t\hat{F}_t' - I\big)\,\mathrm{vech}\big(\hat{F}_{t-j}\hat{F}_{t-j}' - I\big)' \ .$$

$\{\hat{F}_t\}_{t=1}^{T}$ is the PCA estimate of the factors under the identification restriction of $\sum_t \hat{F}_t\hat{F}_t'/T = I$. Sup-LM is:

$$\sup \xi_{LM}^{HI}(\pi_0) \equiv \sup_{\pi \in [\pi_0, 1-\pi_0]} \xi_{LM}^{HI}(\pi) \ .$$

The asymptotic critical value for sup-Wald or sup-LM is reported by Andrew (1993).

3. Data

To obtain a comprehensive macroeconomic DFM, we use the data set consisting of monthly 330 time series variables, which cover a wide range of economic activities, i.e., industrial production, tertiary industry, consumption expenditure, labor, commercial sales, dwelling constructions, machinery orders, stock prices, goods prices, financial sector, and others. All of the series are used on a seasonally adjusted basis with the exception of some variables including stock prices and some of price indexes. The variables are selected under the basic concept of preference for lower aggregation level and enough time periods, and avoidance of coverage duplication. Table 1 lists the series by category (see the Appendix table A1 for the full list). The dataset for our analysis is an unbalanced monthly panel data. The time periods of the sample are effectively from Feb. 1983 to Oct. 2018, which is shortened from original data periods by preliminary transformation of the variables mentioned below.

Because DFM is suitable for the stationary process, the data are converted by logarithmic transform or first- or second-differentiations according to the results of unit root tests. The third column of Table 1 shows the transformation applied to each variable category. The influences of consumption tax increases are excluded from the series of consumer price indexes by excluding the discontinuities as estimated level shifts at time points of the tax introduction (Apr. 1989) and increases (Apr. 1997 and Apr. 2014). The level shift estimation is conducted by X-12-ARIMA of U.S. Census Bureau. The component indicators of consumer confidence index are quarterly before Mar. 2004 and monthly thereafter. The mixed frequency dataset is dealt as incomplete data with missing completely at random by the methods of Stock and Matson (1998). In the baseline case, outliers are trimmed following the method adopted by the Cabinet Office of Japan within the calculation of the indexes of business conditions (see http://www.esri.cao.go.jp/en/stat/di/di2e.html for detail). In addition, following Stock and Watson (2012), the long-term variable trend is removed from every time series by the filter of bi-weight kernel with bandwidth 100 months for leads and lags respectively. Finally, all series are standardized to have a mean of 0 and variance of 1.

4. Results

4.1. Commonality

In table 2, for each category in rows and for each number of factors in columns, we show the average portion of variance of time series driven by common component: $\mathrm{Var}\left(\sum_{j=1}^{r} \lambda_{i,j} F_{j,t}\right) / \mathrm{Var}(X_{it})$. If only one factor is included, 8.8% of variances of all variables is attributed to common components. Three factor model ascribe 20% of the variance to common component, and it requires at least nine factors for common component to account more than 30% of the variance. Attributable fractions of common factors by variable category are lacking in uniformity. In one factor model, the fraction of common fluctuation is 24% for stock prices, around 10% for industrial production, tertiary industry, or commercial sales, and only a few for the rest. If the model consists of ten factors, the commonality is 65% for stock prices, 51% for commercial sales, 29% for industrial production, 28% for tertiary industry, 21% for consumption expenditure, mentioning only noticeable figures. The category of dwelling constructions, machinery orders, producer price indexes, consumer price indexes, and labor show very low commonality. The uneven distribution of commonalities makes a striking contrast to DFM for U.S. quarterly time series (Stock and Watson 2012).

4.2. The number of factors

The results for the estimation of the number of factors in our DFM are displayed in table 3. The full sample is used for the estimation: i.e., the number of factors are estimated under the assumption of no structural break. “Trace R2” is the cumulative eigenvalues in order of diminishing margins, and “marginal trace R2” is the eigenvalues of covariance matrix of the 330 series. The column of trace R2 for DFM with outlier handling is the same as the bottom row of table 2. “BN-ICp2” in table 3 is the second information criterion $IC_{p2}(k) = \ln\|X - F\Lambda'\|^2 + k\,(N+T)\ln\min(N,T)/NT$ (where (t,i) element of $T \times N$ matrix X is X_{it}, t-th row of $T \times r$ matrix F is F_t', and i-th row of $N \times r$ matrix Λ is λ_i') suggested by Bai and Ng (2002). This criterion implies that the number of static factors is four for DFM whether outlier adjustment is applied or not. The columns of “AH-ER” in table 3 show Ahn and Horenstein’s (2013) eigenvalue ratio. As the appropriateness of the functional form of penalty in Bai and Ng’s (2002) criterion is described in asymptotics, the specific functional form is undetermined. This is not matter for infinitely large sample, but is for finite sample. The result of estimation is dependent on the specification of penalty function for finite sample. The method of Ahn and Horenstein (2013) circumvents this problem. According to their way, the number of factors in our model is 3.

Table 4 displays the results of Amengual and Watson’s (2007) method for determination of the number of dynamic factors. In this table, each cell indicates the value of information criterion for each suspected number of dynamic factors in rows by suspected number of static factors in columns. Actuary, the number of dynamic factors is the number of shocks that constitute the innovations in VAR for the static factors. Our DFM implies 2 or 3 dynamic factors.

4.3. Full- and sub-sample CCIs

Fig.1 shows the correlation between sub-sample CCIs and full-sample CCI. For each assumed break date, the sample is divided into before-and-after subsamples, and CCIs are calculated based on these two subsamples. The gray solid line plots correlation between CCI based on the before-subsample and CCI based on the full-sample. The black dashed line plots correlation between CCI based on the after-subsample and CCI based on the full-sample. In fig.1, CCI is the estimated common component of de-trended GDP growth in DFM of monthly 330 series and quarterly GDP. The handling of mixed frequencies data of Stock and Watson (1998) is exploited.

The correlation between before-subsample-CCI and full-sample-CCI is persistently high. The correlation between after-subsample-CCI and full-sample-CCI is high but drops remarkably at the assumed break points of Feb. 2009 and March 2011.

To calculate the CCI with subsamples in fig.2, the number of factors is repeatedly estimated for every subsample. Fig.2 shows the estimated number of factors for each of subsamples. Horizontal axis is assumed break date. The gray solid line plots the estimated number of factors based on the before-subsample. The black dashed line plots the estimated number of factors based on the after-subsample. The black solid line plots the total of the estimated numbers of factors based on before- and after-subsamples. The estimation of the number of factors is in terms of Bai and Ng’s (2002) ICp2. In light of Cheng et al.’s (2016) argument that the sum of estimated numbers of factors for before- and after-subsample is minimized by the true break date split, the black solid line in fig.2 incidentally implies that the date Feb. 2009 and March 2011 are the potential candidates of break date.

To take a close look at the temporary decline of correlation between after-subsample CCI and full-sample CCI, fig.3 shows the first four relative eigenvalues in principal component analysis for each sample split.

4.4. Structural break tests

Fig.4 plots the fraction of 330 series for which the null hypothesis of no structural break at every date in horizontal axis is rejected at 5% significance level based on the LM test of BE. The solid line corresponds to the dataset with outlier adjustment, and the dashed line without the adjustment. Around 10% of series have had structural break during 1990s and 2000s for adjusted data, and the fraction is about 30 or 40% for non-adjusted data.

In contrast to fig.4, which tests for assumed known break date, fig.5 plots the rejected rate of 330 series for unknown break date both by BE and YT for each number of factors in horizontal axis. Dovetailing with the results of simulation study in Yamamoto and Tanaka (2015), test by LM type of BE with heteroscedasticity and autocorrelation consistent (HAC) estimates of estimator variance (the black solid line in the graph) indicates lesser power. If we compare the rejection rates for BE test without HAC (the black dashed line) and YT test (the gray solid line), both tests reject the null of stability for 30 to 50% of the series with 4 or less factors. When the number of factors is greater than 5, YT test rejects for 60 to 80% of the series while the rates of BE test remain under 60%. The figure implies that the non-monotonicity power of BE test does not have much of a problem in our case.

The results of CDG test are as depicted in fig.6. The graphs display the series of Wald test statistics for every envisaged break date for different values of the number of factors. The null of stability is strongly rejected for 3, 4, or 5-factor model. No evidence for break in 2-factor model can be seen as related to the fact that CDG test loses power if the number of factors is underestimated. The Wald test statistics reach their peak around the head of 1990 near the end of the bubble economy.

Fig.7 reports the results of HI test. The series of LM test statistic for every supposed break date are plotted for different values of the number of factors. The instability is found for 4 or 5-factor model. The peak of LM is again near the head of 1990. Although the weaker results of HI test than CDG test have no clear explanation, there are at least possibilities that the type of break in which some factors emerge or disappear is unlikely and that the magnitude of break if any is not large.

5. Conclusion

We study the robustness of CCI to changes in factor loadings in DFM and conduct empirical applications of recently proposed tests for instability in large dimensional DFM. The correlation between CCI calculated based on split subsample and CCI based on full sample is persistently high except the temporary declines at February 2009 and March 2011 for after-subsample CCI.

While the structural break is detected, cursory application of tests for structural change in DFM for Japanese 330 monthly variables from Feb. 1983 to Oct. 2018 provides no clear-cut results about break date. Quick application of the sophisticated methods demonstrate the necessity for more advanced empirical analyses.

Meanwhile, in this study, structural change is defined as a onetime change in factor loading; the tests conducted have power against two or more changes. Though the change of alternative hypothesis is sudden, CCI is also theoretically robust to gradual change in some extent. In the analyses on subsamples pre- and post-break, we first conduct pretreatment of the data (i.e., outlier adjustment, detrending, and standardizing) and then split the sample. Although the split ought to precede the pretreatment, we do not so because the latter requires sufficiently long time period of dataset. In spite of the preliminarily conversion of the data series to de-mean or de-trend the variables, the driver of long-term swing in the data may also confound short- and medium-term modeling in the DFM (Stock and Watson 2016, p.514).

Finally, diagnostics show that commonality of common factors is totally low and lacking uniformity over the included response variables (table 2). Poor fitness of dynamic factor models to the Japanese economy will discourage the introduction of factor-model-based economic monitoring.

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Figures and tables

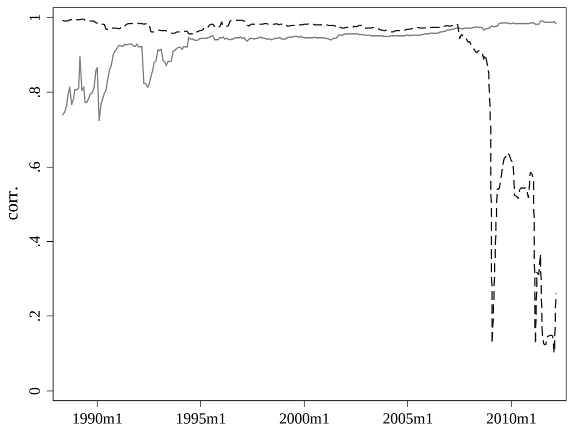

Fig.1 Correlation Between Sub-sample CCIs and Full-sample CCI.

Notes. Horizontal axis is assumed break date. Gray solid line plots correlation between CCI based on the before-subsample and CCI based on the full-sample. Black dashed line plots correlation between CCI based on the after-subsample and CCI based on the full-sample. CCI is the estimated common component of de-trended GDP growth.

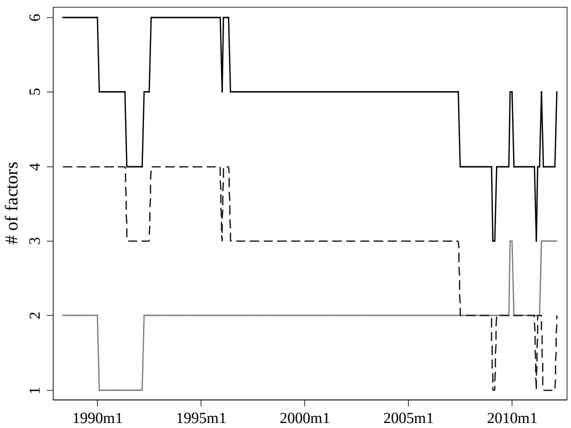

Fig.2 Estimated Number of Factors for Sub-samples.

Notes. Horizontal axis is assumed break date. Gray solid line plots the estimated number of factors based on the before-subsample. Black dashed line plots the estimated number of factors based on the after-subsample. Black solid line plots the total of the estimated numbers of factors based on before- and after-subsamples. The estimation of the number of factors is in terms of Bai and Ng’s (2002) ICp2.

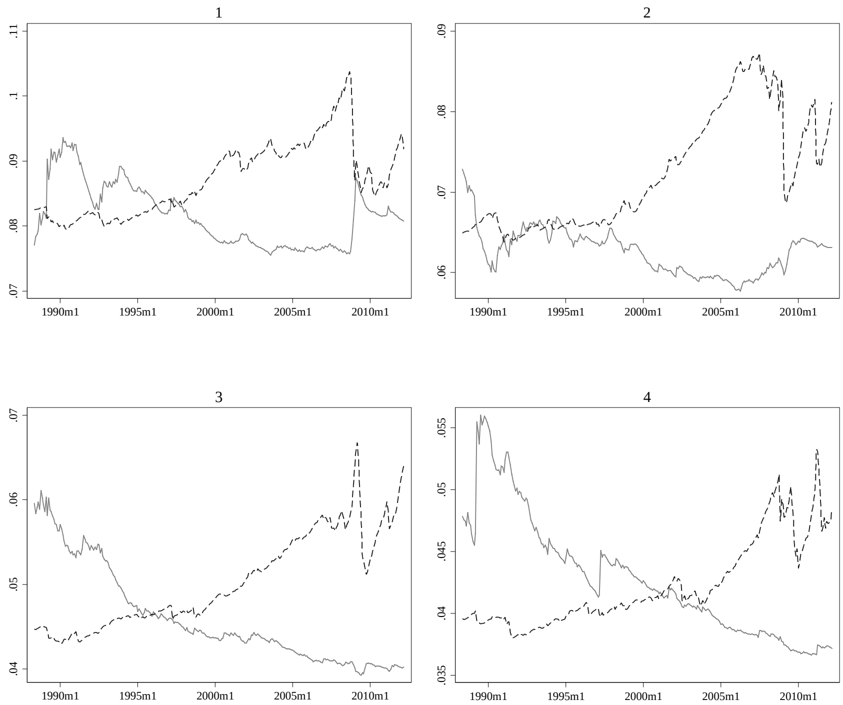

Fig.3 Trace R2 of factors for before- and after-subsamples

Notes: Horizontal axis is assumed break date. Gray solid line plots the relative eigenvalue associated with each factor based on the before-subsample. Black dashed line corresponds to the after-subsample.

Fig.4 BE test

Notes: The fraction of variables for which the null of factor loading stability is rejected at 5% level. The solid line with outlier adjustment and the dashed line without outlier adjustment.

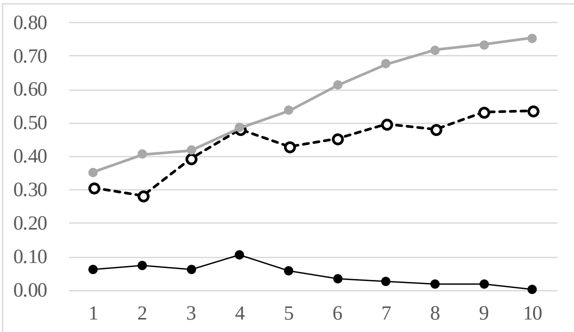

Fig.5 YT test and BE test

Notes: The fraction of variables for which the null of factor loading stability is rejected at 5% level. The number of factors is put on the horizontal axis. The black solid line for sup-LM of BE test with HAC estimation, the black dashed line for sup-LM of BE test without HAC estimation, the gray solid line for YT test with HAC estimation.

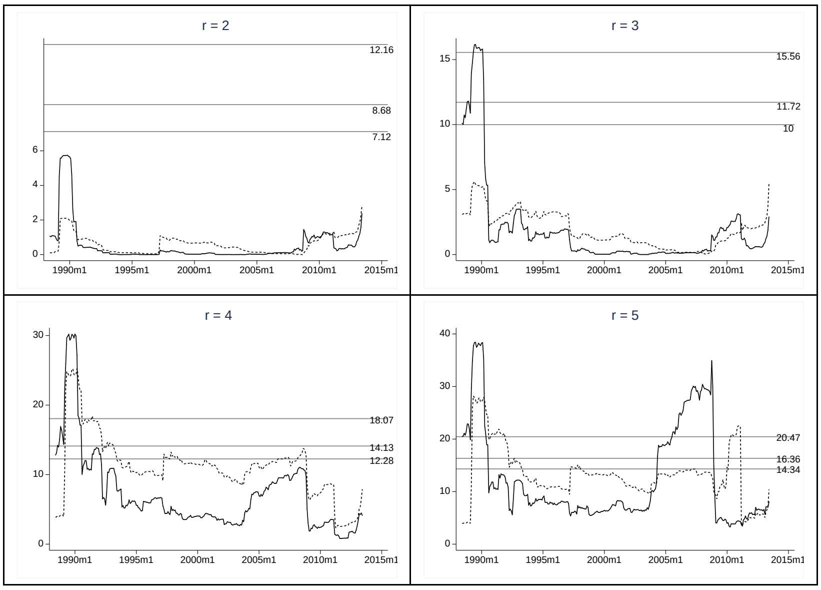

Fig.6 CDG test

Notes: Wald type statistics for each number of factors ranging from 2 to 5. X-axis is the assumed break date. The solid line with outlier adjustment and the dashed line without outlier adjustment. The horizontal lines show the asymptotic critical values of the sup-Wald test for 1%, 5%, and 10% level in the order from top to bottom.

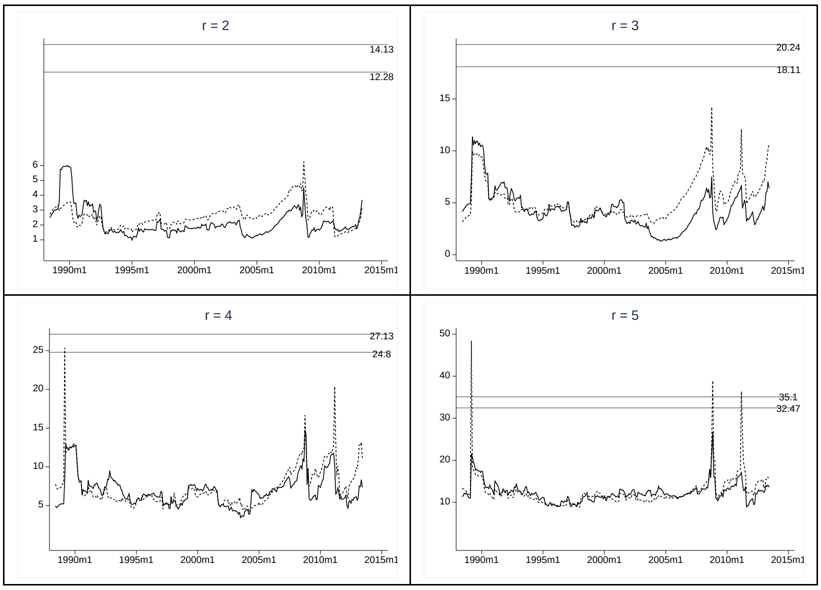

Fig.7 HI test

Notes: LM type statistics for each number of factors ranging from 2 to 5. X-axis is the assumed break date. The solid line with outlier adjustment and the dashed line without outlier adjustment. The horizontal lines show the asymptotic critical values of the sup-LM test for 5%, and 10% level in the order from top to bottom.

Table 1. Monthly time series in the full data set

Category	# of series	Transformation
Industrial production	100	$\Delta\log$
Tertiary industry	43	$\Delta\log$
Consumption expenditure	16	$\Delta\log$
Labor	29	Ratio variables: Δ, Others: $\Delta\log$
Commercial sales	38	$\Delta\log$
Dwelling constructions & Machinery orders	12	$\Delta\log$
Stock prices	36	$\Delta\log$
PPI & CPI	14	$\Delta^2\log$
Interest rate & Money	12	Interest rate: Δ, Spread: level, Money stock: $(1-L^{12})\log$
Others	30	Mind DI: Δ, Others: $\Delta\log$
Total	330	

Table 2. Commonality of common factors

Category	1	2	3	4	5	6	7	8	9	10
Industrial production	0.092	0.124	0.143	0.178	0.196	0.217	0.243	0.263	0.279	0.293
Tertiary industry	0.108	0.167	0.194	0.208	0.218	0.230	0.248	0.259	0.274	0.284
Consumption expenditure	0.030	0.043	0.131	0.156	0.162	0.169	0.184	0.193	0.200	0.212
Labor	0.011	0.014	0.019	0.033	0.042	0.055	0.075	0.081	0.092	0.107
Commercial sales	0.107	0.159	0.424	0.446	0.456	0.464	0.471	0.488	0.498	0.512
Dwelling constructions & Machinery orders	0.013	0.015	0.021	0.026	0.030	0.037	0.044	0.056	0.066	0.082
Stock prices	0.244	0.613	0.615	0.622	0.631	0.639	0.640	0.643	0.646	0.650
PPI & CPI	0.009	0.016	0.018	0.034	0.057	0.063	0.066	0.072	0.082	0.087
Interest rate & Money	0.006	0.017	0.025	0.052	0.066	0.081	0.124	0.143	0.157	0.164
Others	0.037	0.058	0.084	0.131	0.201	0.258	0.260	0.275	0.297	0.320
Total	0.089	0.157	0.206	0.230	0.250	0.268	0.284	0.298	0.312	0.325

Notes: The value of average R2 for the regressions of response variables on common factors up to the number in column head by variable category.

Table 3. Statistics for estimating the number of static factors

	Without outlier-handling				With outlier-handling			
# of F's	Trace R2	Marginal trace R2	BN-ICp2	AH-ER	Trace R2	Marginal trace R2	BN-ICp2	AH-ER
1	0.096	0.096	-0.099	1.396	0.089	0.089	-0.088	1.307
2	0.164	0.069	-0.146	1.481	0.157	0.068	-0.135	1.382
3	0.211	0.046	-0.172	**1.636**	0.206	0.049	-0.164	**2.012**
4	0.239	0.028	**-0.178**	1.298	0.230	0.024	**-0.164**	1.264
5	0.261	0.022	-0.176	1.222	0.250	0.019	-0.159	1.056
6	0.279	0.018	-0.169	1.097	0.268	0.018	-0.152	1.120
7	0.295	0.016	-0.161	1.072	0.284	0.016	-0.144	1.178

Notes: trace R2 is the accumulation of relative eigenvalues for each number of factors in rows. Marginal trace R2 is the relative eigenvalue for each principal component. BN-ICp2 is the second panel information criterion in Bai and Ng (2002). AH-ER is the consecutive eigenvalue ratio of Ahn and Horenstein (2013).

Table 4. Amenguel-Watson estimation of the number of dynamic factors

	Without outlier-handling # of F's						With outlier-handling # of F's					
# of f's	2	3	4	5	6	7	2	3	4	5	6	7
1	-0.106	-0.118	-0.135	-0.148	-0.154	-0.163	-0.094	-0.117	-0.137	-0.142	-0.147	-0.153
2	**-0.147**	-0.159	-0.177	-0.191	-0.197	-0.205	**-0.135**	-0.160	-0.173	-0.178	-0.183	**-0.190**
3		**-0.173**	**-0.184**	**-0.192**	**-0.199**	**-0.206**		**-0.166**	**-0.175**	**-0.180**	**-0.183**	-0.189
4			-0.181	-0.189	-0.195	-0.203			-0.169	-0.171	-0.174	-0.180
5				-0.182	-0.188	-0.196				-0.163	-0.166	-0.172
6					-0.176	-0.183					-0.157	-0.162
7						-0.168						-0.150

Notes: Following Amenguel and Watson (2007), each cell reports the value of ICp2 of Bai and Ng (2002) for each number of dynamic factors in rows given the number of static factors in columns. The number of lags in VAR for static factors is set to 2.

Appendix

Table. A1

	Index of industrial production
1	Capital goods for production facilities
2	Capital goods for electric power
3	Capital goods for communications & broadcasting
4	Capital goods for agriculture
5	Capital goods for construction
6	Capital goods for transportation
7	Capital goods for clerical work
8	Capital goods for other uses
9	Construction goods for building
10	Construction goods for civil engineering
11	Durable consumer goods for homemaking
12	Durable consumer goods for cooling & heating
13	Durable consumer goods for furniture & accessory
14	Durable consumer goods for culture & recreation
15	Durable consumer goods, Automobile & motorcycle
16	Non-durable consumer goods for homemaking
17	Non-durable consumer goods for culture & recreation
18	Non-durable consumer goods, Clothes & footwear
19	Non-durable consumer goods, Food & beverages
20	Producer goods for mining and manufacturing
21	Producer goods for other uses
	Index of producer's shipments
22	Capital goods for production facilities
23	Capital goods for electric power
24	Capital goods for communications & broadcasting
25	Capital goods for agriculture
26	Capital goods for construction
27	Capital goods for transportation
28	Capital goods for clerical work
29	Capital goods for other uses
30	Construction goods for building
31	Construction goods for civil engineering
32	Durable consumer goods for homemaking
33	Durable consumer goods for cooling & heating
34	Durable consumer goods for furniture & accessory
35	Durable consumer goods for culture & recreation
36	Durable consumer goods, Automobile & motorcycle
37	Non-durable consumer goods for homemaking
38	Non-durable consumer goods for culture & recreation
39	Non-durable consumer goods, Clothes & footwear
40	Non-durable consumer goods, Food & beverages
41	Producer goods for mining and manufacturing
42	Producer goods for other uses

	Index of producer's inventories
43	Capital goods for production facilities
44	Capital goods for electric power
45	Capital goods for communications & broadcasting
46	Capital goods for agriculture
47	Capital goods for construction
48	Capital goods for transportation
49	Capital goods for clerical work
50	Capital goods for other uses
51	Construction goods for building
52	Construction goods for civil engineering
53	Durable consumer goods for homemaking
54	Durable consumer goods for cooling & heating
55	Durable consumer goods for furniture & accessory
56	Durable consumer goods for culture & recreation
57	Durable consumer goods, Automobile & motorcycle
58	Non-durable consumer goods for homemaking
59	Non-durable consumer goods for culture & recreation
60	Non-durable consumer goods, Clothes & footwear
61	Non-durable consumer goods, Food & beverages
62	Producer goods for mining and manufacturing
63	Producer goods for other uses
	Index of producer's inventory ratio
64	Capital goods for production facilities
65	Capital goods for electric power
66	Capital goods for communications & broadcasting
67	Capital goods for construction
68	Capital goods for transportation
69	Capital goods for clerical work
70	Capital goods for other uses
71	Construction goods for building
72	Construction goods for civil engineering
73	Durable consumer goods for homemaking
74	Durable consumer goods for furniture & accessory
75	Durable consumer goods for culture & recreation
76	Durable consumer goods, Automobile & motorcycle
77	Non-durable consumer goods for homemaking
78	Non-durable consumer goods for culture & recreation
79	Non-durable consumer goods, Clothes & footwear
80	Non-durable consumer goods, Food & beverages
81	Producer goods for mining and manufacturing
82	Producer goods for other uses

Table. A1 (continued)

	Index of utilization rate
83	Iron & steel
84	Non-ferrous metals
85	Fabricated metals
86	Transport equipment
87	Ceramics, stone & clay products
88	Chemicals
89	Petroleum & coal products
90	Pulp, paper & paper products
91	Textiles
	Index of production capacity
92	Iron & steel
93	Non-ferrous metals
94	Fabricated metals
95	Transport equipment
96	Ceramics, stone & clay products
97	Chemicals
98	Petroleum & coal products
99	Pulp, paper & paper products
100	Textiles

	Index of tertiary industry activity
101	Electricity, gas, heat supply & water
102	Communications
103	Broadcasting
104	Information services
105	Railway passenger transport
106	Railway freight transport
107	Road passenger transport
108	Road freight transport
109	Water passenger transport
110	Water freight transport
111	Air passenger transport
112	Air freight transport
113	Warehousing
114	Transport facilities services for road transport
115	Postal activities, including mail delivery
116	Wholesale trade, General merchandise
117	Wholesale trade, Textile products (except apparel, apparel accessories & notions)
118	Wholesale trade, Apparel, apparel accessories & notions
119	Wholesale trade, Agricultural, animal & poultry farm & aquatic products
120	Wholesale trade, Food & beverages
121	Wholesale trade, Building materials
122	Wholesale trade, Chemicals & related products
123	Wholesale trade, Minerals & metals
124	Wholesale trade, Machinery & equipment
125	Wholesale trade, Furniture, fixture & house furnishings
126	Wholesale trade, Drugs & toiletries
127	Other wholesales trade
128	Financial products transaction & futures commodity transaction dealers
129	Non-life insurance institutions
130	Goods rental & leasing
131	Advertising
132	Retail trade, General merchandise
133	Retail trade, Dry goods, apparel & apparel accessories
134	Retail trade, Food & beverages
135	Retail trade, Motor vehicles
136	Retail trade, Household appliance
137	Other retail trade
138	Real estate
139	Accommodations
140	Travel agency
141	Services for amusement & hobbies
142	Bicycle, horse, motorcar & motorboat race track operations & companies
143	Sports facilities
144	Index of real disposable income (worker's households, 2 or more persons)
145	Average propensity to consume (worker's households, 2 or more persons)

Table. A1 (continued)

	Index of consumption expenditure level
146	Food
147	Housing
148	Fuel, light & water
149	Furniture & household utensils
150	Clothing & footwear
151	Medical care
152	Transportation & communication
153	Education
154	Culture & recreation
155	Miscellaneous
156	Regular employment index (a)
157	Wage index, Contractual cash earnings (a)
158	Real wage index (a)
159	Hours worked index, Non-scheduled hours worked (a)
160	Hours worked index, Scheduled hours worked (a)
	Unemployment rate by age group
161	Male, 15-24 years old
162	Male, 25-34 years old
163	Male, 35-44 years old
164	Male, 45-54 years old
165	Male, 55-64 years old
166	Female, 15-24 years old
167	Female, 25-34 years old
168	Female, 35-44 years old
169	Female, 45-54 years old
170	Female, 55-64 years old
171	Male or Female, 65 years old
	Labor force participation rate by age group
172	Male, 15-24 years old
173	Male, 25-34 years old
174	Male, 35-44 years old
175	Male, 45-54 years old
176	Male, 55-64 years old
177	Male, 65 years old
178	Female, 15-24 years old
179	Female, 25-34 years old
180	Female, 35-44 years old
181	Female, 45-54 years old
182	Female, 55-64 years old
183	Female, 65 years old
	Employment referrals for general workers
184	New job openings-to-applicants ratio (b)
185	New job openings-to-applicants ratio (c)
186	Active job openings-to-applicants ratio (b)
187	Active job openings-to-applicants ratio (c)
188	Persons who found employment (b)
189	Persons who found employment (c)
	Commercial sales value by type of business
190	Wholesale, General marchandise
191	Wholesale, Textiles
192	Wholesale, Apparel & accessories
193	Wholesale, Farm & aquatic products
194	Wholesale, Food & Beverages
195	Wholesale, Building materials
196	Wholesale, Chemicals
197	Wholesale, Minerals & metals
198	Wholesale, Machinery & equipment
199	Wholesale, Furniture & house furnishings
200	Wholesale, Medicines & toiletries
201	Wholesale, Others
202	Retail, General merchandise
203	Retail, Fabrics apparel & accessories
204	Retail, Food & beverages
205	Retail, Motor vehicles
206	Retail, Machinery & equipment
207	Retail, Others
	Department stores sales value by goods
208	Men's clothes
209	Women's & children's clothes
210	Other clothing
211	Accessories
212	Food & Beverages
213	Furniture
214	Household electric appliances
215	Household equipment
216	Others
217	Restaurants & café
	Supermarkets sales value by goods
218	Men's clothes
219	Women's & children's clothes
220	Other clothing
221	Accessories
222	Food & Beverages
223	Furniture
224	Household electric appliances
225	Household equipment
226	Others
227	Restaurants & café

(a) Establishments with 30 employees or more, industries covered

(b) Excluding new school graduates and part-timers

(c) Part-timers

Table. A1 (continued)

	New dwelling construction started
	by type of owner occupant relation (dwelling units)
228	Owned houses
229	Rented houses
230	Issued houses
231	Ready built houses
	Construction started buildings by use (floor area)
232	Mining & manufacturing
233	Commerce
234	Services industry
	Machinery Orders by Sectors
235	From manufacturing
236	From non-manufacturing
237	From overseas
238	From governments
239	Through agencies

	Nikkei average stock price by industry
240	Fish & marine products
241	Mining
242	Construction
243	Foods
244	Textile products
245	Pulp & paper
246	Chemicals
247	Drug
248	Petroleum
249	Rubber products
250	Stone, clay & glass products
251	Tron & steel
252	Non-ferrous metals & metal products
253	Machinery
254	Electric & electronic equipment
255	Ship building & repairing
256	Motor vehicles & auto parts
257	Other transportation equipment
258	Precision equipment
259	Other manufacturing
260	Wholesale trade
261	Retail trade
262	Banks
263	Securities
264	Insurance
265	Credit & leasing
266	Real estate
267	Railroad transportation
268	Trucking
269	Sea transportation
270	Air transportation
271	Warehousing & harbor transportation
272	Communication service
273	Utilities - electric
274	Utilities - gas
275	Services

Table. A1 (continued)

	Producer price index excluding consumption tax
276	Manufacturing industry products
277	Agriculture, forestry & fishery
278	Minerals
279	Electric power, gas & water
280	Scrap & waste
281	Nikkei index of commodity prices (42 items)
	Consumer price index by items
282	Food, less fresh food
283	Housing
284	Fuel, light & water charges
285	Furniture & household utensils
286	Clothes & footwear
287	Transportation & communication
288	Culture & recreation
289	Miscellaneous
	Corporate Goods Price Index
290	Export price index (yen basis)
291	Import price index (yen basis)
292	Real effective exchange rates
293	US.Dollar-Yen spot rate at 17:00 in JST, (d)
294	Turnover of spot, US.Dollar-Yen, (d)
295	Turnover of swap, US.Dollar-Yen, (d)
296	Newly issued government bonds yield (10 years): GB10
	Average contract interest rate on outstanding loans and bills discounted, City banks
297	Short-term loans and discounts: STL
298	Long-term loans: LTL
299	Call Rate, Uncollateralized overnight: CR
300	Spread, GB10 – Basic discount rate
301	Spread, STL – Basic discount rate
302	Spread, LTL – Basic discount rate
303	Spread, CR – Basic discount rate
	Money Stock (Percent changes from the previous year in average amounts outstanding)
304	Currency in circulation
305	Deposit money
306	Quasi-money
307	Certificates of deposit (CDs)
308	Corporation tax revenue
309	Number of bankruptcies
310	Exports quantum index
311	Imports quantum index
	Sales DI of small businesses
312	Construction
313	Equipment investment
314	Automobile
315	Electrical & electronics
316	Food life
317	Clothing life
318	Sales forecast DI of small businesses
319	Profit DI of small businesses
320	Last-3-months profit DI of small businesses
321	Next-3-months profit DI of small businesses
322	Sales price DI of small businesses
323	Purchase price DI of small businesses
324	Inventory DI of small businesses
325	Financing DI of small businesses
326	DI of bank propensity to lend
	Component indicators of Consumer Confidence Index (households of 2 or more persons)
327	Overall livelihood
328	Income growth
329	Employment
330	Willingness to buy durable goods

(d) Average in the month, Tokyo market