Slack in Labor Market and Business Cycles

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Abstract

In this paper, we examine how a focus on an increase in economic slack contributes to developing clear quantitative guidelines about how to identify a recession. We use monthly labor-market indicators of composite indices of Japan. Firstly, we find that 'Index of Non-Scheduled Worked Hours (Industries Covered)' is a promising variable to identify a recession in Japan. Secondly, the unemployment rate, found useful to identify the modern U.S. recessions in the literature, does not produce dates of the turning points consistent with the official reference dates of Japan.

Key words: economic slack, growth cycles, reference dates

JEL classification: E32

1 Introduction

The study of aggregate fluctuations in economy has been a central subject of economics since the nineteenth century (see Persons, 1926). Burns and Mitchell (1946) is a compilation of extensive works the NBER researchers undertook at that time. It has spawned a voluminous literature on the business cycles. One of the key concepts is the "reference dates," the dates of peaks and troughs of business cycles. Burns and Mitchell (1946, pp. 76-77) explained the importance of dating the peaks and troughs in business-cycle analysis. Romer and Romer (2019) claimed that the dates played an important role in establishing the concept of a recession as a repeated, identifiable phenomenon. The reference dates still remain not only a starting point of empirical research, but a great concern from the press and policymakers. Particularly, significant downturns in economic activity are a fundamental motivating concern.

In the business-cycle literature, it is important to distinguish a classical cycle and a growth one, as pointed out by Pagan (1997). The classical cycle consists of peaks and troughs in the *levels* of aggregate economic activities, often represented by the gross national product (GDP). On the other hand, the growth cycle exists in the *detrended* series, on which the real business-cycle literature focuses. The two types of cycles show different cyclical timing in general, that is, different dates of peaks and troughs. When a series has a cyclical component around a deterministic upward trend, typical as in economic data, detrending would make its cyclical peaks earlier, while delaying its cyclical troughs (see Bry and Boschan, 1971, p. 11).

The reference dates of the business cycle, officially published in the U.S. and Japan, conceptually correspond to the timing of peaks and troughs of the classical cycle. For example, the NBER focuses on peaks and troughs in the level of economic activity[1]. The basic dating procedure, widely used in official agencies and academic researchers, is developed by the National Bureau of Economic Research (NBER) in the U.S. It applies the Bry-Boschan procedure (see Bry and Boschan, 1971) to determine turning points of several economic time series selected as coincident indicators. Dates of these turning points are typically pinned down by examining a *historical* diffusion index that shows a share of the number of series with a positive change, the so-called *expanding* series. Pagan (1997, p. 3) argued against detrending transformation of data, because it is not appropriate to analyze and interpret the growth cycle, citing the business-cycle characteristics based on the official reference dates.

1） The NBER press release on June 8, 2020: http://www2.nber.org/cycles/june2020.pdf

Fabricant (1972) suggested defining a recession as a decline in the proportion of available resources employed in production, or as a widening of the gap between potential and actual output, rather than as a decline in aggregate economic activity relative to its trend. Following this line, Romer and Romer (2019) proposed that the NBER should consider replacing its emphasis on a decline in economic activity with a focus on a large and rapid rise in economic slack, claiming that it lead to a narrower and more precise definition of a recession that is more firmly grounded in modern understanding of macroeconomic fluctuations. They showed some supportive evidence for the United States and Japan in the modern low-growth era. They argued that it appeared better suited to identifying episodes of interest in settings where trend growth is low as well as more closely corresponding to how both economists and the public think of a recession.

In this paper, we examine how a focus on an increase in economic slack contributes to developing clear quantitative guidelines about how to identify a recession. We attempt to nail down what variables are useful for analysis of recessions as well as economic slack. We use labor-market data of Japan that has recorded a very low rate of economic growth for more than a quarter of century. We use monthly data of the leading, the coincident, and the lagging indicators, instead of quarterly data that Romer and Romer (2019) used, to enhance comparison with the reference dates published in monthly base.

The main findings are as follows. Firstly, 'Index of Non-Scheduled Worked Hours (Industries Covered)' is a promising variable to identify a recession in Japan. Secondly, the unemployment rate, which Romer and Romer (2019) found useful to find the modern U.S. recessions, does not produce dates of the turning points consistent with the official reference dates of Japan.

The rest of the paper is organized as follows. In section 2, we discuss data for analysis. We use individual indicators of the composite indices, which are related to the labor market in Japan. Section 3 briefly explains the filtering methods used to estimate economic slack. In section 4, we compare the estimated dates of peaks and troughs with the official reference dates to investigate whether we can find economic variables useful for recession identification. The final section is allocated to discussion.

2　Slack in Labor Market: Data

To measure economic slack, we use time series related to labor market, included in the composite indices of Japan (see Table 2). The reason to use labor-market data is that labor market conditions reflect overall economic slack because all industries use labor. Although capacity utilization ratio can be used, its coverage is limited to manufacturing, and removed from the individual indicators of the composite indices in October 2011. Therefore, we focus on the labor-related variables.

Further, Romer and Romer (2019) found that the unemployment rate was useful to study a recession in terms of economic slack in the U.S. They argued that trend growth has been relatively steady at a moderately positive level for the modern United States, and that the recessions are all characterized by large and rapid increases in the unemployment rate. Further, they claimed that a focus on such a characterization does not alter the chronology of peaks and troughs of the U. S. business cycles in any important way. It is true, historically, that the unemployment rate was used extensively to date recessions in the early postwar period. But, it has played no role in the dating process since it was changed to a lagging indicator in 1975.

In Japan, the unemployment rate has been introduced as a lagging indicator in August 1984. Since the growth rate of Japan is less than 1% on average for the last two decades, a mild shortfall from the growth trend leads to a recession. Therefore, it is possible for the unemployment rates to characterize recent recessions, and it would be interesting to reevaluate usefulness of the unemployment in business-cycle analysis.

A caveat is in order. In January 2018, it was revealed that officials at Ministry of Health, Labor and Welfare had incorrectly conducted fundamental statistical survey on labor-related conditions since 2004. Then, in our data set, there are two indicators that are susceptible to this incorrect compilation. One is 'Index of Non-Scheduled Worked Hours' and the other 'Index of Regular Workers Employment (Change from Previous Year).' According to Economic and Social Research Institute (ESRI), affiliated with the Cabinet Office, Government of Japan, it has used the corrected values published by the Monthly Labor Survey since January 2019 for the time period from January 2012 onward as a remedy for the faulty data problem. The earlier part of the series than the correction is connected by a link coefficient method. Such a remedy makes these series good enough for our analysis. Thus, we use them in the later analysis.

In addition, the reason that we choose labor-related variables from the individual indicators of composite indices is that they are supposed to have strong relation with business cycles. ESRI routinely examines and revises the composition of indicators. The latest revision, the 12th revision, was made in July 2020. All the individual indicators are available since January 1975, amounting to more than 500 sample points for each series, which would be long enough for our analysis.

We attempt to estimate economic slack with series discussed above. As Romer and Romer (2019, see p. 12) discussed, a recession can be defined as a sustained decline in the rate of growth of aggregate economic activity relative to its long-term trend. Therefore, the 'slack' concept is better suited to the *growth* cycles than the *level* cycles. In this interpretation, the growth cycles are deemed detrended business cycles because a recession is interpreted as a part of business cycle. We use bandpass filters to suppress a secular trend and noise components and to extract detrended growth cycles. Following Burns and Mitchell (1946), the business cycles are assumed to range from 18 months (1.5 years) to 96 months (8 years), while the secular trend corresponds to the longer-cycle components and the noise to the shorter ones. The technical details are given in section 3.

We compare dates of turning points in the growth cycles with those of the reference dates to investigate usefulness of economic slack in identification of a recession. The reference dates of business cycles in Japan are determined by ESRI that organizes the Investigation Committee for Business Cycle Indicators to inspect historical diffusion indexes calculated from selected series of coincident indexes and other relevant information. Typically, a final decision on turning points is made about two to three years later. To make a historical diffusion index, the peaks and troughs of each individual time series are dated by the Bry-Boschan method. Thus, the reference dates correspond to those of peaks and troughs of the classical cycles, that is, the Burns-and-Mitchell-type cycle based on the level of aggregate economic activity. As pointed by Canova (1999, 1994), the dates of peaks and troughs in the growth cycles deviate from those in the level cycles by two or three quarters, which is confirmed by Otsu (2013). Therefore, it is expected that a monthly comparison would show a deviation by 6 to 9 months.

Table 3 shows the reference dates of peaks and troughs identified by ESRI. It also contains periods of expansion, contraction, and duration of a complete cycle (trough to trough). There are 15 peak-to-trough phases identified after World War II. In these phases, the average period is about 36 months for expansion, 16 for contraction, and 52 for the complete cycle.

Finally, we also refer to the composite index of consistent indicators for judgement on usefulness of the growth cycles to find a recession. The composite coincident index is complied by ESRI, based on individual consistent indicators on and after 1980, and available from 1985 onward for the 12th-revision data. In our analysis, we use the indicators in Table 2 from January 1980 to January 2020 to enhance comparison with the composite index. All data are obtained from the website of ESRI[2).

3 Departure from Secular Trend: Filtering Methods

In the literature, there are various methods to extract and measure cyclical information. Canova (2007) gives a concise description of methods frequently used in macroeconomic analyses. We use bandpass filters to compute departure from secular trends. They allow us to extract business-cycle components and suppress secular trends as well as all the cyclical components shorter than and equal to the seasonal cycles. Therefore, it is possible to obtain detrended components less noisy as much as possible. The cyclical components, if properly extracted, would incorporate all the turns to be identified as peaks or troughs of businesss cycles.

We use three types of bandpass filters among others: the Christiano-Fitzgerald filter (hereafter, CF filter: Christiano and Fitzgerald, 2003), the Hamming-windowed filter (Iacobucci and Noullez, 2005) and the Butterworth filters (e.g. Gomez, 2001; Pollock, 2000). Note that the sine-based Butterworth filter with the second order is equivalent to the Hodrick-Prescott (hereafter, HP) filter proposed by Hodrick and Prescott (1997) (see Gomez, 2001, p. 336).

Canova (1994) examined performance of 11 different detrending methods to replicate NBER dating, assuming that the detrending removes a secular component. Similar analyses are conducted by Canova (1999) with 12 methods including Hamilton (1989)'s procedure. They found that the HP filter and a

2) Indexes of Business Conditions: https://www.esri.cao.go.jp/en/stat/di/di-e.html, Dec. 23, 2020.

frequency domain filter as an approximation to the Butterworth filter (see Canova, 1998, p. 483) would be the most reliable tools to reproduce the NBER dates. Otsu (2013) conducted a comparative analysis among bandpass filters such as the Christiano-Fitzgerald filter (Christiano and Fitzgerald, 2003), the Hamming-windowed filter (Iacobucci and Noullez, 2005) and the Butterworth filters (e.g. Gomez, 2001; Pollock, 2000), using Japanese real GDP data. It showed that the Butterworth filters give the business-cycle dates closest to the official reference dates.

Now we review properties of the three filters in turn: Christiano-Fitzgerald filter, Hamming-windowed filter, and Butterworth filters. To begin with, we consider the following orthogonal decomposition of the observed series x_t:

$$x_t = y_t + \tilde{x}_t \tag{1}$$

where y_t is a signal whose frequencies belong to the interval $\{[-b, -a] \cup [a, b]\} \in [-\pi, \pi]$, while $\tilde{x}_t$ has the complementary frequencies. Suppose that we wish to extract the signal y_t. The Wiener-Kolmogorov theory of signal extraction, as expounded by Whittle (1983, Chapter 3 and 6), indicates y_t can be written as:

$$y_t = B(L) x_t \tag{2}$$

$$B(L) = \sum_{j=-\infty}^{\infty} B_j L^j, \quad L^k x_t \equiv x_{t-k} \tag{3}$$

In polar form, we have

$$B(e^{-i\omega}) = \begin{cases} 1, \text{ for } \omega \in [-b, -a] \cup [a, b] \\ 0, \text{ otherwise} \end{cases} \tag{4}$$

where $0 \leqq a \leqq b \leqq \pi$. In the business-cycle literature, the values of a and b are often set to the frequencies that correspond to 8 and 1.5 years, respectively. In case of monthly data we use later, the frequency range is set to $\left[\frac{2\pi}{96}, \frac{2\pi}{18}\right]$.

Theoretically, we need an infinite number of observations, x_t's, to compute y_t. In practice, the filtering methods approximate y_t by $\hat{y}_t$, a filtered series with a finite filter. To estimate y_t by $\hat{y}_t$, the Christiano-Fitzgerald filtering is performed in the time domain with truncation at both ends of the sample, while other filtering methods in the frequency domain are implemented under the circularity assumption.

Since details of the CF filter and the Hamming-windowed filter are given in Christiano and Fitzgerald (2003) and in Iacobucci and Noullez (2005), we only briefly review them. As for Butterworth filters, we describe them in a little detail. Then, we discuss detrending and boundary treatment.

3.1 Christiano-Fitzgerald Filter

Christiano and Fitzgerald (2003) sought an optimal linear approximation with finite sample observations. They solved a minimization problem based on the mean square error (MSE) criterion in the frequency domain: minimization of a weighted sum of differences between the ideal bandpass-filter's weights and their approximates, using a spectral density of observations as a weight. They derived optimal filter weights, assuming a difference-stationary process of observed data with a trend or a drift removed if any.

In their empirical investigations, they examined the effects of the time-varying weights, the asymmetry, and the assumption on the stochastic process. They compared variance ratios and correlations between the components extracted by the Christiano-Fitzgerald filters and the theoretical components based on the data generating process of observations. To evaluate the second moments of the theoretical components, they used the Riemann sum in the frequency domain. They found that the time-varying weights and the asymmetry of the filter contribute to a better approximation, pointing out that the time-varying feature is relatively more important. Further, they claimed that the time-varying weights should not introduce severe nonstationarity in the filter approximation because the variance ratios do not vary much through the time. The correlation between the filtered-out components and the theoretical ones at different leads and lags symmetrically diminishes as the leads and lags go far away, which might indicate that the degree of asymmetry was not great. Finally, one of the Christiano-Fitzgerald filters derived under the Random-Walk data generating process, the so-called Random Walk filter, gives a good approximation to the optimal filtering that explicitly used the estimated coefficients of an optimal moving average process determined empirically. Therefore, they claimed that we could use the Random Walk filter without inspecting the data generating process even if the random walk assumption was false.

As argued in Otsu (2015), the cyclical components extracted by CF might be distorted in magnitude and timing. Its *gain* function, defined as the modulus of the frequency response function, shows large ripples over the target ranges, indicating a large distortion in estimating the cyclical components. The CF filter also shows *leakage* effects (see Baxter and King, 1999, p. 580) over higher frequencies of more than 8 periods per cycle. Further, phase shifts are indicated by values of its phase function, defined as arctangent of the ratio of the real-valued coefficient of the imaginary part of the frequency response function to the real part value.

3.2　Hamming-Windowed Filter

Iacobucci and Noullez (2005) claimed that the Hamming-windowed filter be a good candidate for extracting frequency-defined components. The proposed filter has a flatter response over the passband than other filters in the literature, such as the HP filter (Hodrick and Prescott, 1997), the BK filter (Baxter and King, 1999), and the CF filter. This means that it has no *exacerbation* (see Baxter and King, 1999, p.

580) and eliminates high-frequency components better than the other three filters.

The Hamming-windowed filtering is implemented in the frequency domain. The procedure is described as follows. First, we subtract, if necessary, the least-square regression line to detrend the observation series to make it suitable for the Fourier transform. Second, we implement the Fourier transform of the detrended series, Third, we convolve the ideal response with a spectral window to find the windowed filter response in the frequency domain. The window is the so-called Tukey-Hamming window (Priestly, 1981, pp. 433-442).

3.3 Butterworth Filters

Pollock (2000) has proposed the tangent-based Butterworth filters in the two-sided expression, which are called rational square-wave filters. The one-sided Butterworth filters are widely used in electrical engineering, and well documented in standard text books, such as Oppenheim and Schafer (1999) and Proakis and Manolakis (2007). The two-sided version guarantees phase neutrality or no phase shift. It has finite coefficients, and its frequency response is maximally flat over the pass band: the first $(2n-1)$ derivatives of the frequency response are zero at zero frequency for the nth-order filter. The filter could stationarize an integrated process of order up to $2n$. The order of the filter can be determined so that the edge frequencies of the pass band and/or the stop band are aligned to some designated frequencies. Further, Gomez (2001) pointed out that the two-sided Butterworth filters could be interpreted as a class of statistical models called UCARIMA (the unobserved components autoregressive-integrated moving average) in Harvey (1989, p. 74). Since the two-sided Butterworth filters are not so often used in the literature, we present relevant equations to look at them a little bit more closely.

The lowpass filter is expressed as

$$BFT_L = \frac{(1+L)^n(1+L^{-1})^n}{(1+L)^n(1+L^{-1})^n + \lambda(1-L)^n(1-L^{-1})^n} \tag{5}$$

where $L^d x_t = x_{t-d}$, and $L^{-d} x_t = x_{t+d}$. Similarly, the highpass filter is expressed as

$$BFT_H = \frac{\lambda(1-L)^n(1-L^{-1})^n}{(1+L)^n(1+L^{-1})^n + \lambda(1-L)^n(1-L^{-1})^n} \tag{6}$$

Note $BFT_L + BFT_H = 1$, which is the complementary condition discussed by Pollock (2000, p. 321). Here, λ is the so-called smoothing parameter. We observe that the Butterworth highpass filter in eq.(6) can handle nonstationary components integrated of order $2n$ or less. Let ω_c the *cutoff point* at which the gain is equal to 0.5. It is shown

$$\lambda = \{tan(\omega_c/2)\}^{-2n} \tag{7}$$

To see this, we replace the L by $e^{-i\omega}$ in eq.(5) to obtain the frequency response function in polar form as

$$\phi_L(e^{-i\omega}; \lambda, n) = \frac{1}{1+\lambda(i(1-e^{-i\omega})/(1+e^{-i\omega}))^{2n}} \tag{8}$$

$$= \frac{1}{1+\lambda\{tan(\omega/2)\}^{2n}} \tag{9}$$

Here, it is easy to see that eq.(7) holds when $\phi_L(e^{-i\omega}) = 0.5$. We also observe in eq.(9) that the first $(2n-1)$ derivatives of $\phi_L(e^{-i\omega})$ are zero at $\omega = 0$; thus, this filter is maximally flat. Note that the gain is the modulus of the frequency response function, and indicates to what degree the filter passes the amplitude of a component at each frequency. The Butterworth filters considered here are symmetric and their frequency response functions are non-negative. Therefore, the gain is equivalent to the frequency response. Then, we can use eq.(9) to specify ω_c so that the gain at the edge of the pass band is close to one and that of the stop band close to zero. Let the pass band $[0, \omega_p]$, and the stop band $[\omega_s, \pi]$, where ω_p is smaller than ω_s. As in Gomez (2001, p. 372), we consider the following conditions for some small positive values of δ_1 and δ_2,

$$1-\delta_1<|\phi_L(e^{-i\omega}, \lambda, n)|\leqq 1 \quad \text{for} \quad \omega\in[0, \omega_p] \tag{10}$$

$$0\leqq|\phi_L(e^{-i\omega}, \lambda, n)|<\delta_2 \quad \text{for} \quad \omega\in[\omega_s, \pi] \tag{11}$$

That is, we can control leakage and *compression* (see Baxter and King, 1999, p. 580) effects with precision specified by the values of δ_1 and δ_2. These conditions can be written as follows:

$$1+\left(\frac{tan(\omega_p/2)}{tan(\omega_c/2)}\right)^{2n}=\frac{1}{1-\delta_1} \tag{12}$$

$$1+\left(\frac{tan(\omega_s/2)}{tan(\omega_c/2)}\right)^{2n}=\frac{1}{\delta_2} \tag{13}$$

Then, we can solve for the cutoff frequency (ω_c) and the filter's order (n), given ω_p, ω_s, δ_1 and δ_2. The closer to zeros both δ_1 and δ_2, the smaller the leakage and the compression effects. If n turns out not an integer, the nearest integer is selected.

The Butterworth filters could be based on the sine function. Instead of eq.(5) and eq. (6), the lowpass and the highpass filters can be written as follows, respectively.

$$BFS_L=\frac{1}{1+\lambda(1-L)^n(1-L^{-1})^n} \tag{14}$$

$$BFS_H=\frac{\lambda(1-L)^n(1-L^{-1})^n}{1+\lambda(1-L)^n(1-L^{-1})^n} \tag{15}$$

where

$$\lambda=\{2\,sin(\omega_c/2)\}^{-2n} \tag{16}$$

These are the so-called sine-based Butterworth filters. When n is equal to two, eq. (15) is the HP cyclical filter, derived in King and Rebelo (1993, p. 224). Thus, as pointed out by Gomez (2001, p. 336), the sine-based Butterworth filter with order two $(n=2)$ can be viewed as the HP filter. As in the case of the tangent-based one, the cutoff point, ω_c, can be determined with the following conditions:

$$1+\left(\frac{sin(\omega_p/2)}{sin(\omega_c/2)}\right)^{2n}=\frac{1}{1-\delta_1} \tag{17}$$

$$1+\left(\frac{sin(\omega_s/2)}{sin(\omega_c/2)}\right)^{2n}=\frac{1}{\delta_2} \tag{18}$$

We observe that the Butterworth highpass filter in eq.(6) or eq.(15) can handle nonstationary components integrated of order $2n$ or less. Thus, the HP filter can stationarize the time series with unit root components up to the fourth order. Gomez (2001, p. 367) claimed that the BFT would give better approximations to ideal low-pass filters than the BFS. A simulation study in Otsu (2007) confirmed it.

In the paper, we apply the Butterworth filters to extraction of components over a certain band $[\omega_1, \omega_2]$, where ω_1 is smaller than ω_2. The bandpass filter is obtained as the difference between two highpass filters in eq.(6), or two lowpass filters in eq.(5) with different values of λ, as in Baxter and King (1999, p. 578). Suppose a lowpass filter has the pass band $[0, \omega_{p1}]$ and the stop band $[\omega_1, \pi]$. Here, ω_{p1} indicates a frequency at which the cycle is longer by some periods than at ω_1 and corresponds to ω_p in eq.(12), while ω_1 corresponds to ω_s in (13). This lowpass filter has the cutoff frequency of ω_{c1} and the order of n_1 determined in eq. (12) and (13). Let λ_1 the corresponding value of λ. Similarly, another lowpass filter has the pass band $[0, \omega_2]$ and the stop band $[\omega_{p2}, \pi]$. Here, ω_{p2} indicates a frequency at which the cycle is shorter by some periods than at ω_2. In short, we assume that $\omega_{p1}<\omega_1<\omega_2<\omega_{p2}$. ω_2 corresponds to ω_p in (12), and ω_{p2}

corresponds to ω_s in (13). The filter has the cutoff frequency of ω_{c2} and the order of n_2. Then, the value of λ is λ_2. The bandpass filter, $BFT^{bp}(\lambda_1, n_1, \lambda_2, n_2)$, can be obtained as

$$BFT^{bp}(\lambda_1, n_1, \lambda_2, n_2) = BFT_L(\lambda_2, n_2) - BFT_L(\lambda_1, n_1) \quad (19)$$

The corresponding frequency response is expressed as

$$h(\omega; \lambda_1, n_1, \lambda_2, n_2) = \phi_L(e^{-i\omega}; \lambda_2, n_2) - \phi_L(e^{-i\omega}; \lambda_1, n_1) \quad (20)$$

We can obtain the bandpass filter for the sine-type, $BFS^{bp}(\lambda_1, n_1, \lambda_2, n_2)$, and its frequency response in a similar manner.

Alternatively, we sequentially apply the highpass filter with a lower cutoff frequency to a series, and then further apply the lowpass filter with a higher cutoff frequency to the filtered series. Although Pedersen (2001, p. 1096) reported that the sequential filtering has less distorting effects than use of the linear combination of the filters, the empirical results in the following sections do not change whether we use the difference method (the linear combination) or the sequential method. Yet another method is to convert the lowpass filter to the bandpass filter by the frequency transformation, described in a standard textbook (e. g. Proakis and Manolakis, 2007, p. 733), and explicitly obtain the bandpass filter (see Gomez, 2001, p. 371). This filter, however, has only one order parameter, implicitly assuming n_1 is equal to n_2. But, the values of n_1 and n_2 are very different in fact (see Otsu, 2015). Therefore, we would not use the transformation method later in the paper. Here, we use the difference method, because it is easy to control leakage and compression effects at a specific frequency.

We need specify two parameter values, n and λ, in eq. (5) or eq. (6) to implement the Butterworth filtering. We obtain these values from eqs.(7), (12) and (13) for target frequency bands, that is, values of ω_p and ω_s with given values of δ_1

and δ_2. We set both δ_1 and δ_2 to 0.01.

In the paper, we attempt to extract cyclical components with periods per cycle of 1.5 years to 8 years. In terms of a period per cycle (p), a frequency (ω) is expressed as $\frac{2\pi}{p}$. Therefore, using the notation in the previous section, the target band, $[\omega_1, \omega_2]$, is $\left[\frac{2\pi}{96}, \frac{2\pi}{18}\right]$ in months. Following Otsu (2015), we set ω_{p1} to $\frac{2\pi}{132}$ and ω_{p2} to $\frac{2\pi}{12}$. In this case, the transition bands are $\left[\frac{2\pi}{132}, \frac{2\pi}{96}\right]$ and $\left[\frac{2\pi}{18}, \frac{2\pi}{12}\right]$, respectively. Setting ω_{p1} to ω_p in eq.(12) and ω_1 to ω_s in eq.(13), we find n_1 and ω_c. λ_1 is obtained from eq.(7). Similarly, we find n_2 and λ_1 by setting ω_2 to ω_p in eq.(12) and ω_{p2} to ω_s in eq.(13), together with eq.(7). In a similar way, we compute the parameter values of the sine-based Butterworth filter from eq.(16), eq.(17) and eq.(18).

Two remarks are in order. As is always the case, the sine-based filter commands a higher order than the tangent-based on under the same precision values of δ_1 and δ_2. In addition, as already mentioned, the well-known HP filter is viewed as the sine-based Butterworth filter with an order of two. This implies that the HP filter either does not preserve the precision or requires a very wide transition band. In the literature, it is pointed out that it might mislead researchers to false empirical results (Harvey and Jaeger, 1993), or it could generate spurious business-cycle dynamics (Cogley and Nason, 1995). In the paper, we use the HP filter for completeness.

Turning to implementation, we can implement the Butter-worth filtering either in the time domain or in the frequency domain. Following Pollock (2000), Otsu (2007) implemented it in the time domain, and found that when the cycle period is longer than seven, the matrix inversion is so inaccurate that it is impossible to control leakage and compression effects with a certain precision specified by eq.(12) and eq.(13), or eq.(17) and eq.(18). Further, the filters at the endpoints of data have no symmetry due to the finite truncation of filters. This implies that the time-domain implementation introduces phase shifts. Therefore, we do not choose the time-domain filtering.

Alternatively, we can implement the Butterworth filtering in the frequency domain. In the frequency-domain filtering, cyclical components are computed via the inverse discrete Fourier trans-form, using the Fourier-transformed series with the frequency response function as their weights. In contrast to the time-domain filtering, the frequency-domain filtering does not introduce any phase shifts, as the theoretical background of the symmetrical filters dictates. For the frequency-domain procedures to work well, it is required that a linear trend be removed and circularity be preserved in the time series, which we discuss next.

3.4 Detending Method

To obtain better estimates of cyclical components, it is desirable to remove a linear trend in the raw data. The linear regression line, recommended by Iacobucci and Noullez (2005), is often used for trend removal. As shown by Chan, Hayya, and Ord (1977) and Nelson and Kang (1981), however, this method can produce spurious periodicity when the true trend is stochastic. Another widely-used detrending method is the first difference, which reweighs toward the higher frequencies and can distort the original periodicity, as pointed out by Baxter and King (1999), Chan, Hayya, and Ord (1977), and Pedersen (2001).

Otsu (2011) found that the drift-adjusting method employed by Christiano and Fitzgerald (2003, p. 439) could preserve the shapes of autocorrelation functions and spectra of the original data better than the linear-regression-based detrending.

There-fore, this detrending method would create less distortion. Let the raw series z_t, $t=1, \cdots, T$. Then, we compute the drift-adjusted series, x_t, as follows:

$$x_t = z_t - (t+s)\hat{\mu} \tag{21}$$

where s is any integer and

$$\hat{\mu} = \frac{z_T - z_1}{T-1} \tag{22}$$

Note that the first and the last points are the same values:

$$x_1 = x_T = \frac{Tz_1 - z_T + s(z_1 - z_T)}{T-1} \tag{23}$$

In Christiano and Fitzgerald (2003, p. 439), s is set to -1. Although Otsu (2011) suggested some elaboration on the choice of s, it does not affect the results of our subsequent analyses in the paper. Thus, we also set s to -1.

It should be noted that the drift-adjusting procedure in eq.(21) would make the data suitable for filtering in the frequency domain. Since the discrete Fourier transform assumes circularity of data, the discrepancy in values at both ends of the time series could seriously distort the frequency-domain filtering. The eq.(23) implies that this adjustment procedure avoids such a distortionary effect.

3.5　Boundary Treatment

In addition to the detrending method, we make use of another device to reduce variations of the estimates at ends of the series: extension with a boundary treatment. As argued by Percival and Walden (2000, p. 140), it might be possible to reduce the estimates' variations at endpoints if we make use of the so-called *reflection boundary treatment* to extend the series to be filtered. We modify the *reflection boundary treatment* so that the series is extended antisymmetrically instead of symmetrically as in the conventional reflecting rule. Let the extended series f_j ,

$$f_j=\begin{cases} x_j & \text{if} \quad 1\leqq j\leqq T \\ 2x_1-x_{2-j} & \text{if} \quad -T+3\leqq j\leqq 0 \end{cases} \tag{24}$$

That is, the $T-2$ values, folded antisymmetrically about the initial data point, are appended to the beginning of the series. We call this extension rule the *antisymmetric reflection*, distinguished from the conventional reflection.

It is possible to append them to the end of the series. The reason to append the extension at the initial point is that most filters give accurate and stable estimates over the middle range of the series. When we put the initial point in the middle part of the extended series, the starting parts of the original series would have estimates more robust to data revisions or updates than the ending parts. Since the initial data point indicates the farthest past in the time series, it does not make sense that the estimate of the initial point is subject to a large revision when additional observations are obtained in the future. Otsu (2010) observed that it moderately reduced compression effects of the Butterworth and the Hamming-windowed filters. We note that this boundary treatment makes the estimates at endpoints identically zero when a symmetric filter is applied. We filter the extended series, f_j , and extract the last T values to obtain the targeted components.

4 Empirical Analysis

4.1 Dating Algorithm

To identify dates of peaks and troughs, we use a modified version of the Bry-Boschan (BB) method developed by Bry and Boschan (1971). Otsu (2017) investigated whether the bandpass filtering could simplify the BB algorithm and found that it would be a good substitute for smoothing procedures involved in the BB procedure, such as the 12-month moving average, Spencer filtering, and the short-term moving average with a span of months defined by Months of Cyclical

Dominace (see Bry and Boschan, 1971, p. 25). Therefore, it is possible to substantially shorten the procedure. Table 1 shows the modified procedure. In the following analysis, we do not put back the deterministic linear trend in Step I, because our purpose is not to examine changes in the level of economic activity, but those in economic slack. Furthermore, we use a couple of filtering methods other than the tangent-based Butterworth filter for comparison.

4.2　Comparison with Reference Dates

Figure 1 through Figure 5 show the business-cycle components of the five series. On the whole, they move differently from the official coincident composite index (CCI) after the last official trough of November 2012. In addition, Figure 1 of 'New Job Offers (Excluding New School Graduates)' shows dates of a peak and a trough in the latter half of 2000s that are quite different from those of the official CCI. Further, the cyclical component of 'Index of Regular Workers Employment' tends to show more turning points than those of other series, as shown in Figure 4. In Figure 5 of 'Unemployment Rate,' the troughs tend to lag behind those of the official reference cycle. It may not be surprising that the two coincident indicators, 'Index of Non-Scheduled Worked Hours' and 'Index of Effective Job Offer Rate,' produce the cyclical components that are better aligned with the official CCI, as shown in Figure 2 and Figure 3.

Table 4 and 5 show the estimated dates of peaks and troughs with 'New Job Offers (Excluding New School Graduates).' In the first ('Official Ref.') and the second ('Official CCI') columns of Table 4, we find that dates of peaks differ between the official reference cycle and the official CCI, except March 2012. When we use the original BB procedure instead of the abridged procedure, we have a similar result based on the 9th-revision data as shown in Otsu (2019), except that it identified May's in 1985 and in 1997 as peaks instead of July in 1985 and March in 1997.

On the other hand, the official dates of troughs are better identified in Table 5. Although no trough is pinned down around February 1983 that is identified in Otsu (2019), it would be fair to say that the different dating procedures produce a qualitatively similar result as a whole. Therefore, the main difference between the official reference dates and the turning points of the official CCI in Table 4 and 5 comes from the fact that the dating committee uses more information than the CCI.

Turning to the peak dates of the business-cycle components, we find more dates identified than the official reference dates. They do not identify the official peaks in 1980, 1985, 2008, and 2018. Since the sample period starts from 1980, it is not surprising that the first peak is not identified due to insufficient data. Their deviations from the other peaks of the reference cycle are one or two months at most.

The last row shows the average deviation in months. For each filtering method, it is computed by averaging the number of months that is the sum of absolute differences between the dates of the reference-cycle peaks and the nearest dates of the peaks in the estimated cycle. It ranges from around 5 to 6 months.

Table 5 shows the dates of troughs. In contrast with the case of peaks, we find that dates of troughs in the official reference cycle and the official CCI match well, except in February 1983 and January 1999. The estimated business-cycle components identify the troughs in 1986, 1993, and 2002, but fail to identify other official troughs. The average deviations, similarly computed as in the case of peaks, are different across the filtering methods, ranging from 2.7 to 7.3 months.

Table 6 and 7 show the results for 'Index of Non-Scheduled Worked Hours.' The cyclical components well identify the official dates of peaks after 1997, while better identifying those of troughs. The average deviations in the peak dates are around 4 months for the cases of the Butterworth, the Hamming-windowed, and the CF filters, and less than 3 months for the HP filter. They mark smaller deviations less than and equal to 2.5 months after 1997 onward. As for the troughs, the deviations are less than 2 months, slightly smaller for the cases of the Hamming-windowed and the HP filters.

In Table 8, the peak in 2008 is not identified by the Butterworth and the HP filters with ‘Index of Effective Job Offer Rate.’ However, in general, the peaks after 1991 are well identified. The average deviations are slightly larger than those in Table 6. As for the troughs in Table 9, the reference dates are not well identified, and the average deviations range from 3.6 to 8.0 months, much larger than those in Table 7.

The ‘Index of Regular Workers Employment’ seems not useful to identify the turning points of the official reference cycle. As shown in Table 10 and 11, the average deviations are much larger than those of the other indicators. Particularly, they are substantially large in case of the troughs: more than 10 months. The ‘Unemployment Rate’ does not identify the official reference dates, either. In Table 12 and 13, the peaks in 2000, 2008, and 2012 are well identified with the cyclical components obtained by the Hamming-windowed and the CF filters. However, the average deviations range from 3.0 to 4.9 months for the peaks and from 5.1 to 7.4 months for the troughs. That is, the unemployment rate produces a chronology of the turning points that is rather different from those of the official reference cycle. In contrast to the finding of Romer and Romer (2019), it implies whether a focus on economic slack or on the level of economic activity gives rise to a different result.

In sum, the variable, ‘Index of Non-Scheduled Worked Hours,’ can be used to identify the turning points of the business cycles based on economic slack. Other variables may not be useful to identify a recession on the supposition that the official reference dates are true.

Finally, we examine how useful the magnitude of deviation from secular trends is for recession identification. As discussed above, 'Index of Non-Scheduled Worked Hours' gives rise to the dates of turning points closer to the official reference dates compared to the other series. Then, we show deviation of the business-cycle components from the secular trends for this series in Table 14 and 15.

In Table 14, the CF and the HP filters indicate negative values, -0.04 and -0.09, respectively. This implies that the economy reaches the peaks even when the non-scheduled worked hours are less than a trend, that is, a 'normal' level. In many cases, however, the peaks come up when they go above the normal level. Particularly, they are well beyond the normal level on the dates close to the official reference dates. A similar finding comes from Table 15: the economy reaches the troughs when the index is well below the normal level. In general, a large deviation is marked around the official reference dates. Therefore, the index can be used as an indicator of economic slack to locate recessions. Note that the magnitude of deviation varies across the different filters. Thus, a further investigation is required to set a specific value of criterion to determine peaks and troughs.

5 Discussion

This paper has examined how a focus on an increase in economic slack contributes to developing clear quantitative guidelines about how to identify a recession. We use labor-market data of Japan that has recorded a very low rate of economic growth for a long time. We use monthly data of the leading, the coincident, and the lagging indicators, instead of quarterly data used by Romer and Romer (2019), to enhance comparison with the reference dates published in monthly base.

The main findings are as follows. Firstly, 'Index of Non-Scheduled Worked Hours (Industries Covered)' is a promising variable to identify a recession in Japan.

Secondly, the unemployment rate, which Romer and Romer (2019) found useful to find the modern U.S. recessions, does not produce dates of the turning points consistent with the official reference dates of Japan.

Note that, in compilation of the coincident composite index, the Investigation Committee for Business Cycle Indicators, ESRI, decided to replace 'Index of Non-Scheduled Worked Hours (Industries Covered)' with 'Total Hours Worked (Industries Covered)' times 'Employee [by number of persons engaged in non-agricultural industries]' provided by Ministry of Health, Labour and Welfare, Japan, at the meeting held on July 30, 2020. The new series is to be supplied after January 2021 onward. The committee has argued that the former series shows a downward trend due to social policies introduced to improve the work-life balance in Japan, and that it should be replaced by some other variables that would better indicate as a whole how firms adjust employment and hours worked. Thus, one of the remaining problems is how such a replacement contributes to identifying recessions in terms of economic slack.

Another problem is to find a quantitative criterion, that is, the magnitude of deviation from the normal level, to pin down peaks or troughs. It crucially depends on how to set the normal level, and might give a very different picture of the business cycles, compared to one drawn by the official reference cycle. These problems are left for future research.

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Table 1　Abridged Bry-Boschan Procedure

Step	Procedure
I	Business cycle extraction : Extracting business-cycle components by a two-sided tangent-based Butterworth filter. The deterministic linear trend in Section 3.4 is put back.
II	Dating with the business-cycle components: 1. Identification of peaks and troughs: Find the maximum (peak) or the minimum (trough) of the extracted components within ±6 months (leads and lags). 2. Enforcement of alternation: Ensure the peaks and the troughs are alternate. If not, choose a peak with a greater value and a trough with a smaller value. If the values are same, choose an earlier peak and a later trough. 3. Elimination of turns within 6 months at endpoints: Eliminate peaks and troughs within 6 months of beginning and end of series. 4. Enforcement of the first and last peak (or trough) to be extrema: Eliminate peaks (or troughs) at both ends of series which are lower (or higher) than values closer to end. 5. Enforcement of the minimum cycle duration: Check if the peak-to-peak and the trough-to-trough cycles are less than 15 months. If not, eliminate lower peaks (or higher troughs), or if equal, a later peak and an earlier trough. 6. Enforcement of the minimum phase duration: Eliminate phases (peak to trough or trough to peak) whose duration is less than 5 months.

Table 2 Labor Market Indicators of Japan

	Series Name	Mnemonic (ESRI)
1.	New Job Offers (Excluding New School Graduates, persons)	L3 (leading)
2.	Index of Non-Scheduled Worked Hours (Industries Covered, 2015=100)	C4 (coincident)
3.	Effective Job Offer Rate (Excluding New School Graduates, times)	C9 (coincident)
4.	Index of Regular Workers Employment (Change from Previous Year, %)	Lg2 (lagging)
5.	Unemployment Rate (Inverted Scale, %)	Lg6 (lagging)

Note: Seasonally-adjusted series of the 12th-revision composite indices, July 30, 2020.

Table 3 Reference Dates of Business Cycles: Japan

Dates (month, year)		Number of Periods (in months)		
Peak	Trough	Expansion	Contraction	Duration
June, 1951	October, 1951	—	4	—
January, 1954	November, 1954	27	10	37
June, 1957	June, 1958	31	12	43
December, 1961	October, 1962	42	10	52
October, 1964	October, 1965	24	12	36
July, 1970	December, 1971	57	17	74
November, 1973	March, 1975	23	16	39
January, 1977	October, 1977	22	9	31
February, 1980	February, 1983	28	36	64
June, 1985	November, 1986	28	17	45
February, 1991	October, 1993	51	32	83
May, 1997	January, 1999	43	20	63
November, 2000	January, 2002	22	14	36
February, 2008	March, 2009	73	13	86
March, 2012	November, 2012	36	8	44
October, 2018*		71	—	—

* Provisional date, as of July 30, 2020.

Source: *Indexes of Business Conditions*, Economic and Social Research Institute, Cabinet Office, Government of Japan, July 30, 2020.

Table 4　Month at Peaks: New Job Offers

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1980	2					
1981			10	10	9	8
1984			3	4	7	8
1985	6	7				
1989					3	1
1990		10	12			
1991	2			2	2	1
1997	5	3	4	3	3	3
2000	11	12	10	11	11	11
2006			12	12	12	12
2007		8				
2008	2					
2012	3	3	4	3	2	3
2013			8			10
2014		3				
2017		12				
2018	10					
2019			6	5	4	6
Deviation (avg. months)**			6.0	5.3	4.9	5.0

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1985.

Table 5　Month at Troughs: New Job Offers

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1980				8	11	
1981						1
1982			9	9	9	9
1983	2					
1986	11	11	12	12	12	12
1989					11	12
1993	10	12	10	10	10	10
1999	1		8	7	6	5
2001		12				
2002	1			3	3	4
2003			1			
2009	3	3	7	7	7	7
2012	11	11				
2013			2			1
2015				8	6	4
2016		5	4			
Deviation (avg. months)**			4.6	7.3	6.9	2.7

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1983.

Table 6 Month at Peaks: Index of Non-Scheduled Worked Hours

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1980	2			7		
1981			10	12	12	9
1984			3	4	5	
1985	6	7				3
1988					9	
1989						2
1990		10	9			11
1991	2			1	2	
1997	5	3	5	3	3	4
2000	11	12	10	10	10	10
2004			3	2	1	2
2007		8				
2008	2		3	2	3	2
2010			6	7	7	8
2012	3	3	3	1	1	1
2013					12	
2014		3	1	1		3
2017		12				
2018	10					
2019			7	7	4	5
Deviation (avg. months)**			4.4	4.1	3.6	2.4

Note: * Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1985.

Table 7 Month at Troughs: Index of Non-Scheduled Worked Hours

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1981				3	5	3
1982					12	
1983	2		1	1		1
1986	11	11				
1987			1	1	1	1
1989					3	8
1993	10	12	12	11	10	11
1998		12		12	12	
1999	1		3			1
2001		12	12	12	11	12
2002	1					
2005			4	6	9	6
2009	3	3	5	5	5	5
2011			3	3	3	5
2012	11	11	12	11	12	12
2016		5		11	6	6
2017			9			
Deviation (avg. months)**			1.6	1.1	1.4	1.1

Note: * Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1983.

Table 8　Month at Peaks: Index of Effective Job Offer Rate

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by: Butterworth	Hamming	CF	HP
1980	2		7			
1981			11		12	9
1982				1		
1984			3			
1985	6	7		1	3	2
1990		10				
1991	2		3	4	4	4
1997	5	3	7	4	3	4
2000	11	12	11	12		12
2001					1	
2004					11	
2006				12	11	
2007		8	5			7
2008	2			1	2	
2012	3	3	6	5	4	5
2013			12	11		
2014		3				2
2017		12				
2018	10					
2019			4	4	2	1
Deviation (avg. months)**			5.1	4.4	4.1	2.9

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1985.

Table 9　Month at Troughs: Index of Effective Job Offer Rate

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by: Butterworth	Hamming	CF	HP
1980			12			
1981				3	5	2
1982			9	10	9	11
1983	2					
1986	11	11				
1987			4	4	5	4
1993	10	12	12	11	11	11
1999	1		7	2	1	2
2001		12				
2002	1			6	5	8
2003			3			
2005					4	
2009	3	3	8	8	8	8
2012	11	11				
2013			3	3		2
2015			11		10	7
2016		5		9		
Deviation (avg. months)**			5.9	3.6	8.0	3.6

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1983.

Table 10 Month at Peaks: Index of Regular Workers Employment

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1980	2					
1981			7	5	5	7
1985	6	7	1	2	3	2
1989					1	
1990		10	4	4	4	3
1991	2		8	9	10	8
1993					5	
1997	5	3	12	1	12	12
2000	11	12	8			12
2001				1	4	
2004			9	8	6	8
2007		8				
2008	2		1	2	3	2
2011					8	6
2012	3	3	4	4		
2014		3	2	3	2	3
2015			9	9	9	10
2017		12	8	7	7	7
2018	10					
Deviation (avg. months)**			5.3	5.3	6.6	6.0

Note: * Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1985.

Table 11 Month at Troughs: Index of Regular Workers Employment

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by:			
			Butterworth	Hamming	CF	HP
1983	2		10	10	9	9
1986	11	11				
1987			10	10	11	10
1989					6	
1990			10	9	9	10
1992					11	
1993	10	12				
1995			7	7	10	8
1998		12				
1999	1		10	11	10	10
2001		12				
2002	1		12			12
2003				1	2	
2006			4	6	6	5
2009	3	3				
2010			1	1	1	1
2012	11	11		12		
2013			1		2	1
2014			12			12
2015				2	2	
2016		5	10	9	8	8
2018			8	8	8	9
Deviation (avg. months)**			10.3	10.4	11.1	10.3

Note: * Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1983.

Table 12　Month at Peaks: Unemployment Rate (Inverted Scale)

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by: Butterworth	Hamming	CF	HP
1980	2					
1982			1	2	2	1
1985	6	7	4	5	6	5
1988					8	
1990		10	7	4	3	4
1991	2					
1992			2	1	9	5
1995			2	1	1	2
1997	5	3	9	9	8	8
2000	11	12	12	11	12	11
2004					8	
2005				8		1
2007		8	7			
2008	2			4	4	4
2011						10
2012	3	3	11	2	2	
2013				9	8	
2014		3	2			3
2017		12				
2018	10		5		7	5
2019				7		
Deviation (avg. months)**			4.9	3.9	3.0	3.7

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1985.

Table 13　Month at Troughs: Unemployment Rate (Inverted Scale)

Year	Official Ref.	Official CCI*	Business Cycle Components obtained by: Butterworth	Hamming	CF	HP
1981			1	2	3	2
1983	2			3	2	5
1984			5			
1986	11	11				
1987			4	6	7	4
1989					3	
1990					12	
1991			7	1		5
1993	10	12				
1994			4	4	3	3
1995			10	11	11	12
1998		12				
1999	1		2	2	2	3
2001		12				
2002	1					
2003			3	3	3	2
2005						11
2006				1	2	
2009	3	3	8	10	10	9
2012	11	11		10	12	
2013			5			3
2016		5				4
2017			5	3	2	
2018					12	
2019			1			
Deviation (avg. months)**			7.4	5.1	5.1	5.4

Note: *　Composite Coincident Indicator. Base year = 2015.
** Between the official dates and the nearest estimates on and after 1983.

Table 14 Values at Peaks: Index of Non-Scheduled Worked Hours

Official Ref.		Business Cycle Components obtained by:			
Year	Month	Butterworth	Hamming	CF	HP
1980	2		1.19		
1981		2.62	1.49	-0.04	-0.09
1984		4.40	4.72	4.96	
1985	6				2.94
1988				1.35	
1989					3.04
1990		9.23			6.53
1991	2		8.15	6.86	
1997	5	10.31	9.17	8.52	7.22
2000	11	2.58	3.15	3.24	3.38
2004		1.56	2.01	2.88	1.47
2007					
2008	2	7.80	7.36	6.37	6.80
2010		0.31	2.13	3.78	1.18
2012	3	1.78	2.78	4.04	0.62
2013				2.79	
2014		4.63	4.13		2.77
2017					
2018	10				
2019		0.53	0.66	2.44	1.25

Note: Values of deviation from secular trends. Base year = 2015.

Table 15 Values at Troughs: Index of Non-Scheduled Worked Hours

Official Ref.		Business Cycle Components obtained by:			
Year	Month	Butterworth	Hamming	CF	HP
1981			0.51	-0.58	-0.49
1982				-3.15	
1983	2	-1.32	-2.05		-3.71
1986	11				
1987		-11.25	-10.05	-8.76	-7.05
1989				1.02	2.81
1993	10	-10.63	-9.17	-8.00	-7.63
1998			-4.42	-5.85	
1999	1	-3.12			-3.92
2001		-6.99	-5.42	-4.14	-4.61
2002	1				
2005		-0.28	-0.65	-1.55	-0.96
2009	3	-14.94	-13.77	-13.21	-11.28
2011		-1.28	-1.26	0.53	-0.64
2012	11	-0.88	-0.67	-0.54	-1.82
2016			-2.35	-3.09	-0.75
2017		-2.17			

Note: Values of deviation from secular trends. Base year = 2015.

Figure 1　Slackness: New Job Offers

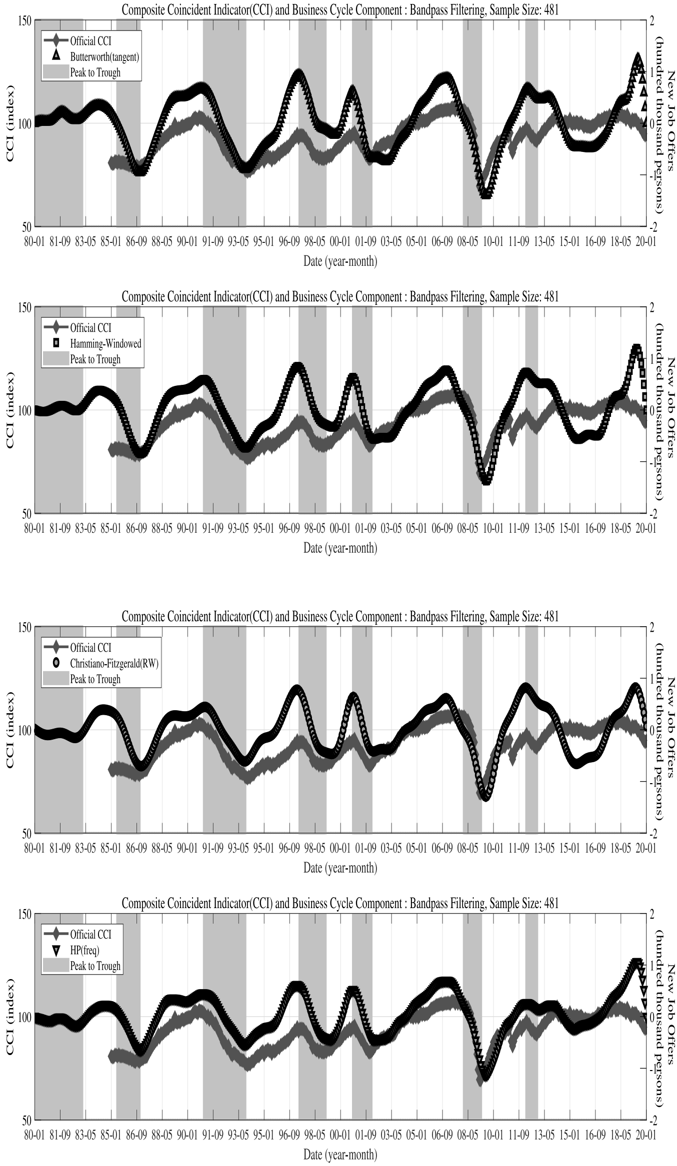

Figure 2 Slackness: Index of Non-Scheduled Worked Hours (Industries Covered)

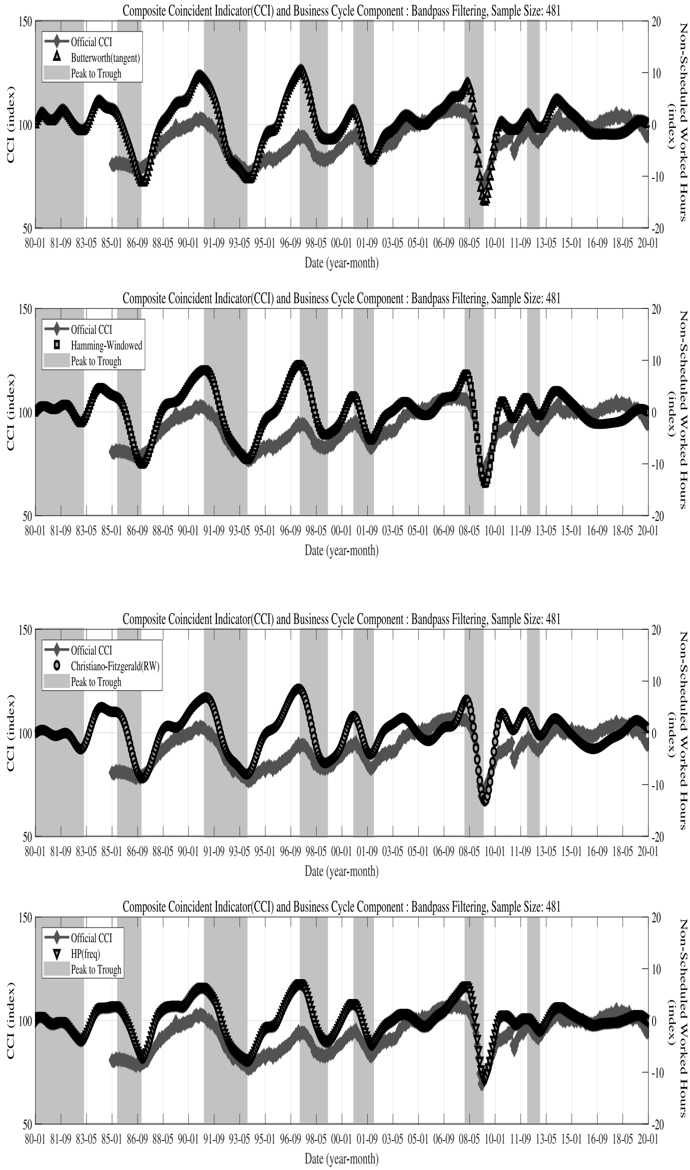

Figure 3　Slackness: Index of Effective Job Offer Rate

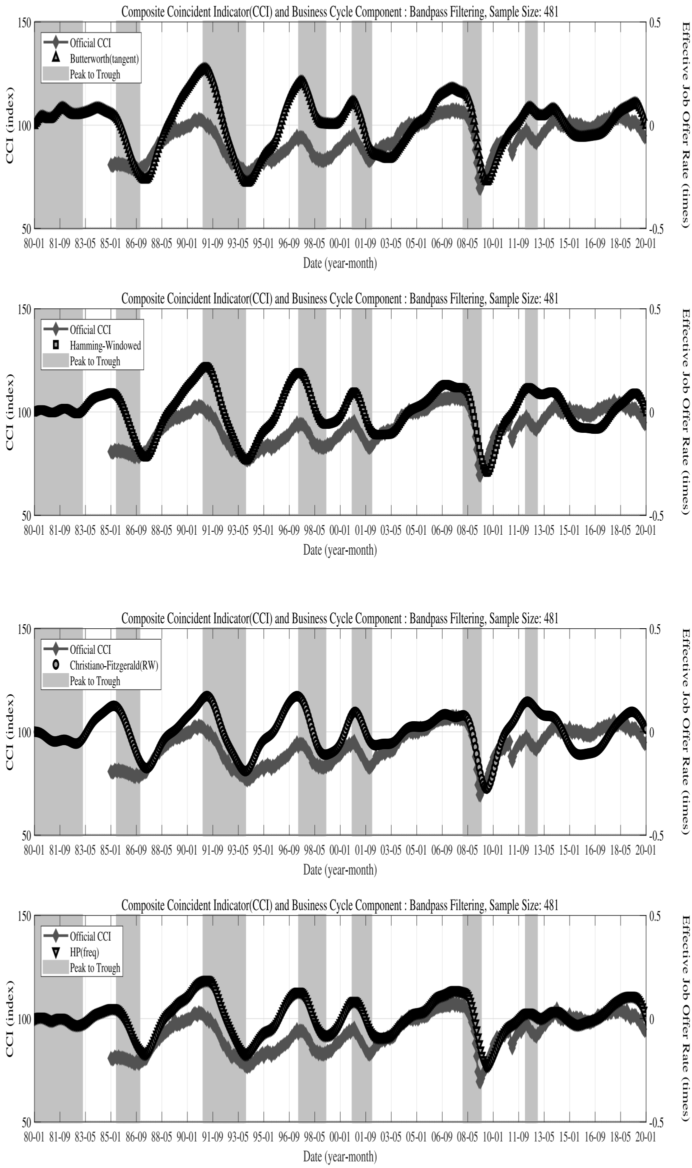

Figure 4 Slackness: Index of Regular Workers Employment

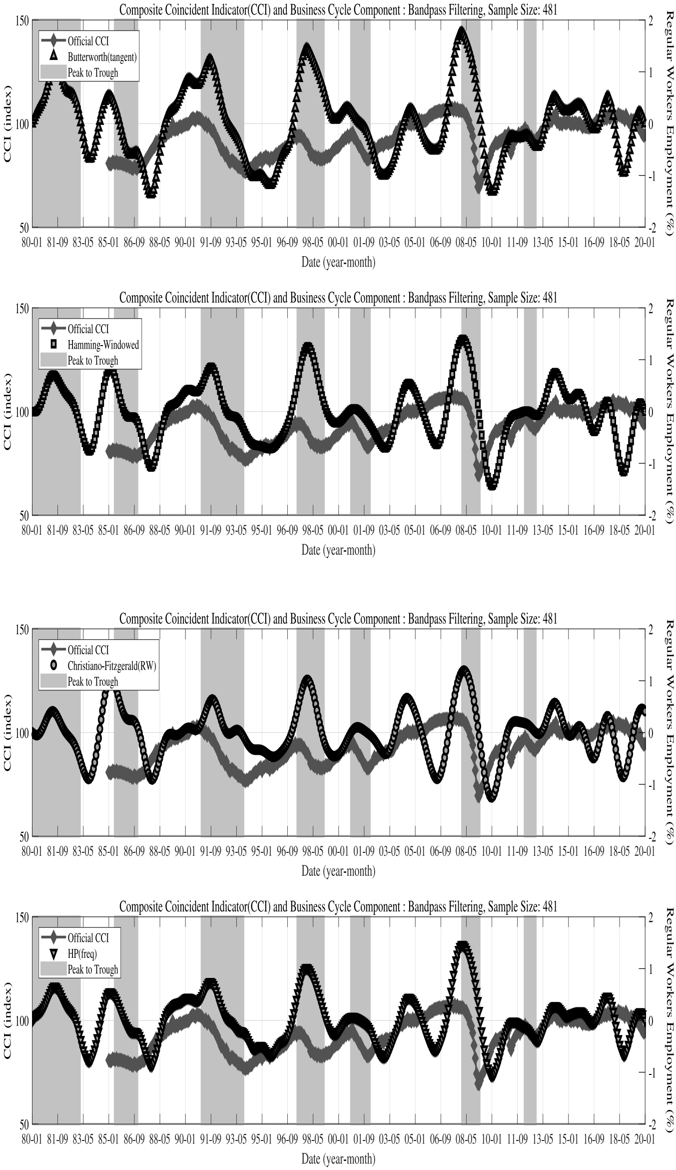

Figure 5　Slackness: Unemployment Rate