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The business cycle effects of Christmas ☆

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Abstract

Why do countries and industries with large seasonal fluctuations also have large business cycles? It is well known that seasonal fluctuations account for the bulk of total output fluctuations, yet it is unknown whether seasonal fluctuations can trigger business cycles. Using a procedure that allows for identification of seasonal innovations, I found that seasonal shocks explain 50% of the business cycle in aggregate output. Such findings provide a novel and powerful explanation for the observed strong correlation between seasonal fluctuations and business cycles. The implication is that in addition to trying to determine whether it is monetary, technology, or other types of shocks that cause business cycles, we should be looking at what causes seasonality.

JEL classification: C13; C40; E30; E32

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1. Introduction

Can the tremendous rise and fall in consumption demand around Christmas time generate business cycles? The question is intriguing. Conventional wisdom

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emphasizes demand shocks as a major source of the business cycle, yet the most visible, most synchronized, and most frequently encountered demand shocks take place seasonally. Output grows rapidly in the fourth quarter at an annual rate of 19%, and declines sharply in the first quarter at an annual rate of −32%. These quarterly growth rates vary tremendously across years and are largely driven by Christmas.[1]

Most research on the business cycle, however, has worked only with seasonally adjusted data. Underlying this practice is the view that business fluctuations are generated by fundamentally different sources than seasonal fluctuations. Such a view is challenged by a stylized fact: Countries and industries with large seasonal cycles also have large business cycles (e.g., Beaulieu et al., 1992).[2]

Despite strong empirical evidence suggesting that seasonal cycles and business cycles may be closely related, the mechanism and the extent of interactions between seasonal and business cycles have not been well understood. This is due to the lack of effective methods for independently measuring and identifying seasonal components of a time series. Traditional methods of measurement and identification (such as the use of seasonal dummies to isolate seasonal components) are simply inadequate, because they fail to take into account possible interactions between seasonal fluctuations and business cycle fluctuations.

What is needed is a specification that allows for identification of seasonal versus nonseasonal (business cycle) shocks. Without such an identification, it is impossible to know, for example, how much of the total variations in output at the business cycle frequency can be explained by disturbances at the seasonal frequency (e.g., by the unanticipated aspect of Christmas demand).

Applying the methodology developed by Wen (2001) to form a specification that allows for identification of seasonal shocks, I am able to uncover in this paper important roles of seasonal disturbances in explaining the business cycle. I show that innovations at the seasonal frequency explain about 50% of the variations in output growth at the business cycle frequency. The same is also true for consumption and investment. Such findings provide a powerful explanation for the observed strong correlation between seasonal fluctuations and business cycles. They also offer a novel explanation for Cochrane's failure to find "large, identifiable, exogenous shocks" in seasonally adjusted data to account for the bulk of the US business cycle (Cochrane, 1994).[3]

The underlying mechanism for the importance of seasonal shocks in explaining the business cycle is not difficult to comprehend. Business cycles have characteristic

[1] The standard deviation of the fourth quarter growth rate, for example, is at least as large as the standard deviation of the quarterly average growth rate in seasonally adjusted data, indicating a substantial amount of seasonal uncertainty. Consumption is far more volatile than output at the seasonal frequency. It grows at an annual rate of 28% in the fourth quarter and declines at an annual rate of −41% in the first quarter (Barsky and Miron, 1989).

[2] Also see Canova and Ghysels (1994), Cecchetti et al. (1997), and Ghysels (1994) for more recent findings regarding the interactions between seasonal cycles and the business cycle.

[3] When seasonal adjustment removes all seasonal fluctuations associated with seasonal shocks but not the part of the business cycle due to seasonal shocks, it leaves a fraction of the business cycle unexplained.

frequencies (e.g., the spectrum of US GDP growth has maximum power centered around the 4–6 year cycle frequency),[4] and these characteristic frequencies are determined by the economy's underlying endogenous propagation mechanisms. Business cycles, however, become visible only when the economy is subject to exogenous shocks. The seasonal disturbances are simply a special type of such shocks that regularly hits the economy at an exogenously determined frequency—the seasonal frequency. When the economy constantly absorbs a substantial volume of seasonal disturbances, one should expect the economy to exhibit fluctuations not only at the exogenously determined frequency (the seasonal frequency), but also at the endogenously determined frequency (the characteristic business cycle frequency).

My method of identification implemented in this paper complements the method proposed by Blanchard and Quah (B–Q 1989). The long-run restriction on impulse responses imposed by Blanchard and Quah to identify the business cycle effects of transitory demand shocks is essentially a restriction imposed on the power spectrum of output growth at frequency zero. My method identifies the business cycle effects of seasonal shocks by imposing restrictions at frequencies other than zero (i.e., at the seasonal frequency).[5,6]

In what follows, I describe my identification method in Section 2. Section 3 provides an economic model to help interpret the identifying assumptions adopted in Section 2. Section 4 reports the empirical estimation results for the US economy. Sensitivity analyses are conducted in Section 5 and Section 6 concludes the paper.

2. Econometric methodology

Consider a world with two types of innovations, ε_1 and ε_2, where ε_1 is called a nonseasonal innovation and ε_2 a seasonal innovation. These innovations are assumed to be orthogonal i.i.d processes with standard deviation normalized to one. It is also assumed that nonseasonal innovations have minimum contributions to seasonal fluctuations and that seasonal innovations are primarily responsible for seasonal fluctuations.[7]

[4] See Watson (1993) and Wen (1998).

[5] See Gali (1992, 1999), Cochrane (1994), and Gamber and Joutz (1993) for interesting applications of the B–Q methodology. Also see Uhlig (2000) for discussions related to restrictions on impulse responses in other ways.

[6] For using general equilibrium models to study the seasonal cycle, the readers are referred to Chatterjee and Ravikumar (1992), Braun and Evans (1995, 1998), and Liu (2000).

[7] The above identifying assumption is based on the understanding that seasonal cycles are exogenous and are caused primarily by external events such as Christmas and seasonal weather changes. Therefore, nonseasonal innovations (e.g., the conventional business cycle shocks) should have little responsibility for seasonal cycles. The orthogonality assumption, on the other hand, is based on the understanding that most business cycle shocks such as technological innovations, oil price crises, or unexpected monetary policy changes are nonseasonal and are independent of the season. It is arguable that some seasonal shocks are correlated with business cycle shocks. In light of this, the so-called seasonal shocks identified in the paper are only the ones that are orthogonal to business cycle shocks. Section 3 provides an economic model that motivates these identifying assumptions.

Let x_t be a 2×1 vector of jointly stationary time series with a moving average representation:

$$x_t = a_1(L)\varepsilon_{1t} + a_2(L)\varepsilon_{2t}, \quad \mathrm{var}(\varepsilon) = I. \tag{1}$$

Assuming that x_{1t} is the variable under interest and x_{2t} is the covariate functioning as an instrument variable. The stationarity assumption of x_t implies that it also has a Wold-moving average representation:

$$x_t = b_1(L)v_{1t} + b_2(L)v_{2t}, \quad \mathrm{var}\ (v) = \Sigma. \tag{2}$$

I am interested in recovering the structural representation (1) from the Wold representation (2) which can be uniquely and consistently estimated via a bivariate VAR. To achieve that, I need to find a mapping:

$$v = A_0\varepsilon,$$

(where A_0 is a 2×2 real matrix with full rank) so that (2) can be written as

$$x_t = [b_1(L) \quad b_2(L)]A_0 \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}. \tag{3}$$

Given A_0, the structural representation (1) can be completely recovered from the data with the equations

$$[a_1(L) \quad a_2(L)] = [b_1(L) \quad b_2(L)]A_0,$$

and

$$\varepsilon = A_0^{-1}v.$$

Since $v = A_0\varepsilon$, the data impose the following identifying restrictions on A_0:

$$\Sigma = A_0A_0'. \tag{4}$$

Restriction (4) has only 3 independent equations but 4 unknowns (since Σ is symmetric), hence it is not sufficient for identifying the four elements of A_0. One more restriction is required to identify A_0. This gives me a degree of freedom to define the dynamic nature of the innovations involved.

Blanchard and Quah (B–Q 1989) utilize that degree of freedom to identify a "demand shock" (ε_1) and a "supply shock" (ε_2), by specifying that demand shocks have no long-run effect on x_1. In terms of the structural representation (1), that restriction means the first element in $a_1(1)$ is zero:

$$a_{11}(1) = 0.$$

In terms of the Wold representation (2), that restriction also implies:

$$[A_0]_{11}b_{11}(1) + [A_0]_{21}b_{21}(1) = 0, \tag{5}$$

where b_{j1} is the first row element in the vector b_j. Obviously, conditions (5) and (4) together uniquely determine A_0.

From the point of view of spectral analysis, the B–Q (1989) identifying scheme (restriction 5) amounts to assert that a demand shock is an innovation that has minimum contributions to the variance of x_1 at frequency zero, whereas a supply shock is an innovation that has maximum contributions to the variance of x_1 at frequency zero. To see this, notice that the Fourier transform of specification (2) (i.e., the power spectrum) is given by:[8]

$$\begin{aligned} f(\mathrm{e}^{-\mathrm{i}\omega}) &= [b_1(\mathrm{e}^{-\mathrm{i}\omega}) \quad b_2(\mathrm{e}^{-\mathrm{i}\omega})]\Sigma[b_1(\mathrm{e}^{\mathrm{i}\omega}) \quad b_2(\mathrm{e}^{\mathrm{i}\omega})]' \\ &= [b_1(\mathrm{e}^{-\mathrm{i}\omega}) \quad b_2(\mathrm{e}^{-\mathrm{i}\omega})]A_0A_0'[b_1(\mathrm{e}^{\mathrm{i}\omega}) \quad b_2(\mathrm{e}^{\mathrm{i}\omega})]'. \end{aligned}$$

The spectrum of the first variable in x is given by the upper left-hand entry:

$$\|[A_0]_{11}b_{11}(\mathrm{e}^{-\mathrm{i}\omega}) + [A_0]_{21}b_{12}(\mathrm{e}^{-\mathrm{i}\omega})|^2 + \|[A_0]_{12}b_{11}(\mathrm{e}^{-\mathrm{i}\omega}) + [A_0]_{22}b_{12}(\mathrm{e}^{-\mathrm{i}\omega})|^2, \tag{6}$$

in which the first term is the partial spectrum of x_1 with respect to the innovation ε_1, and the second term is the partial spectrum of x_1 with respect to the innovation ε_2.

The identifying assumption that ε_1 has minimum contributions to the power spectrum of x_1 at a frequency ω implies that the partial spectrum of x_1 with respect to ε_1 is minimized at ω. Namely, I can choose $[A_0]_{11}$ to solve:

$$\min_{[A_0]_{11}} f_{11}(\mathrm{e}^{-\mathrm{i}\omega}) = \|[A_0]_{11}b_{11}(\mathrm{e}^{-\mathrm{i}\omega}) + [A_0]_{21}b_{21}(\mathrm{e}^{-\mathrm{i}\omega})|^2.$$

The spectrum is nonnegative at each frequency ω, hence the objective function is convex with respect to $[A_0]_{ij}$. The solution is given by

$$[A_0]_{11} = -[A_0]_{21}\left(\frac{[b_{11}(\mathrm{e}^{-\mathrm{i}\omega})b_{21}(\mathrm{e}^{\mathrm{i}\omega}) + b_{21}(\mathrm{e}^{-\mathrm{i}\omega})b_{11}(\mathrm{e}^{\mathrm{i}\omega})]}{2|b_{11}(\mathrm{e}^{-\mathrm{i}\omega})|^2}\right). \tag{7}$$

Let $\omega = 0$, Eq. (7) simplifies to

$$[A_0]_{11} = -[A_0]_{21}\frac{b_{21}(1)}{b_{11}(1)}, \tag{8}$$

which is identical to (5). Therefore, the B–Q (1989) identification scheme can be interpreted as a special case of (7).[9]

Eq. (7) can also be implemented to identify the business cycle effects of seasonal shocks. Let y denote an aggregate US time series under interest (e.g., the growth rate of real GDP), and r denote a covariate that is "stationary" at the seasonal frequency.[10] In addition, let x be the vector $(y, r)'$ and ε be the vector $(\varepsilon_1, \varepsilon_2)'$, where ε_1

[8] The power spectrum (spectral density function) decomposes the total variance of a stationary time series into "variance density distributions" across frequencies. The power at each frequency measures the contribution of cycles at that frequency to the total variance.

[9] Notice that the minimized spectral density may not necessarily be zero. It is zero, for example, at the zero frequency; because when $\omega = 0$, we have $\mathrm{e}^{-\mathrm{i}\omega} = 1$, hence the function, $[A_0]_{11}b_{11}(\mathrm{e}^{-\mathrm{i}\omega}) + [A_0]_{21}b_{21}(\mathrm{e}^{-\mathrm{i}\omega})$, and its conjugate are both real. Consequently, the minimum can be found simply by setting $\sqrt{f_{11}} = [A_0]_{11}b_{11}(1) + [A_0]_{21}b_{21}(1) = 0$.

When $\omega \neq 0$, however, the expression, $[A_0]_{11}b_{11}(\mathrm{e}^{-\mathrm{i}\omega}) + [A_0]_{21}b_{21}(\mathrm{e}^{-\mathrm{i}\omega})$, is generally a complex quantity. The only way to ensure a zero value for $f_{11}(\cdot)$ at an arbitrary frequency ω is to have $[A_0]_{11} = [A_0]_{21} = 0$, which results in overidentification.

[10] As in B–Q (1989), the covariate must be stationary with respect to the frequency at which identifying restrictions are imposed. Since my identifying restriction requires that the non-seasonal innovation has minimum effects at the seasonal frequency, a sensible covariate is a seasonally unadjusted series that does not have seasonal unit root in it (i.e., being "stationary" at the seasonal frequency). Empirical studies found that the US interest rates and prices have very little seasonal component (e.g., see Miron, 1996), I

denotes nonseasonal innovations and ε_2 denotes seasonal innovations. The stationarity assumption of x ensures the structural moving average representation (1) and the Wold-moving average representation (2), where the later can be obtained by first estimating and then inverting the vector autoregressive representation of x in the usual way.[11] Taking the Fourier transform of the Wold representation and choosing $[A_0]_{11}$ to minimize the partial spectrum of y with respect to ε_1 at the seasonal frequency $\omega = \pi/2$ (for quarterly data) gives

$$[A_0]_{11} = -[A_0]_{21}\left(\frac{b_{11}(\mathrm{e}^{-(\pi/2)\mathrm{i}})b_{21}(\mathrm{e}^{(\pi/2)\mathrm{i}}) + b_{21}(\mathrm{e}^{-(\pi/2)\mathrm{i}})b_{11}(\mathrm{e}^{(\pi/2)\mathrm{i}})}{2|b_{11}(\mathrm{e}^{-(\pi/2)\mathrm{i}})|^2}\right), \tag{9}$$

which is a special case of (7) with $\omega = \frac{\pi}{2}$. The system of equations that can be used to solve for the four elements in A_0 is then given by the identifying restriction (9) and the relation $A_0A_0' = \Sigma$.[12]

With the knowledge of A_0, I can then examine the business cycle effects of seasonal innovation ε_2 using representation (6), which decomposes the total spectrum of y into two parts: the part due to nonseasonal shocks (the first term) and the part due to seasonal shocks (the second term). If seasonal innovations are important for causing business cycles in output, then at the business cycle frequencies the partial spectrum of y with respect to ε_2 should constitute a significant fraction of the total spectrum of y at those frequencies.

3. Interpretation

My interpretation of innovations with minimal effects at the seasonal frequency as nonseasonal shocks (e.g., conventional business cycle shocks), and of innovations with maximum effects at the seasonal frequency as being seasonal shocks that may also have effects at the business cycle frequency is motivated by a simple multiplier-accelerator model of the business cycle (Samuelson, 1939, and Hicks, 1950).[13] The

(*footnote continued*)
choose the 3-month T bill rate as the covariate. The results are robust when the CPI price index is used as the covariate.

[11] The assumption that seasonalities can be modeled (or approximated) as indeterministic processes is not 100% realistic, but it can nevertheless serve as a benchmark for further investigations. Section 5 will investigate the sensitivity and robustness of this assumption.

[12] When seasonal cycles also exist at harmonic frequencies, the identifying restriction (9) can be modified to:

$$[A_0]_{11} = -[A_0]_{21}\left(\frac{\sum_j\ [b_{11}(\mathrm{e}^{-(2\pi j/4)\mathrm{i}})b_{21}(\mathrm{e}^{-(2\pi j/4)\mathrm{i}}) + b_{21}(\mathrm{e}^{-(2\pi j/4)\mathrm{i}})b_{11}(\mathrm{e}^{-(2\pi j/4)\mathrm{i}})]}{2\ \sum_j\ [|b_{11}(\mathrm{e}^{-(2\pi j/4)\mathrm{i}})|^2]},\right)$$

where $j = 1, 2$, indicating that nonseasonal shocks have minimal effect at both the fundamental frequency, $\pi/2$, and the harmonic frequency, π. See Wen (2001) for a general treatment on the issue.

[13] For simplicity, I have adopted an ad hoc business cycle model. But the structural equations in the model can be interpreted as reduced-form equilibrium decision rules derived from a rational expectations general equilibrium model with fully specified preferences and technologies. I believe that the mechanism of interactions between seasonal cycles and business cycles is well captured by this simple model. At the

model has three equations:

$$Y_t = C_t + I_t + G_t, \tag{A}$$

$$C_t = \alpha_0 + \alpha Y_{t-1} + S_t, \tag{B}$$

$$I_t = \beta(Y_{t-1} - Y_{t-2}). \tag{C}$$

The variables Y, C, I, G denote output, consumption, investment, and government spending respectively. The time period is assumed to be one quarter. Eq. (A) is the goods market equilibrium condition with G_t as an aggregate demand shock (the nonseasonal business cycle shock). Eq. (B) is a simple consumption function where $\alpha_0 \geqslant 0$ is autonomous consumption, $\alpha \in (0, 1)$ is the marginal propensity to consume, and S_t is a seasonal forcing variable that impacts consumption demand (e.g., the Christmas effect). Eq. (C) describes investment behavior as responding primarily to changes in last period aggregate demand with the accelerator coefficient $\beta > 0$.

To close the model, I need to specify how G_t and S_t evolve. As an illustration, I assume that:

$$G_t = \varepsilon_{gt},$$
$$S_t = -\rho(S_{t-1} + S_{t-2} + S_{t-3}) + \varepsilon_{st}, \quad 0 < \rho \leqslant 1, \tag{10}$$

where ε_g and ε_s are serially uncorrelated, orthogonal innovations to the nonseasonal and seasonal impulses, respectively.[14] Solving for output in the above system gives:[15]

$$Y_t = (\alpha + \beta) Y_{t-1} - \beta Y_{t-2} + G_t + S_t,$$

or

$$(1 - \lambda_1 L)(1 - \lambda_2 L) Y_t = G_t + S_t, \tag{11}$$

where L is the lag operator, and λ_1 and λ_2 are the characteristic roots of Eq. (11) satisfying

$$\lambda_1 + \lambda_2 = \alpha + \beta,$$

$$\lambda_1 \lambda_2 = \beta.$$

It is well known that for reasonable values of α and β, the above system exhibits dampened endogenous business cycles (i.e., the characteristic roots λ_1 and λ_2 form a complex conjugate pair, $a \pm bi$). For example, when $\alpha = \beta = 0.9$, we have

(*footnote continued*)
end of this section, I will allow forward looking behavior into the model and show that the insight gained from this model carries over to more general settings.

[14] There are many different ways to model seasonalities. An alternative model for the seasonal variable is $S_t = \rho S_{t-4} + \varepsilon_{st}$, $0 < \rho \leqslant 1$. In this section which model to choose does not matter, but the indeterministic model in Eq. (10) seems to capture the seasonalities in the US data quite well. My identifying procedure as well as the empirical results obtained in the rest of the paper, however, do not require knowledge about the true model of the seasonalities, except the assumptions that S_t possesses stochastic cycles at the seasonal frequency and has a well-defined spectrum. See Section 5 for the case of deterministic seasonal cycles.

[15] For simplicity, I have set $\alpha_0 = 0$.

$\lambda = 0.9 \pm 0.3i$, implying dampened oscillations at frequency

$$\omega = \frac{1}{2\pi}\cos^{-1}\left(\frac{0.9}{\sqrt{0.9^2+0.3^2}}\right) \simeq 0.05 \text{ (cycle per quarter)},$$

or a periodicity (average cycle length) of 20 quarters per cycle.

Let the structural parameters α and β be such that the characteristic roots of the model are $a \pm bi$. To see how business cycle fluctuations in output Y depend both on the nonseasonal and seasonal innovations, I rewrite Eq. (11) as

$$\begin{aligned} Y_t &= \frac{1}{(1-\lambda_1 L)(1-\lambda_2 L)}\varepsilon_{gt} + \frac{1}{(1-\lambda_1 L)(1-\lambda_2 L)(1+\rho L+\rho L^2+\rho L^3)}\varepsilon_{st} \\ &\equiv B(L)\varepsilon_{gt} + B(L)S(L)\varepsilon_{st}, \end{aligned} \tag{12}$$

where $B(L) \equiv [(1-\lambda_1 L)(1-\lambda_2 L)]^{-1}$ represents the endogenous business cycle propagation mechanism and $S(L) \equiv (1+\rho L+\rho L^2+\rho L^3)^{-1}$ represents the exogenous propagation mechanism that transmits the impact of seasonal innovations (ε_s) in a manner that mimics seasonal cycles.

The corresponding power spectrum of Y is given by

$$\begin{aligned} F_y(\mathrm{e}^{-\mathrm{i}\omega}) &= \frac{\sigma_g^2}{|(1-\lambda_1\,\mathrm{e}^{-\mathrm{i}\omega})(1-\lambda_2\,\mathrm{e}^{-\mathrm{i}\omega})|^2} \\ &\quad + \frac{\sigma_s^2}{|(1-\lambda_1\,\mathrm{e}^{-\mathrm{i}\omega})(1-\lambda_2\,\mathrm{e}^{-\mathrm{i}\omega})|^2|1+\rho\,\mathrm{e}^{-\mathrm{i}\omega}+\rho\,\mathrm{e}^{-2\mathrm{i}\omega}+\rho\,\mathrm{e}^{-3\mathrm{i}\omega}|^2} \\ &\equiv B(\mathrm{e}^{-\mathrm{i}\omega})\sigma_g^2 + B(\mathrm{e}^{-\mathrm{i}\omega})S(\mathrm{e}^{-\mathrm{i}\omega})\sigma_s^2, \end{aligned} \tag{13}$$

where

$$B(\mathrm{e}^{-\mathrm{i}\omega}) \equiv \frac{1}{|(1-\lambda_1\,\mathrm{e}^{-\mathrm{i}\omega})(1-\lambda_2\,\mathrm{e}^{-\mathrm{i}\omega})|^2},$$

and

$$S(\mathrm{e}^{-\mathrm{i}\omega}) \equiv \frac{1}{|1+\rho\,\mathrm{e}^{-\mathrm{i}\omega}+\rho\,\mathrm{e}^{-2\mathrm{i}\omega}+\rho\,\mathrm{e}^{-3\mathrm{i}\omega}|^2}.$$

Eq. (12) is the moving-average, time-domain representation of the dynamics of output, with the first component showing the dynamic effects of the nonseasonal innovation on Y, and the second component showing the dynamic effects of the seasonal innovation on Y. Eq. (13) is the frequency-domain analogue of the decomposition.

Both representations clearly indicate that fluctuations in output at the characteristic business cycle frequency, $\omega = \cos^{-1}(a/\sqrt{a^2+b^2})$, are determined by the model's endogenous propagation mechanism (i.e., by the business cycle polynomial $B(\cdot)$), and that fluctuations in output at the seasonal frequency are determined by the exogenous propagation mechanism (i.e., by the seasonal cycle polynomial $S(\cdot)$). Hence, the power spectrum of Y has two maxima (spectral peaks). One of them centers at the business cycle frequency $\omega = \cos^{-1}(a/\sqrt{a^2+b^2})$, at which the function, $B(\mathrm{e}^{-\mathrm{i}\omega}) = 1/|(1-\lambda_1\,\mathrm{e}^{-\mathrm{i}\omega})(1-\lambda_2\,\mathrm{e}^{-\mathrm{i}\omega})|^2$, attains its maximum;

and the other one centers at the seasonal frequency, $\omega = \pi/2$, at which the function, $S(\mathrm{e}^{-\mathrm{i}\omega}) = 1/|1 + \rho\,\mathrm{e}^{-\mathrm{i}\omega} + \rho\,\mathrm{e}^{-2\mathrm{i}\omega} + \rho\,\mathrm{e}^{-3\mathrm{i}\omega}|^2$, attains its maximum.[16]

Eqs. (12) and (13) also indicate clearly that the dynamic impact of the nonseasonal innovation (ε_g) is not propagated by the seasonal factor $S(\cdot)$, whereas the dynamic impact of the seasonal innovation (ε_s) is propagated both by the seasonal factor $S(\cdot)$ and by the business cycle factor $B(\cdot)$. In other words, the nonseasonal disturbance (ε_g) can generate fluctuations in Y only through the endogenous propagation mechanism: $B(\cdot)$. But the seasonal disturbance (ε_s) can generate fluctuations in Y through two different propagation mechanisms: $B(\cdot)$ and $S(\cdot)$; the first of which generates stochastic business cycles, and the second generates stochastic seasonal cycles.[17]

Consequently, compared with ε_s, the nonseasonal innovation (ε_g) has little contributions to the spectrum of output at the seasonal frequency. In fact, the ratio of the partial spectra of Y with respect to ε_g and ε_s is given by:

$$\frac{1}{S(\mathrm{e}^{-\mathrm{i}\omega})}\frac{\sigma_g^2}{\sigma_s^2},$$

which attains a minimum at the seasonal frequency $\omega = \pi/2$.[18]

On the other hand, the seasonal innovation ε_s not only has maximum contributions to the spectrum of Y at the seasonal frequency, but also has potentially a very large contribution to the spectrum of Y at the business cycle frequency. This is so because the partial spectrum of Y with respect to ε_s is given by

$$B(\mathrm{e}^{-\mathrm{i}\omega})S(\mathrm{e}^{-\mathrm{i}\omega})\sigma_s^2,$$

which has one maximum at the seasonal frequency $\omega = \pi/2$ (at which the seasonal factor $S(\mathrm{e}^{-\mathrm{i}\omega})$ attains its maximum), and another maximum at the characteristic business cycle frequency $\omega = \cos^{-1}(a/\sqrt{a^2+b^2})$ (at which the business cycle factor $B(\mathrm{e}^{-\mathrm{i}\omega})$ attains its maximum).

Hence, the economic model as represented by Eq. (13) clearly satisfies the identifying restrictions of the previous section. Namely, with respect to the seasonal frequency $\pi/2$, ε_g has minimal impact on Y and ε_s has maximal impact on Y.

The dynamic implications of (13) can be better appreciated by a graphic illustration. Fig. 1 plots the total spectrum and the partial spectrum of Y with respect to ε_s as defined in (13). The parameterization adopted is given by: $\alpha = \beta = 0.9, \rho = 0.97$, and $\sigma_g = \frac{1}{4}\sigma_s = 1$. The picture shows that the total spectrum of output

[16] The power spectrum decomposes the total variance of a stationary time series into contributions across frequencies. If a stochastic time series contains characteristic cycles at frequency ω, then its spectrum will exhibit a peak (concentration of power) at frequency ω, indicating large contributions from the characteristic cycle to the total variance of that time series.

[17] This means that the accelerator effects of seasonal changes in aggregated demand can carry over to periods beyond the seasonal frequency.

[18] This is so because $S(\mathrm{e}^{-\mathrm{i}\omega})$ attains its maximum at the seasonal frequency $\omega/2$. Note that the minimum does not have to be zero. In empirical applications, the minimum is determined by the nature of the data series used. See also footnote 8.

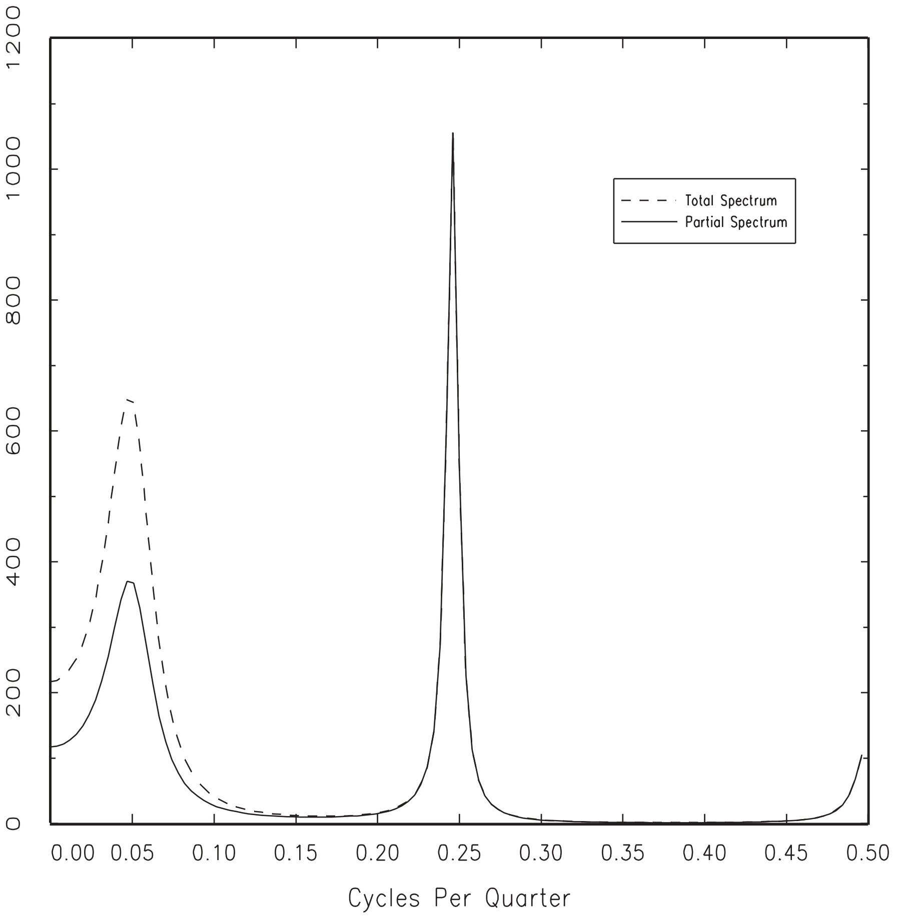


Fig. 1. Spectral decomposition of output in the theoretical business cycle model. Dashed line represents the total spectrum under both shocks. Solid line represents the partial spectrum under the seasonal shock only.

(dashed lines) has two peaks, one centering at the seasonal frequency ($\omega = 0.25$ cycles per quarter), another centering at the business cycle frequency ($\omega = 0.05$ cycles per quarter). Hence fluctuations at these two frequencies are the two major contributors to the total variance of output (which is the total area underneath the spectral density function).

The single most important and interesting feature to notice in Fig. 1, however, is that the partial spectrum of output with respect to the seasonal innovation (solid line) dictates the shape of the total spectrum (i.e., the two spectral peaks). It shows that seasonal shocks explain not only virtually all of the variance in output around the seasonal frequency $\omega = 0.25$, but also a substantial fraction of the variance of output around the business cycle frequency $\omega = 0.05$, leaving nonseasonal shocks to explain only a very limited portion of the business cycle in output.[19] Therefore, the model clearly illustrates that innovations primarily responsible for seasonal fluctuations can also be the culprit of business cycles.

One potential objection to using the above model for helping interpret my identifying assumptions is the lack of forward looking behavior. I show below that such omission is not essential. Suppose the investment equation is modified to

$$I_t = \beta(Y_{t-1} - Y_{t-2}) + \gamma E_t(Y_{t+1} - Y_t),$$

so that investment depends also on the expected changes in future income. The law of motion for expected output is then given by a third order expectations difference equation:

$$\left(1 - \frac{1+\gamma}{\gamma}L + \frac{\alpha+\beta}{\gamma}L^2 - \frac{\beta}{\gamma}L^3\right)L^{-1}E_{t-1}Y_t = -\frac{1}{\gamma}E_{t-1}X_t,$$

where $X_t = G_t + S_t$. Factorization gives

$$(1-\lambda_1 L)(1-\lambda_2 L)(1-\lambda_3 L)L^{-1}E_{t-1}Y_t = -\frac{1}{\gamma}E_{t-1}X_t.$$

It can be shown that for suitable parameter values, the equation has one explosive root and a pair of stable complex roots.[20] Let λ_3 be the explosive root, I can solve for the expected income $E_{t-1}Y_t$ forward to obtain

$$(1-\lambda_1 L)(1-\lambda_2 L)E_{t-1}Y_t = \frac{1}{\gamma\lambda_3}\sum_{j=0}^{\infty}\left(\frac{1}{\lambda_3}\right)^j E_{t-1}X_{t+j}.$$

This also gives $E_t Y_{t+1}$.

Substituting out $E_t Y_{t+1}$ in the investment function then gives the following law of motion for output:

$$\left(1 - \frac{\alpha+\beta-\gamma\lambda_1\lambda_2}{1+\gamma-\gamma(\lambda_1+\lambda_2)}L + \frac{\beta}{1+\gamma-\gamma(\lambda_1+\lambda_2)}L^2\right)Y_t$$
$$= \frac{1}{1+\gamma-\gamma(\lambda_1+\lambda_2)}\left(X_t + \frac{1}{\lambda_3}\sum_{j=0}^{\infty}\left(\frac{1}{\lambda_3}\right)^j E_t X_{t+1+j}\right),$$

where the left-hand side can be factorized as $(1-\tilde{\lambda}_1 L)(1-\tilde{\lambda}_2 L)Y_t$.[21] Hence, output follows

$$Y_t = \frac{\eta}{(1-\tilde{\lambda}_1 L)(1-\tilde{\lambda}_2 L)}\left(X_t + \frac{1}{\lambda_3}\sum_{j=0}^{\infty}\left(\frac{1}{\lambda_3}\right)^j E_t X_{t+1+j}\right). \quad (14)$$

The endogenous business cycle propagation mechanism is therefore given by a

[19] Of course, the variance ratio of the two innovations matter a lot. But the point is that a larger seasonal cycle does imply a larger business cycle.

[20] For example, when $\alpha = \beta = 0.9$, and $\gamma = 0.1$, we have $\lambda_1 = 0.931 + 0.344i$, $\lambda_2 = 0.931 - 0.344i$, and $\lambda_3 = 9.12$.

[21] In this particular example, it happens that $\tilde{\lambda}_i = \lambda_i, i = 1, 2$. The implied business cycle frequency for quarterly time series is about 0.56 cycles per quarter or 18 quarters per cycle.

similar second order polynomial as before:

$$\tilde{B}(L) = \frac{1}{(1-\tilde{\lambda}_1 L)(1-\tilde{\lambda}_2 L)}.$$

Since $X_t = G_t + S_t$, we see that the nonseasonal impulse G_t and the seasonal impulse S_t generate similar business cycles since they are both propagated by the same internal propagation mechanism specified in Eq. (14).[22]

4. Estimation

This section estimates the business cycle effects of seasonal innovations for a set of post war US aggregates using the identifying procedure outlined in Section 2. Since the US housing construction sector is most volatile both at the business cycle frequency and at the seasonal cycle frequency, and many related variables are stationary without detrending (see Fig. 2), I report first my estimation results for housing starts for the US economy (1947:1–1996:2).[23] The covariate used is the 3-month T bill rate (see footnote 9).

Fig. 3 shows the estimated dynamic responses of housing starts to innovations in nonseasonal and seasonal impulses (the time period is a quarter). The left window shows the response of housing starts to a nonseasonal innovation. It exhibits the typical hump-shaped pattern, reflecting the endogenous business cycle propagation mechanism. The right window shows the response of housing starts to a seasonal innovation. It exhibits large seasonalities as well as business cycle frequency movements.[24]

At the impact period, the magnitude of the response to a seasonal innovation is about 80 times larger than the response to a nonseasonal innovation, indicating that housing starts are extremely sensitive to seasonal disturbances and relatively insensitive to nonseasonal disturbances. Both type of responses show hump-shaped transition patterns at the business cycle frequency in returning to the steady state. The maximum effect of nonseasonal shocks, however, is reached only 5 quarters after the impact, indicating a delayed multiplier effect. With respect to seasonal shocks, the low-frequency effect decays gradually (intertwined with seasonal cycles)

[22] In other words, taking the forward looking expectations into account, if innovations in G_t can generate the business cycle, so do innovations in S_t.

[23] I use stationary data first to conduct my analyses, as it is well known that pre-filtering using either the first difference filter or the HP filter may cause distortions (see Cogley and Nason, 1995). In the empirical analyses, all variables are logged and 8 lags are used in the estimation.

[24] An indeterministic model of seasonality implies that the seasonal cycle can be observed only after the economy is subject to random shocks at the seasons. A deterministic model of seasonality, on the other hand, implies that the seasonal cycle can be observed even in the steady state without seasonal shocks. I have adopted the indeterministic approach in my identifying procedure. Consequently, the term "seasonal shock" is defined as innovations that can trigger the seasonal cycle, and "nonseasonal shock" is defined as innovations that do not trigger the seasonal cycle. Section 5 conducts a sensitivity analysis with regard to this assumption. It shows that taking deterministic seasonal cycles into consideration does not change my empirical results significantly.

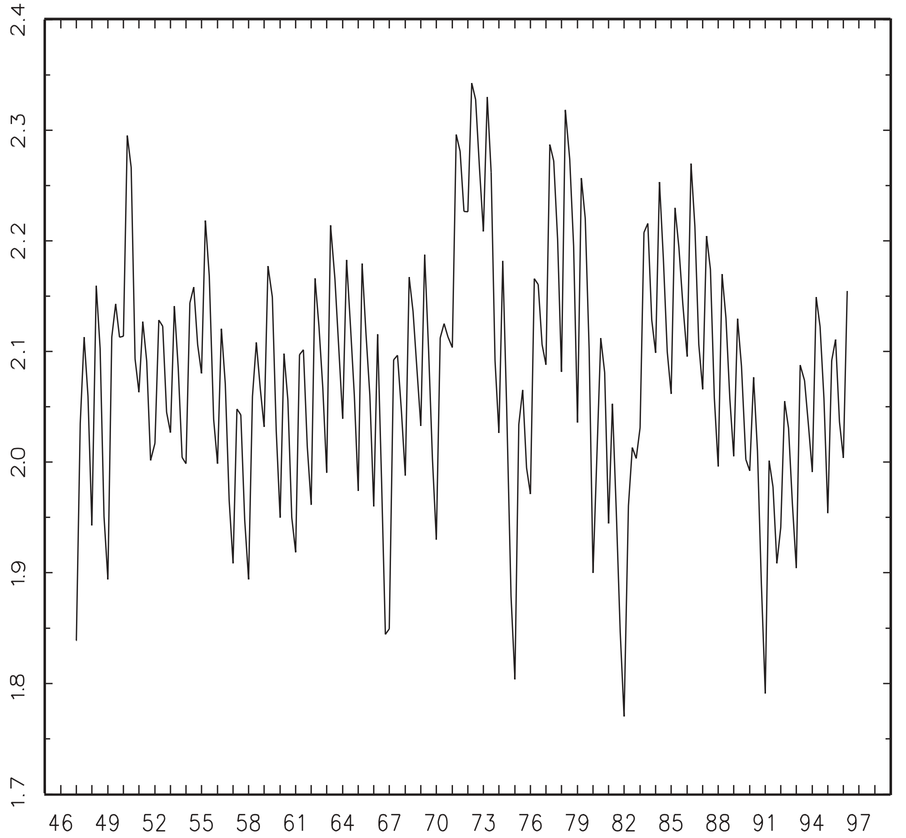
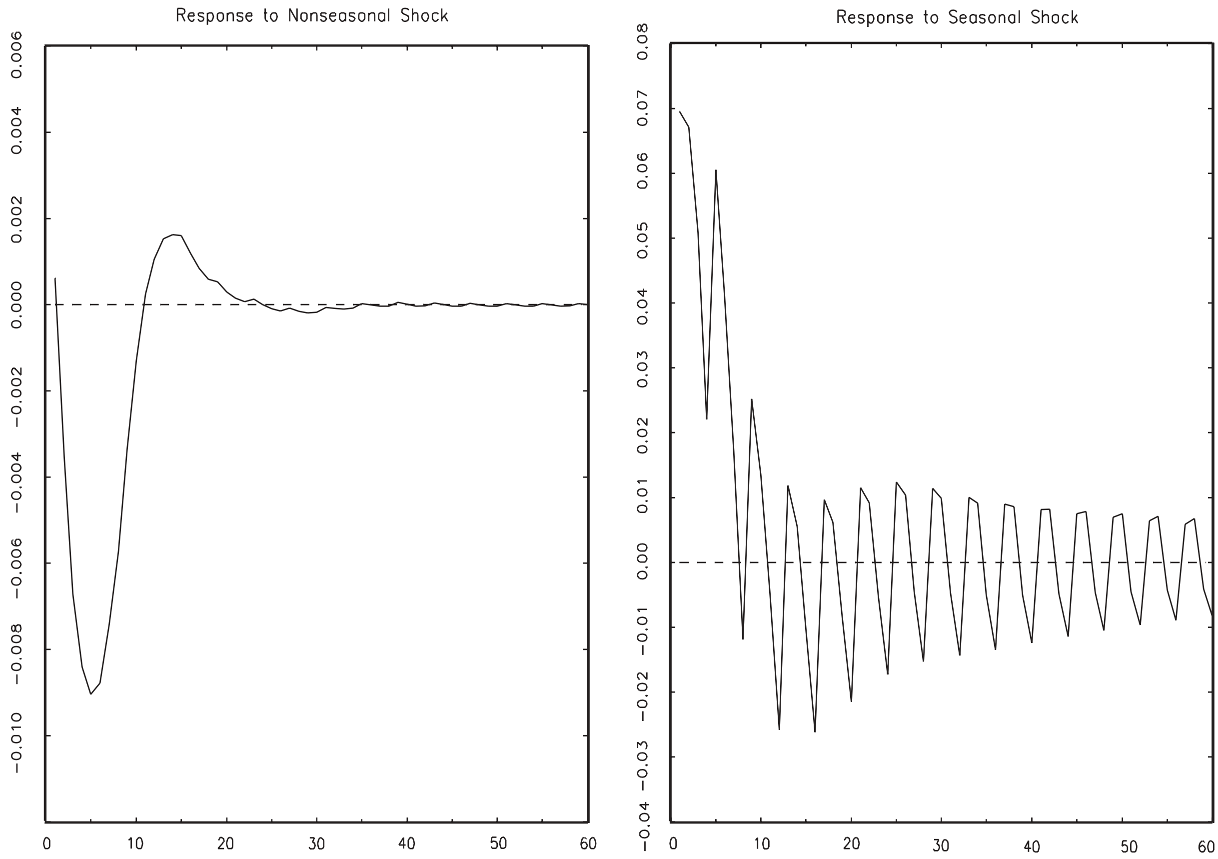


Fig. 2. US housing starts (1947:1–1996:2) (Source: CITIBASE).

with its trough being reached only 10 quarters after, indicating that seasonal shocks do have a strong business cycle effect.

Fig. 4 shows the time-series decomposition for housing starts. The top window shows the time series representation of housing starts in the absence of seasonal disturbances. The bottom window shows the time series representation of housing starts due to seasonal disturbances. It is clear from the top window that housing starts would have been much less volatile if the seasonal shocks were absent. But most importantly, the bottom window shows that the business cycle would still be present in housing starts even without the business cycle shocks!

To better appreciate the business cycle effect of seasonal shocks, Fig. 5 presents the spectral decomposition of the total variance of housing starts across frequencies. The total spectrum (short dashed lines) has two peaks: one at the seasonal frequency (0.25 cycles per quarter or 4 quarters per cycle) and another at the business cycle frequency (0.035 cycles per quarter or 28 quarters per cycle). Looking at the partial spectrum with respect to seasonal shocks (solid line), it is very striking to see how



(a) (b)

Fig. 3. Impulse responses of housing starts to different shocks.

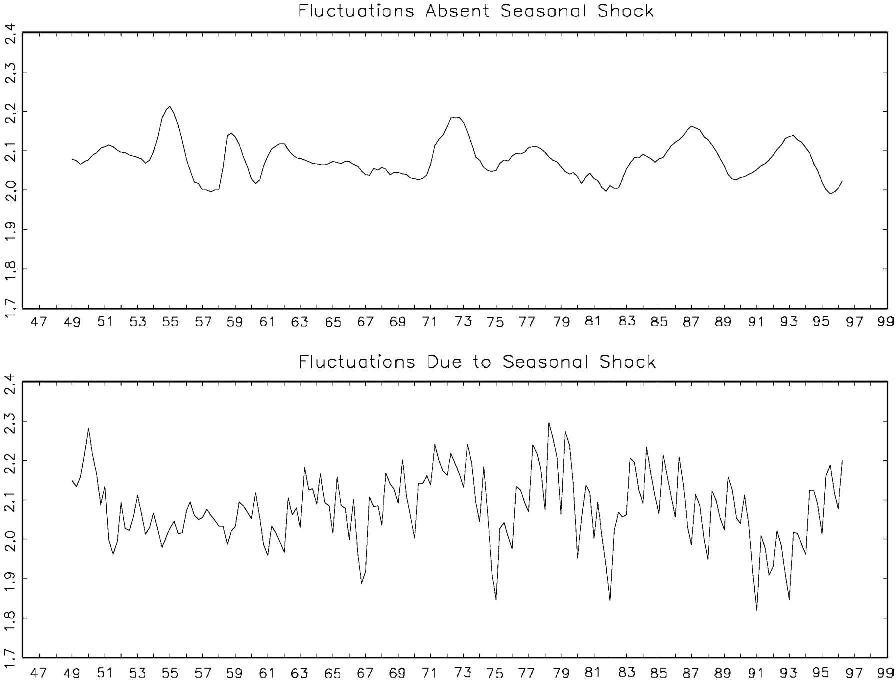


Fig. 4. Time series decomposition of housing starts (Top: Fluctuations absent seasonal shocks. Bottom: Fluctuations due to seasonal shocks).

much the seasonal shocks can contribute to the business cycle movement in housing starts: an exceptionally large fraction of power around the business cycle frequency is due to seasonal shocks! Across all frequencies, seasonal shocks explain 81% of the total variance in housing starts. Around the business cycle frequencies (6–40 quarters per cycle), at which the conventional business cycle shocks are expected to dominate, seasonal shocks still explain about 69% of the total variance of housing starts.

Now I turn to the case of real GDP, consumption and investment.[25] Fig. 6 shows the time series of real GDP growth for the US economy (1947:1–1987:4). It is clear in the picture that seasonal fluctuations completely dominate the business cycle in output. What is not clear from Fig. 6, however, is to what degree business cycles in output are due to seasonal fluctuations.

To answer the question, Figs. 7 and 8 show the decomposition of output growth in time and in frequency respectively.[26] The top window in Fig. 7 shows the time-series

[25] The price index used for deriving real quantities is seasonally unadjusted CPI. All variables (including the instrument) are logged and then first differenced. Six lags are included in the VARs.

[26] Fig. 8 shows that the power spectrum of GDP growth has another peak at the two-period cycle frequency $\omega = 0.5$, indicating harmonic cycles. In such a case, the minimization program should be solved with respect to a sum of all harmonic frequencies (see Wen (2001) for detailed discussions). It turns out,

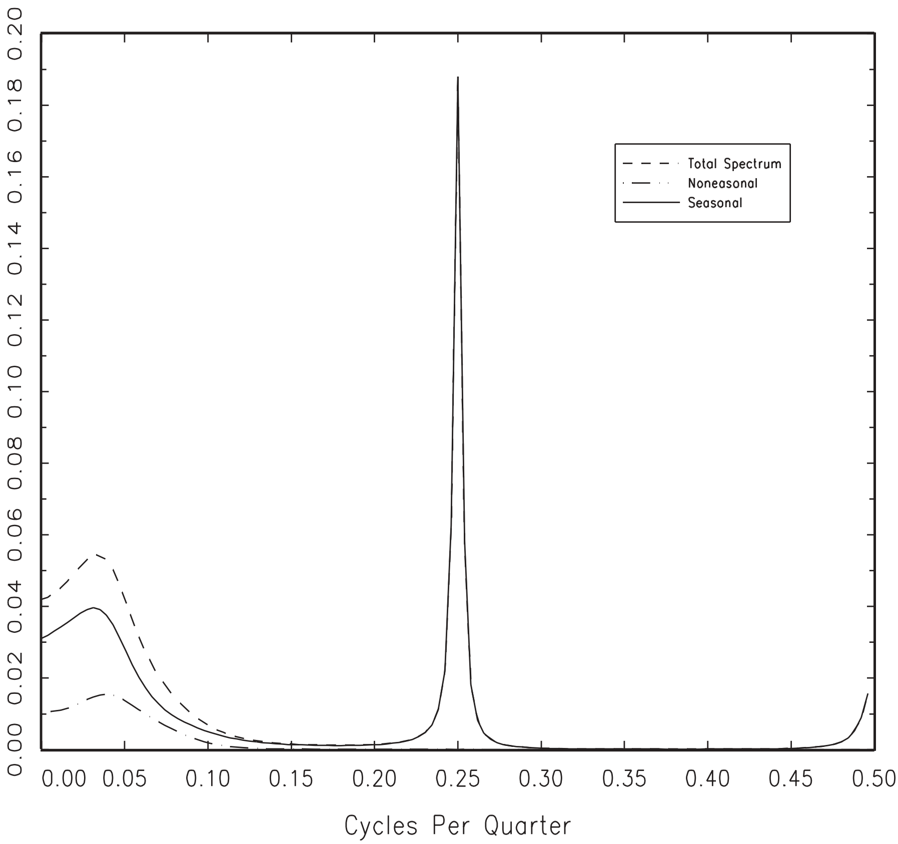


Fig. 5. Spectral decomposition of housing starts.

representation of GDP growth in the absence of seasonal innovations. The bottom window in Fig. 7 shows the time series of GDP growth due to seasonal disturbances. In particular, Fig. 8 (where the bottom window is a zoom-in) shows the effects of seasonal shocks across frequencies. There we see a similar picture to that of housing starts. Firstly and not surprisingly, the largest contributor to the total spectrum of GDP growth is the seasonal disturbance (solid line in the bottom window).[27] Conventional business cycle disturbances explain only 6% of the total power spectrum of GDP growth (dashed lines).

What is surprising and striking are the actions around the business cycle frequency (between $\omega = 0.025$ and $\omega = 0.15$, corresponding to 6–40 quarter cycles), where

(*footnote continued*)
however, minimizing the impact of nonseasonal shocks with respect to the seasonal frequency in our case is good enough to induce a minimum at the two-period cycle frequency.

[27] The spectral peak at $\omega = 0.5$ indicates harmonic cycles.

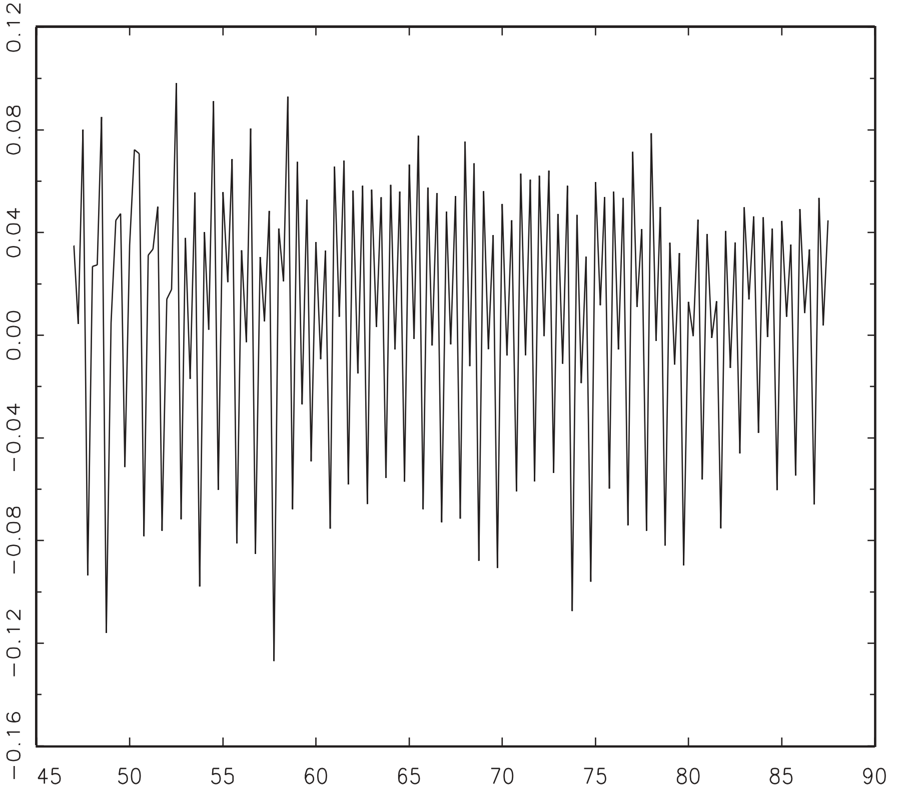


Fig. 6. Real GDP growth (1947:1–1987:4).

Table 1
Contributions of seasonal shocks to variance (%)

Variables	All frequencies	Business cycle frequencies
y	0.94	0.48
c	0.94	0.53
i	0.95	0.53

seasonal disturbances still explain about 48% of the variance in GDP growth, leaving the nonseasonal shocks to explain only about half of the business cycles in GDP. In addition, the spectral decomposition at the zero frequency indicates that seasonal disturbances also have a dominant long-run effect on output. The results are very similar for the case of consumption and investment. They are summarized in Table 1, where we see that with respect to fluctuations at the business cycle frequency (6–40 quarters per cycle), seasonal shocks explain about 53% of both consumption growth and investment growth.

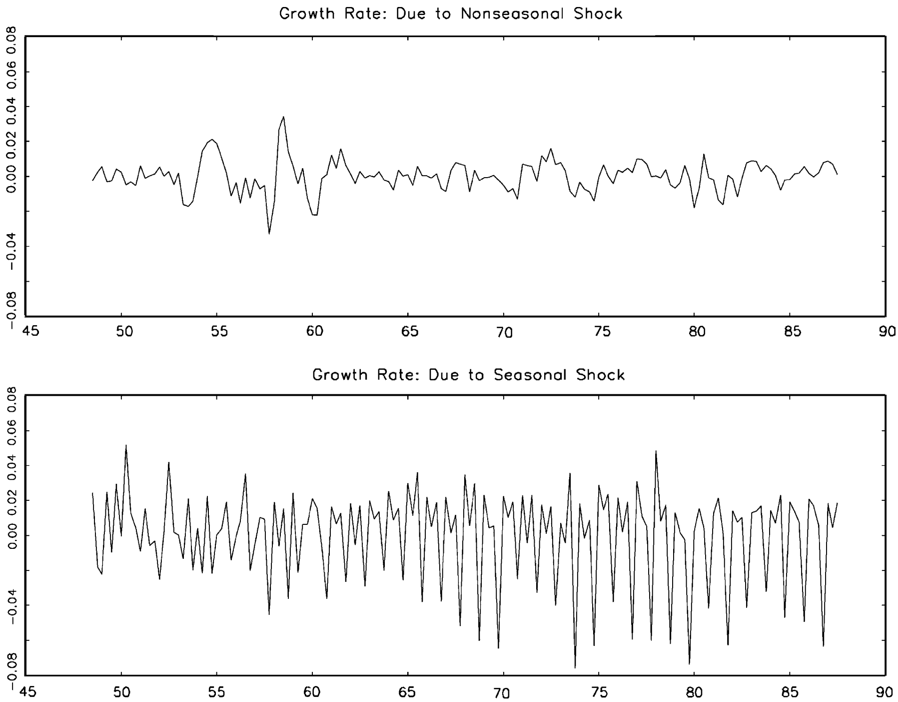


Fig. 7. Time series decomposition of GDP growth (Top: Fluctuations absent seasonal shocks. Bottom: Fluctuations due to seasonal shocks).

To summarize, despite the limited number of data series examined, I found consistent empirical results suggesting that seasonal shocks have surprisingly large contributions to business cycles in the US economy. These results are generally robust to the covariate used. For example, when the GDP price index was used instead as the covariate, I found similar (even slightly larger) contributions to business cycles by seasonal shocks.

5. Sensitivity analyses

My empirical results so far are based on the assumption that seasonal cycles in the US data are indeterministic, so that they can be modeled as ARMA processes. This is an extreme assumption. There are probably both deterministic and indeterministic seasonal cycles in the US data. If deterministic seasonal cycles do exist, it may be desirable to remove them prior to applying the identification method, because deterministic seasonals may mask the true contributions of indeterministic seasonals (which are the source for extracting seasonal shocks). One potential problem is that, however, there does not exist a priori knowledge regarding the exact composition of deterministic and indeterministic seasonals. For the sake of argument, I pretend that

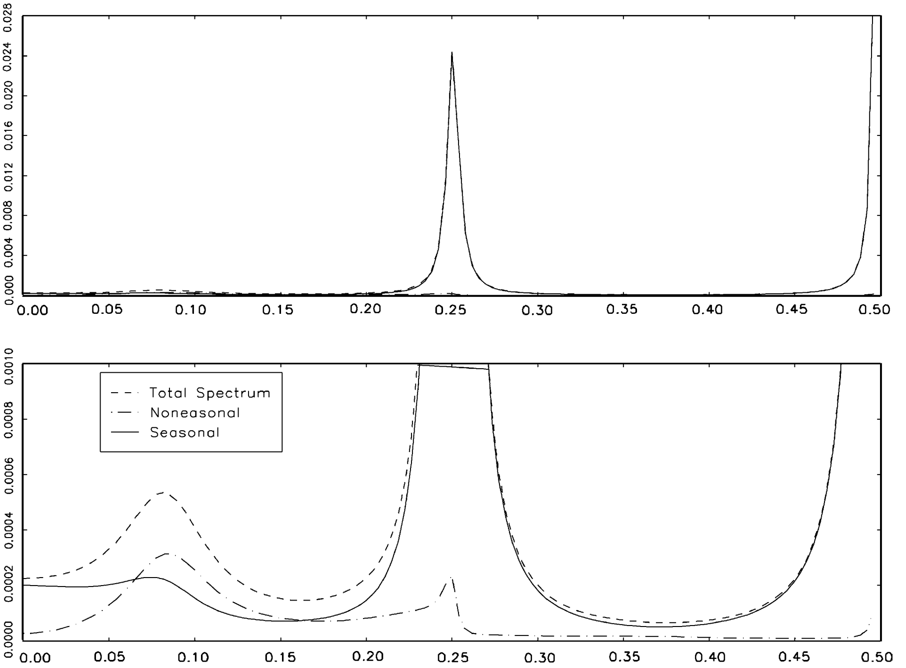


Fig. 8. Spectral decomposition of GDP growth (the bottom window zooms in the top window).

all the forecastable component in seasonal cycles are due to deterministic seasonal movement. Hence, I conduct the following sensitivity analyses.

Prior to applying my procedure to identifying seasonal shocks, I remove the "deterministic" seasonals by regressing the growth rates of output, consumption, and investment on seasonal dummies. If such adjustment substantially reduces the estimated contribution of seasonal shocks to the business cycle, it inevitably casts serious doubt on the reliability of my empirical results.

Fig. 9 plots the decomposition of GDP growth into a "deterministic" component (bottom window) and the residual ("indeterministic") component (top window). It shows that seasonal dummies are able to extract a substantial fraction of GDP fluctuations. Despite the attribution of a very large portion of GDP growth to the "deterministic" component, however, we are still left with a fairly large amount of seasonal fluctuations that are not attributable to deterministic seasonals. This is clearly seen in Fig. 10, which shows the time-domain decomposition of the dummy-adjusted GDP growth into components due to seasonal and nonseasonal shocks respectively. The part of GDP growth due to nonseasonal business cycle shocks (top window in Fig. 10) looks almost identical to that in Fig. 7. The part of GDP growth due to seasonal shocks (bottom window in Fig. 10), although quite different from that in Fig. 7, still has detectable seasonal movement at the seasonal frequency.

The picture becomes even sharper when looking at the spectrum of the dummy-adjusted GDP growth in Fig. 11 (top window). There one sees a large peak at the

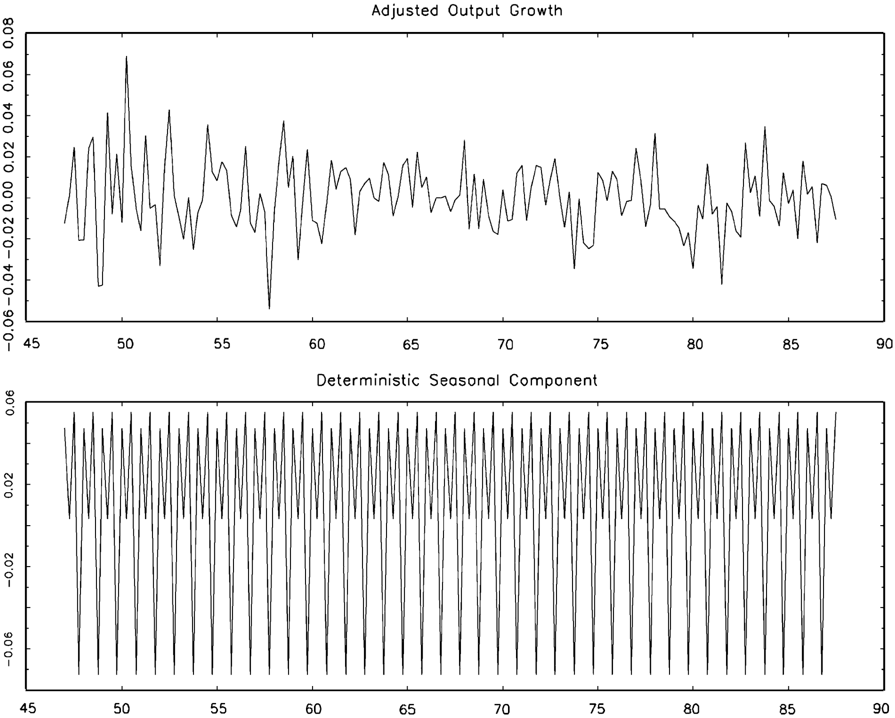


Fig. 9. Indeterministic and deterministic component in GDP growth.

seasonal frequency, indicating that these seasonal fluctuations are not forecastable by seasonal dummies.[28] The bottom window of Fig. 11 shows the spectral decomposition of the variance of the dummy-adjusted GDP growth into its seasonal and nonseasonal components due to seasonal and nonseasonal shocks. It shows that the part due to seasonal shocks (solid lines) still account for a large portion (about 49%) of the variations in the dummy-adjusted GDP growth around the business cycle frequencies. This implies that seasonal adjustment by seasonal dummies has very little effect on my identification method that identifies the business cycle effects of seasonal shocks.

The adjustment by seasonal dummies does, however, change the point estimates of contributions to the business cycle of seasonal shocks for the other data series. Over the business cycle frequencies, for example, the contribution of seasonal shocks to the variance of consumption growth was 53% for the pre-adjusted series. It is now 59% for the post-adjusted series. The contribution of seasonal shocks to the variance of investment growth was 53% for the pre-adjusted series. It is now 63% for the post-adjusted series (see Table 2).

[28] Comparison between Fig. 10 and Fig. 8, however, shows that the bulk of the seasonal cycle has been removed by deterministic seasonal dummies.

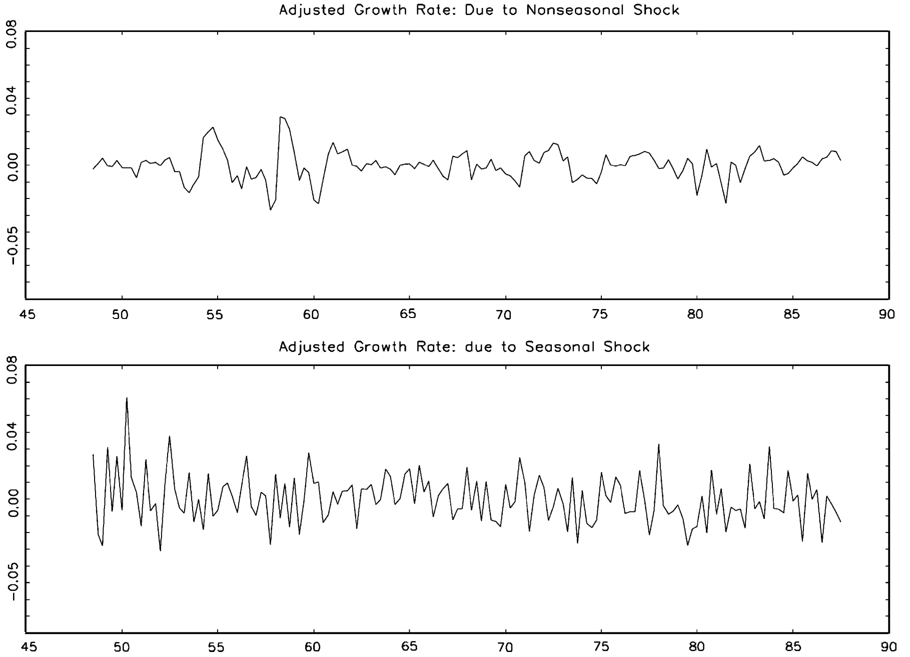


Fig. 10. Time series decomposition of dummy-adjusted GDP growth (Top: Fluctuations absent seasonal shocks. Bottom: Fluctuations due to seasonal shocks).

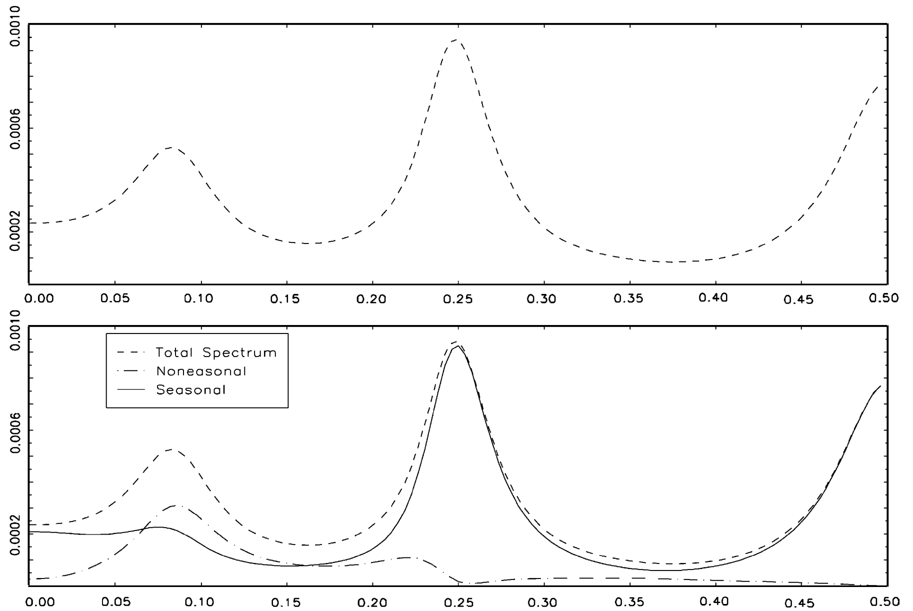


Fig. 11. Spectral decomposition of dummy-adjusted GDP growth (Top: Total spectrum. Bottom: Decomposed spectrum).

Table 2
Contributions of seasonal shocks to variance (%) (for seasonal-dummy adjusted data series)

Variable	All frequencies	Business cycle frequencies
y	0.77	0.49
c	0.88	0.59
i	0.81	0.63

Using Monte Carlo, I show that these changes are due to estimation errors. To be more specific, I generate three artificial time series, y_{1t}, y_{2t}, and z_t according to the base-line economic model presented in Section 3:

$$y_{1t} = (\alpha + \beta)y_{1t-1} - \beta y_{1t-2} + g_t + s_t,$$

$$y_{2t} = y_{1t} + x_t,$$

$$z_t = (\alpha + \beta)z_{t-1} - \beta z_{t-2} + g_t + 0.1s_t,$$

where g_t and s_t represent respectively the business cycle shocks and the seasonal cycle shocks as specified in Section 3,[29] and x_t is a deterministic seasonal component generated using seasonal dummies.[30] We can interpret the series y_{1t} and y_{2t} as two different series of GDP growth with the difference that y_{2t} has a deterministic seasonal component. The series z_t is used as the covariate, the 3 month T bill rate.[31]

My task is three-fold. First, I want to know whether my estimation procedure correctly captures the true contribution to the business cycle by seasonal shocks. Secondly, I want to know whether adjustment by seasonal dummies on y_{1t} would cause distortions to the estimated contribution to the business cycle from seasonal shocks, when there is no deterministic seasonals in the original series. And lastly, I want to know whether my estimation procedure gives biased results when the original time series contains both deterministic and indeterministic seasonal cycles (y_{2t}).

The first aspect of the task can be accomplished simply by applying my procedure to the series y_{1t}. The true contribution to the business cycle by seasonal shocks is 55% by construction. The second aspect of the task can be accomplished by comparing the contributions to the business cycle from seasonal shocks in the two series y_{1t} and $\hat{y}_{1t}$, where the later is the adjusted y_{1t} using deterministic seasonal dummies. The Third aspect of the task can be accomplished by comparing the contributions to the business cycle of seasonal shocks in the two series y_{2t} and $\hat{y}_{2t}$, where the later is the adjusted y_{2t} using deterministic dummies.

[29] Namely, the specifications used to generate Fig. 1.

[30] The dummy coefficients in x_t are calibrated using their counter parts of actual GDP growth. I have increased the dummy coefficients proportionally so that the magnitude of x_t is sufficiently large to significantly affect the seasonal component of y_{1t}.

[31] Since the covariate should have relatively less seasonality in it, I attach a small weight to s_t in constructing z_t. Also see footnote 10.

Table 3
Contributions of seasonal shocks to business cycle (truth = 0.55)

Pre-adjustment		Post-adjustment	
Series y_{1t}			
μ_{y_1}	0.54	$\mu_{\hat{y}_1}$	0.51
σ_{y_1}	(0.18)	$\sigma_{\hat{y}_1}$	(0.20)
Series y_{2t}			
μ_{y_2}	0.50	$\mu_{\hat{y}_2}$	0.51
σ_{y_2}	(0.19)	$\sigma_{\hat{y}_2}$	(0.20)

I generate 500 samples for each time series in each Monte Carlo analysis, with sample size of 164 observations (= the US sample size). I compute my statistics by applying the identification procedure to each sample created. Table 3 summarizes the results, where the μ's are the means of the point estimates and $\sigma's$ are the standard errors, all numbers referring to the percentage contribution of seasonal shocks to the variance of y_{jt} $(j = 1, 2)$ at the business cycle frequencies (6–40 quarters per cycle).

Several features of Table 3 are worth mentioning. First of all, the identifying procedure captures the truth very well. The true value is 0.55 by construction, my estimate is 0.54 (the upper left corner of Table 3). Secondly, adjustment by deterministic dummies has no significant distortionary effect on all of the series considered. The estimated contribution of seasonal shocks to the business cycle in y_{1t}, for example, is 54% before the adjustment; and it is 50% after the adjustment by seasonal dummies. Thirdly, treating deterministic seasonal cycles as indeterministic causes no significant distortion to the estimated true contribution of seasonal shocks to the business cycle. The estimated contribution of seasonal shocks to the business cycle in y_{2t}, for example, is 50% without the adjustment by seasonal dummies; and it is also about 50% after the adjustment by seasonal dummies. And lastly, the estimation errors are by no means small, making my estimates imprecise to a certain degree. This is largely due to the small sample size used, however.

Overall, these Monte Carlo experiments provide strong support to my empirical results obtained in Section 4. Seasonal shocks do appear to account for a substantial fraction of the US business cycle, regardless whether the data are adjusted by seasonal dummies or not. An important caveat is in order, however. My sensitivity analyses by no means imply that any seasonal adjustment (such as the X-11 procedure used by the US government) will have no serious distortions to the business cycle properties of a times series as in the case of seasonal dummies (e.g., see Sargent, 1987, pp. 336–342). In fact, large adverse effects could result. In particular, if a seasonal adjustment procedure is able to remove completely the seasonal component of a time series, especially the indeterministic seasonal component, it then becomes virtually impossible to identify the source and the volume of seasonal shocks, because there would be little seasonal frequency variations left for identifying seasonal innovations, still less to evaluate the contribution of seasonal shocks to the business cycle. In that case, the part of the business cycle that is originally caused by seasonal shocks would either appear to be unexplainable or be attributed (mistakenly) to nonseasonal shocks.[32]

The implication that removing the "deterministic" seasonal cycles has little distortionary effect in the current context is an important issue that is worth further theoretical investigations. Christiano and Todd (2000) examines this issue using artificial data generated from a simple general equilibrium business cycle model with seasonality. They show that removing deterministic seasonal fluctuations using seasonal dummies does not cause serious distortions to the business cycle properties of the original time series, when the true data generating process has only deterministic seasonal component. However, they find larger discrepancies between seasonal and aseasonal models when the seasonal is indeterministic than when it has a deterministic component.

6. Conclusions

By developing a specification that allows for identification of seasonal versus nonseasonal shocks, It is made possible in this paper a quantitative evaluation of the contribution of seasonal shocks to the business cycle. Under the identification scheme, seasonal shocks are found accounting for a substantial fraction of the business cycles in the US.

At first glance the finding that seasonality is so important for the business cycle perhaps seems both astonishing and puzzling. However, pondering it in light of the economic model provided in Section 3 makes it obvious that seasonal shocks ought to be able to have a significant effect on business cycles. This is so because seasonal shocks are by far the most frequent, most synchronized, and on average the severest disturbances among all. What type of economies (or their underlying propagation mechanisms) could possibly be immune to such shocks? Perhaps none.

The empirical findings provide a powerful explanation to the empirical puzzle that countries and industries with large seasonal cycles also have large business cycles.[33] They also suggest that models relying heavily on technology shocks to explain business cycles are misspecified,[34] and that theories, as well as government policies

[32] I think this is perhaps the reason behind Cochrane's failure to find "large, identifiable, exogenous shocks" in seasonally adjusted data to account for the bulk of the US business cycle (Cochrane, 1994).

[33] According to the economic model presented in Section 3 the relative contributions of seasonal shocks to the business cycle depends on the variance ratio of seasonal disturbances and nonseasonal disturbances, σ_s^2/σ_g^2. So for larger σ_s^2, not only is the business cycle larger, but also is the fraction of the business cycle due to seasonal shocks.

A good empirical example is the comparison of housing starts and GDP. In terms of growth rates, the volatility of housing starts is 43 times that of GDP. For both series, seasonal movements account for about 95% of the total variance. The contribution of seasonal shocks to business cycle fluctuations, however, is 70% for housing starts, and only 48% for GDP. This suggests that large seasonal cycles give rise to large business cycles not only in absolute terms, but also in relative terms.

[34] This point has also been made by Chatterjee and Ravikumar (1992), and Braun and Evans (1995, 1998). More recently, Benhaibib and Wen (2000) show that by allowing for aggregated demand shocks a

concerning the business cycle ought to address seasonal fluctuations seriously. In other words, in addition to trying to determine whether it is monetary, technology, or other types of shocks that cause business cycles, we should be looking at what causes seasonality.

While I find this simple exercise to have been worthwhile, I also believe that further work is needed, especially to validate and to refine the definition of seasonal shocks. One specific extension is to find a way to identify the demand-side seasonal shocks (e.g., the "Christmas" effect) and the supply-side seasonal shocks (e.g., the weather effect). Research along this line can help address welfare questions regarding the issue of smoothing seasonal cycles. If seasonal cycles are largely demand driven, clearly the welfare gains from smoothing them are very different as compared to when they are largely supply driven.

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(*footnote continued*)
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