

Sticky prices, fair wages, and the co-movements of unemployment and labor productivity growth*

Fabien Tripier[‡]

September 20, 2005

Abstract

This paper studies the co-movements of unemployment and labor productivity growth for the U.S. economy. Measures of co-movements in the frequency domain indicate that co-movements between variables differ strongly according to the frequency. First, long-term and business cycle co-movements are larger than short-term co-movements. Second, co-movements are negative in the short and long run, but positive over the business cycle. A New Keynesian model that combines nominal rigidity on the goods market (sticky prices) and real rigidity on the labor market (fair wages) is shown to be quantitatively consistent with the observed co-movements both in the long term and over the business cycle. However, the model fails to explain the short-term co-movements.

Keywords: growth, unemployment, sticky prices, fair wages, spectral analysis

JEL Classification: C32, E31, E32, J41

*With many thanks for their helpful comments to Kevin Beaubrun-Diant, Patrick Fève, Julien Matheron, Tristan-Pierre Maury, Jean-Christophe Péreau and to the participants of the 19th EEA Madrid Meeting and of the Universities of Orléans, Paris X and Marne la Vallée seminars. I also wish to thank an anonymous referee and express my gratitude to editor Wouter den Haan for his most valuable remarks and suggestions. Any remaining errors are mine.

[†]*Affiliation:* EconomiX, University of Paris X Nanterre

[‡]*Adress:* EconomiX, Université Paris X Nanterre (bât G), 200 Av. de la République, 92001 Nanterre Cedex, France. *Email address:* tripier@u-paris10.fr. *Tel:* 33 1 40 97 78 17. *Fax:* 33 1 40 97 77 84.

1 Introduction

The long-standing debate still goes in macroeconomics over the relationship between unemployment and labor productivity growth. This paper studies the importance of periodicity for a better understanding of the relationship. I analyze the behavior of unemployment and labor productivity growth in the short and long run and argue that such an approach is necessary to reconcile the (apparently) contradictory views on this relationship.

The first view is that productivity growth increases unemployment. It has been put forward for the U.S. economy by Blanchard (1989) and Blanchard and Quah (1989) who show that technological shocks first increase unemployment and by Evans (1989) who finds that shocks that instantaneously increase unemployment have a positive long-term effect on output.¹ Gali (1999) demonstrates that this result² is still valid for total hours worked (which decrease after a positive technological shock). This evidence supports the New Keynesian's view of fluctuations and contradicts the Real Business Cycle approach of fluctuations which was first proposed by Kydland and Prescott (1982) and Long and Plosser (1983), and later applied to unemployment dynamics by Hansen (1985) among others.

The second view is that productivity growth decreases unemployment. It aimed to account for the "roaring nineties" experienced by the U.S. economy. Ball and Moffitt (2002) and Staiger et al. (2002) explain the exceptionally low unemployment rate of the 1990s with the equally exceptional productivity gains over the same period. The study of steady state properties in the tradition of Pissarides (2000) and Aghion and Howitt (1994) also provided evidence to support this view. Whereas the relation between growth and unemployment at the steady state is theoretically indeterminate³, the empirical studies of Hoon and Phelps (1997), Blanchard and Wolfers (2000), and Vallanti (2004) suggest that permanent growth

¹See Balmaseda et al. (2000) for evidence from OECD countries.

²This result has been the topic of intense debate over the last few years (see references in section 2.4).

³Theoretically, the relation between growth and unemployment in matching models of unemployment is either negative or positive according to the assumption of embodied or disembodied technical progress (see also Mortensen and Pissarides, 1998).

increase pulls down unemployment.⁴

The first view induces positive co-movements, whereas the second induces negative co-movements. This paper argues that both views are relevant: positive and negative co-movements can coexist, because they are associated with cycles of different periodicities. To make the distinction between the different periodicities, from the short to the long run, the co-movements are studied in the frequency domain by means of spectral analysis. Spectral analysis has become very popular in macroeconomics for describing the dynamic properties of time series as well as the co-movements between series (see, for example, Watson, 1993, Diebold et al., 1998, and Wen, 1998).⁵ The usefulness of spectral analysis is twofold for the purpose of this study. First, it gives an overall view of the co-movements of unemployment and labor productivity growth, which can be appraised according to different frequencies. Second, one can evaluate models on their ability to reproduce empirical co-movements at different frequencies. The distinction can then be drawn between the short run – which corresponds to the highest frequencies –, the long run – which corresponds to the lowest frequencies –, and the business cycle – which corresponds to the medium frequencies.

I begin by describing the empirical co-movements of unemployment and labor productivity growth for the U.S. economy. Measures of co-movements in the frequency domain indicate that these two variables are closely related and that the sign of their co-movements differs strongly according to the frequency studied: they co-move negatively in the short and long run yet positively over the business cycle. In addition, co-movements are concentrated in the low and medium frequencies rather than in the high frequencies. Interestingly, the same pattern (with the opposite sign of course) is obtained for co-movements between labor productivity growth and hours worked instead of unemployment. The use of spectral analysis therefore

⁴These contributions take productivity growth as exogenous. Daveri and Tabellini (2000) also describe a negative correlation, but they interpret it in an endogenous growth framework where causality is from the labor market to productivity growth.

⁵Spectral analysis also supplies tools for extracting frequency components of time series such as the high-pass filter of Hodrick and Prescott (1997) or the band-pass filters of Baxter and King (1999) and Christiano and Fitzgerald (2003).

provides an overall view of the co-movements of unemployment and labor productivity growth. I then turn to theory to attempt to explain these empirical facts.

I study a New Keynesian explanation of these facts based on the interaction of nominal and real rigidities. Nominal goods prices move sluggishly because firms face a quadratic cost of price adjustment, as originally suggested by Rotemberg (1982).⁶ As emphasized by Blanchard (1989) and Blanchard and Quah (1989), and more recently by Basu et al. (2004) and Gali (1999), nominal rigidities constitute a relevant mechanism to explain the short-term negative effects of technological improvements on the use of labor. Real rigidity on the labor market comes from the fair-wage hypothesis as originally suggested by Akerlof (1982) and recently extended by Collard and de la Croix (2000) and de la Croix et al. (2000). The extended fair-wage model leads to a persistence in the workers' wage aspiration that positively links a current increase in productivity with future employment increases. The general idea is close to the proposition of Blanchard and Katz (1999) that introduces past wages in the reservation wage to explain wage dynamics. The two types of rigidity have recently been combined by Ball and Moffitt (2002) (who provide an estimation of the Phillips Curve) and by Danthine and Kurmann (2004) (who give results for the business cycle).

The model is estimated to reproduce the empirical spectra of labor productivity growth and unemployment. Next comes the assessment of the model's ability to replicate the empirical co-movements between the variables. When a positive productivity shock hits the economy, the model predicts that an unemployment increase is followed by an unemployment decrease. Hence, the co-movements are positive at high and medium frequencies and then become negative at low frequencies. This theoretical timing of events appears consistent with the empirical relationship between labor productivity and unemployment in the long run and over the business cycle, but not in the short run. This conclusion is confirmed by the study of two models. A model with fair wages and flexible prices can only account for the long-term co-movements whereas a model with sticky prices and indivisible labor supply

⁶This assumption has been incorporated into dynamic, stochastic, and general equilibrium models, notably by Hairault and Portier (1993), Rotemberg (1996), and Ireland (2000).

can only account for the business cycle co-movements.

The remainder of the paper is organized as follows. Empirical facts are described in Section 2. The model is exposed in Section 3. Results are presented in Section 4. Section 5 concludes.

2 Empirical facts

I first study the co-movements of unemployment and labor productivity growth by means of spectral analysis. The spectra, the co-spectrum, and the measures of correlation in the frequency domain are computed. I then apply the measure of co-movements proposed by den Haan (2000), which is based on VAR forecast errors. Finally, the same analysis of co-movements is conducted with hours worked instead of unemployment.

2.1 Spectra and co-spectrum

The bivariate data set comes from the U.S. Bureau of Labor Statistics and covers the 1948:1 to 2000:4 period at a quarterly periodicity for the U.S. economy. The series considered are the first difference of logged labor productivity (its mean value is removed) and the logdeviation of the unemployment rate from its empirical mean.⁷ They are denoted g and u , respectively.

In the frequency domain⁸, frequencies can be interpreted in terms of cycle duration in the time domain. Frequency ω corresponds to the cycles of period $2\pi/\omega$ (namely the length of time required for the process to repeat a full cycle). For example, frequency $\pi/16$ corresponds to a cycle of 32 periods, i.e. of 8 years for quarterly data. It is common in macroeconomics⁹ to divide the frequency interval $[0, \pi]$ into three bands: the low-frequency band – which cor-

⁷I take the logarithm of unemployment to facilitate comparison with the model's predictions, where the logdeviation (and not the deviation) from the steady state value of the variables is simulated. This has no consequence on the results.

⁸This section is mainly drawn on Hamilton (1994).

⁹See Baxter and King (1999) amongst others.

responds to the long run –, the medium-frequency band – which corresponds to the business cycle –, and the high-frequency band – which corresponds to the short run. In practice, the following standard division is used: the low-frequency band is $[0, \pi/16]$ (i.e., cycles of 8 years or longer), the medium-frequency band is $[\pi/16, \pi/3]$ (i.e., cycles of 1.5–8 years), and the high-frequency band is $[\pi/3, \pi]$ (i.e., cycles of 1.5 years or less).

The process $[g, u]$ is stochastic, zero-mean, and stationary. Let $\mathcal{S}(\omega)$ be the spectral density matrix of the process at frequency ω , for $\omega \in [-\pi, \pi]$, and $\Omega = [\underline{\omega}, \bar{\omega}]$ be a frequency band, where $\underline{\omega} \in [-\pi, \pi]$ is the lower bound of the frequency range of Ω and $\bar{\omega} \in [-\pi, \pi]$ the upper bound, with $\underline{\omega} < \bar{\omega}$. The spectral density matrix at frequency ω is a 2×2 matrix :

$$\mathcal{S}(\omega) = \begin{bmatrix} \mathcal{S}_g(\omega) & \mathcal{S}_{gu}(\omega) \\ \mathcal{S}_{ug}(\omega) & \mathcal{S}_u(\omega) \end{bmatrix} \quad (1)$$

where $\mathcal{S}_x(\omega)$ is the spectrum of x and $\mathcal{S}_{xy}(\omega)$ is the cross spectrum between x and y (which is equal to $\mathcal{S}_{yx}(\omega)$), for $x = g, u$ and $y = g, u$, with $x \neq y$. Since the spectral density matrix is symmetric around $\omega = 0$, only positive frequencies are considered in the sequel ($0 \leq \omega \leq \pi$) and it may be multiplied by two when necessary.

The integral of the spectrum of series x over the frequency band Ω , denoted $\tilde{\mathcal{S}}_x(\Omega) = \int_{\Omega} \mathcal{S}_x(\omega) d\omega$, can be interpreted as the portion of the variance of x that is attributable to cycles with Ω frequencies. For example, if the complete range of frequencies is considered (i.e., for $\Omega = [0, \pi]$), $\tilde{\mathcal{S}}_g(\Omega)$ gives the variance of g , whereas for the medium-frequency band (i.e., for $\Omega = [\pi/16, \pi/3]$), $\tilde{\mathcal{S}}_g(\Omega)$ gives only the variance that can be attributed to cycles of 1.5–8 years (namely the business cycle). A similar interpretation applies to the low and high-frequency bands.

To describe co-movements between series, it is necessary to study the off-diagonal elements of the spectral density matrix. Generally, the cross spectrum is not real and is thus difficult to interpret. It is therefore more convenient to study the real part of the cross spectrum which is known as the co-spectrum: $\mathcal{C}_{gu}(\omega) = \text{real}(\mathcal{S}_{gu}(\omega))$. The integral of the co-spectrum over the frequency band Ω , denoted $\tilde{\mathcal{C}}_{xy}(\Omega) = \int_{\Omega} \mathcal{C}_{gu}(\omega)$, can be interpreted as the portion of

the covariance between the x and y series attributable to cycles with Ω frequencies. Once again, if the complete range of frequencies is considered (i.e., for $\Omega = [0, \pi]$), $\tilde{\mathcal{C}}_{gu}(\Omega)$ gives the covariance between g and u , whereas in the medium-frequency band (i.e., for $\Omega = [\pi/16, \pi/3]$), $\tilde{\mathcal{C}}_{gu}(\Omega)$ gives only the covariance that can be attributed to cycles of 1.5–8 years. A similar interpretation applies to the low and high-frequency bands.

Subsequently, to compute the spectra of g and u and the cross spectrum from u to g , the spectral density matrix of $[g, u]$ has to be estimated. To this end, a bivariate VAR is estimated¹⁰ and the associated spectral density matrix derived. Confidence Intervals (CI) of 90% for the spectra and the co-spectrum are also computed.¹¹

Figure 1 depicts the spectra of g and u . The spectrum of labor productivity growth has three peaks: two at the extremities of the frequency range (for $\omega = 0$ and $\omega = \pi$) and one within the medium-frequency band. A peak indicates a strong contribution of the associated frequency to the variance of the series. Hence, I conclude that the three frequency bands contribute notably to the volatility of labor productivity growth. This is not the case for unemployment. The spectrum of unemployment¹² is highly concentrated within the low-frequency band. It peaks at $\omega = 0$ and then decreases steadily to its lowest value for $\omega = \pi$. Clearly, the low-frequency band is responsible for the main part of unemployment volatility.

Figure 2 depicts the co-spectrum of g and u . The co-spectrum takes its lowest value at frequency zero and reaches a peak in the medium-frequency band. Between these two frequencies, the co-spectrum increases and crosses the zero line around frequency $\pi/24$ (which corresponds to cycles of 12 years). The values are always positive for the medium-frequency band. The co-spectrum is lower (in absolute value) for the high-frequency band, but becomes

¹⁰The lag in the VAR is chosen by minimization of the Schwartz criterion and is found to be equal to 6.

¹¹ CIs were computed using the bootstrap Monte Carlo procedure described in Edelberg et al. (1999) with 2000 replications.

¹²This figure cannot easily be compared with other studies (e.g., Watson, 1993, for the spectrum of total hours), because the calculation concerns the spectrum of the unemployment level and not of its first difference. This choice is motivated by the interest in the co-spectrum between the level of (and not the first difference of) unemployment and the labor productivity growth rate.

negative and significantly different from zero at the highest frequencies. Two facts emerge from this figure. First, the unemployment and labor productivity growth rates seem more connected in the long run and over the business cycle than in the short run. Second, the relation between these variables differs strongly according to the frequency considered: co-movements are positive over the business cycle, but negative in the short and long run. In addition, these co-movements are significantly different from zero for the main part of the medium frequencies as well as for the lowest and highest frequencies – see the 90% confidence intervals.¹³ I now investigate the robustness of this finding to the choice of co-movement measure.

2.2 Correlation in the frequency domain

I consider alternative measures of co-movements, which are also based on frequency domain analysis. To measure bivariate co-movements, Croux et al. (2001) define the dynamic correlation that combines the spectra and the co-spectrum as:

$$\mathcal{D}_{gu}(\omega) = \mathcal{C}_{gu}(\omega) / \sqrt{\mathcal{S}_g(\omega) \cdot \mathcal{S}_u(\omega)} \quad (2)$$

$\tilde{\mathcal{D}}_{gu}(\Omega) = \int_{\Omega} \mathcal{D}_{gu}(\omega) d\omega$ can accordingly be interpreted as the correlation coefficient between g and u that is attributable to cycles with Ω frequencies. Table 1 reports the dynamic correlation coefficient over the three frequency bands of interest. It is strongly negative for the low-frequency band, strongly positive for the medium-frequency band, and negative (and also not very strong) for the high-frequency band.¹⁴ To obtain these values, the same spectral density matrices as above are used (see Figures 1 and 2). To assess the robustness of the results, the dynamic correlation coefficient is computed for a larger VAR (two variables are added: real interest rate and inflation). Both VARs lead to very close dynamic correlation values for each frequency band (see Table 1).

¹³This remains true for 95% confidence intervals. For 99% confidence intervals the co-spectrum is significantly different from zero only for some business cycle frequencies.

¹⁴In Tripier (2002) I show that this pattern is robust to the choice of the estimation procedure of the spectral density matrix.

To complete the set of measures, I compute the correlation coefficient of filtered series. To preserve the temporal division of co-movements, band pass filters are used. Table 1 reports the results obtained with the filters proposed by Baxter and King (1999) and Christiano and Fitzgerald (2003). In both cases, the filters' parameters are fixed to extract the short-term movements (less than 1.5 years), the business cycle movements (between 1.5 and 8 years), and the long-term movements (above 8 years). Both filters lead to similar values, which again confirms the two facts. First, the correlation between unemployment and labor productivity growth is stronger in the long run and over the business cycle than in the short run. Second, this correlation is positive for the business cycle and negative otherwise.

2.3 Correlation of VAR forecast errors

Den Haan (2000) proposes an alternative measure of co-movements which is not based on frequency domain analysis but on VAR forecast errors of variables. By studying different forecast horizons, this measure also permits to distinguish short-term co-movements from long-term co-movements. I apply this measure to the co-movements of unemployment and labor productivity growth.

After the empirical VAR has been estimated¹⁵, the method consists in looking at co-movements between forecast errors of variables at different horizons with two measures. The first is the correlation coefficient of forecast errors, denoted $\text{COR}(K)$, which converges to the unconditional correlation coefficient of two stationary variables as the forecast horizon K goes to infinity. The second is the covariance of the updates of forecast errors, denoted $\text{COV}^\Delta(k)$, which has an attractive property: it can be directly compared with the product of the Impulse Response Functions (IRFs) to the shocks. The two measures are linked by the covariance of forecast errors, denoted $\text{COV}(K)$, which is given by:

$$\text{COV}(K) = \sum_{k=1}^K \text{COV}^\Delta(k) \quad (3)$$

¹⁵Den Haan (2000) underlines the great flexibility of his method. In particular, it does not require assumptions about the order of integration.

and $\text{COV}^\Delta(k)$ to satisfy:

$$\text{COV}^\Delta(k) = \sum_{i=1}^m \left(\text{IRF}_{i,k}^g \times \text{IRF}_{i,k}^u \right) \quad (4)$$

where m is the total number of shocks and $\text{IRF}_{i,k}^x$ is the IRF of variable x to shock i after k periods.

The bivariate VAR described in section 2.1 is used to compute the correlation of forecast errors and covariance of the updates of forecast errors. Results are reported in Figure 3 for forecast horizons ranging from one quarter to sixteen years with 90% confidence intervals. They confirm the results previously obtained in the frequency domain for the business cycle and the short run: forecast errors are negatively related at horizons less than three quarters and positive for higher horizons. However, this measure does not capture the negative co-movements in the long run observed with measures in the frequency domain. This fact indicates that co-movements in the frequency domain are quite different from correlation of forecast errors even if the forecast horizon is equal to the period of cycles associated to the frequency. Den Haan and Sumner (2004) also find similar differences in their study of co-movements between real activity and prices. To explain the discrepancy, the authors point out that very persistent changes are only associated to the lowest frequencies whereas they are captured by the VAR forecast errors at all forecast horizons.

2.4 Results for hours worked

Results for the business cycle are close to the puzzling empirical fact known as the Dunlop-Tarshis observation. Contrary to the prediction of standard Real Business Cycle models, the empirical correlation between the cyclical components of labor productivity and employment is not strongly positive, but rather close to zero or even negative depending on the data set used (see Christiano and Eichenbaum, 1992, and Hansen and Wright, 1992). This observation has recently been strengthened by Basu et al. (2004) and Gali (1999) who obtain a negative

correlation when only technological shocks are taken into account¹⁶. However, these studies do not consider the unemployment rate in their description of labor market dynamics, but rather total hours worked. Hence, it is important to assess the robustness of the empirical results to the measure of labor market activity. The analysis of co-movements is then carried out with total hours worked¹⁷ instead of unemployment. Results are reported in Figure 4 and in Table 2.¹⁸ The empirical pattern with total hours worked is indeed very close to the previously described unemployment pattern (with the opposite sign naturally). First, co-movements are still stronger in the low and medium-frequency bands than in the high-frequency band (for both the co-spectrum and the correlation coefficients). Second, co-movements are negative at business cycle frequencies and positive otherwise.

3 The model

The economy is inhabited by infinitely-lived households which supply effort at work according to the fair-wage principle. They consume, accumulate money, and receive the firms' profits. Monopolistically competitive firms operate using labor as sole input and face a quadratic cost of price adjustment in an intermediate goods sector. Production technology is stochastic and labor productivity follows a random walk process with drift.

¹⁶This provocative conclusion has been widely debated. While Christiano et al. (2003, 2004) provide evidence against this fact, Neville and Ramey (2003) and Gali (2004) confirm it (Gali and Rabanal, 2004, provide the most complete currently available synthesis on this issue). Interestingly, whereas the question is on the short-run adjustment of employment, the results deeply rely on assumptions about the behavior of employment in the medium and long run as discussed by Uhlig (2004) and Gali (2005).

¹⁷The series of hours for all individuals in the business sector is that of the U.S. Bureau of Labor Statistics. It is divided by the civilian non-institutional population for the same period (1948:1-2000:4).

¹⁸The spectra of the variables are not reported, since they are similar to those reported in Figure 1. In particular, there is a concentration of the variance of total hours worked for low frequencies.

3.1 Households

The representative household seeks to maximize the expected discounted utility function with respect to consumption c_t , real balances m_t , and work effort s_t according to:

$$\max_{c_t, m_t, s_t} \mathbb{E}_t \sum_{k=0}^{\infty} \beta^{t+k} [u(c_{t+k}, m_{t+k}) - v(s_{t+k})] \quad (5)$$

where \mathbb{E} is the expectation operator and β is the subjective discount factor, with $0 < \beta < 1$. The per-period stream of utility is the sum of two functions. The first function is $u(c_t, m_t)$ where c_t denotes household consumption and $m_t = M_t/P_t$ denotes the household's real balances. M_t represents the nominal balances and P_t the final goods price. The specification of the function is:

$$u(c_t, m_t) = \log(c_t) + \gamma \log(m_t) \quad (6)$$

The second function determines the well-known "effort function" of efficiency wage models. As in Collard and de la Croix (2000), the function is:

$$v(s_t) = q_t \left[s_t - \delta_c - \delta_a \log\left(\frac{w_t}{w_t^a}\right) - \delta_s \log\left(\frac{w_t}{w_t^s}\right) \right]^2 \quad (7)$$

where q_t is a dummy variable equal to 1 when the worker is employed and 0 otherwise. When the worker is employed, both effort and job satisfaction are taken into account in the utility function. The satisfaction related to the job depends on three elements. The first is constant and measured by δ_c . The two other elements are connected to the real wage paid by the firm to the worker, namely $w_t = W_t/P_t$ where W_t is the nominal wage. The worker compares his real wage to w_t^a , his current alternative opportunities on the labor market, and to w_t^s a reference index of past wages. The higher is the real wage (compared with the intertemporal and intratemporal wage norms), the more satisfied is the worker. The two norms are weighted in the effort function by parameters δ_a and δ_s . The current alternative opportunities and the reference index of past wages are defined by:

$$w_t^a = n_t \mathbf{w}_t \quad (8)$$

and

$$w_t^s = \rho_s \sum_{j=1}^{\infty} (1 - \rho_s)^{j-1} (\mathbf{w}_{t-j}) \quad (9)$$

where n_t is the employment rate, \mathbf{w}_t is the real average wage, and ρ_s measures the persistence of past wages in the reference index with $0 < \rho_s < 1$.

The first order condition of eq. (5) with respect to s_t gives the following equilibrium effort function¹⁹:

$$s_t = \delta_c + \delta_a \log \left(\frac{w_t}{w_t^a} \right) + \delta_s \log \left(\frac{w_t}{w_t^s} \right) \quad (10)$$

These specifications call for a few comments. As in Collard and de la Croix (2000) and Ball and Moffitt (2002), the logarithm used in the effort function aims to simplify the model's solution (see de la Croix et al., 2000, for an alternative assumption). Danthine and Kurmann (2004) consider a more general effort function, which breaks down each parameter (δ_a and δ_s) into two: one concerning the wage and the other the employment. Danthine and Donaldson (1990) introduce unemployment benefits in the current alternative opportunities and de la Croix et al. (2000) consider that past alternative opportunities are part of the intertemporal wage norm. Eq. (9) represents the reference index of past wages, which corresponds to the particular case of habit formation studied by Collard and de la Croix (2000). It is worth noting that Ball and Moffitt (2002) also consider a habit formation process, although one based on wage growth rather than on wage level as considered here. Finally, contrary to Collard and de la Croix (2000), only the social norm case is studied and not the personal norm case where the presence of past wages is explicitly taken into account within the labor contract. Here, past wages act as a pure externality.

To avoid household heterogeneity induced by the individual's history on the labor market, a perfect insurance market is assumed to exist.²⁰ The households' real revenues from the labor market are $w_t n_t$. The household carries M_{t-1} units of money and B_{t-1} bonds into period t and receives a lump-sum transfer T_t^r from the monetary authority and nominal profits D_t from the intermediate goods producers. Households revenues are used to consume, purchase

¹⁹As in Collard and de la Croix (2000), the equilibrium value of $v(s_t)$ is zero.

²⁰See the appendix in Collard and de la Croix (2000) for an explicit treatment.

bonds, and store money. Bonds' gross nominal interest rate between period t and $t + 1$ is denoted r_t . The budget constraint is:

$$m_t + \frac{b_t}{r_t} + c_t \leq m_{t-1} + b_{t-1} + \tau_t^r + w_t n_t + d_t \quad (11)$$

where $b_t = B_{t-1}/P_t$, $\tau_t^r = T_t^r/P_t$, and $d_t = D_t/P_t$ represent the real values of bonds, transfer, and profits, respectively.

3.2 Firms

The final goods sector is perfectly competitive and uses $y_t(i)$ units of intermediate good i to produce y_t units of the final good according to a constant return to scale technology:

$$y_t = \left(\int_0^1 y_t(i)^{(\varepsilon-1)/\varepsilon} di \right)^{\varepsilon/(\varepsilon-1)} \quad (12)$$

where ε is the elasticity of substitution between goods, with $\varepsilon > 1$. The profit maximization program of the representative firm in the sector of the final good gives the following intermediate goods demand function:

$$y_t(i) = \left(\frac{P_t(i)}{P_t} \right)^{-\varepsilon} y_t \quad (13)$$

where $P_t(i)$ is intermediate good's i nominal price and where final good price P_t satisfies:

$$P_t = \left(\int_0^1 P_t(i)^{1-\varepsilon} di \right)^{1/(1-\varepsilon)} \quad (14)$$

The intermediate goods producer faces a quadratic cost of adjusting its nominal price, which is measured in final good:

$$\frac{\psi}{2} \left(\frac{P_t(i)}{\pi P_{t-1}(i)} - 1 \right)^2 P_t y_t \quad (15)$$

where π is the steady-state gross rate of inflation. The quantity of intermediate goods is produced according to technology:

$$y_t(i) = z_t [n_t(i) \times s_t(i)] \quad (16)$$

where z_t represents stochastic labor productivity at date t common to all producers and $n_t(i) \times s_t(i)$ the effective labor input, namely the product of workers $n_t(i)$ and their individual effort $s_t(i)$. The labor productivity law of motion is:

$$\log(z_t) = \log(g) + \log(z_{t-1}) + \zeta_t \quad (17)$$

where g is the steady state gross rate of labor productivity and ζ_t is the productivity shock, with $\zeta_t \sim iid(0, \sigma_\zeta^2)$. In the sequel, $g_t = \log(z_t / (gz_{t-1})) = \zeta_t$ is the logdeviation of the growth factor of z_t from its steady-state value g .

The per period nominal profits flow of producer i is:

$$D_t(i) = P_t(i) y_t(i) - W_t(i) n_t(i) - \frac{\psi}{2} \left(\frac{P_t(i)}{\pi P_{t-1}(i)} - 1 \right)^2 P_t y_t \quad (18)$$

where $\psi > 0$. Due to the presence of the efficiency wage, the wage becomes part of the intermediate goods producer maximization program:

$$\max E_0 \sum_{t=0}^{\infty} \left(\beta^t \lambda_t \frac{D_t(i)}{P_t} \right) \quad (19)$$

with respect to $y_t(i)$, $n_t(i)$ and $W_t(i)$, and subject to constraints (10), (13), (16), and where the relation $s_t(i) = s[W_t(i)]$ is implied by the efficiency wage hypothesis. λ_t is the multiplier's value of the budget constraint in the representative household maximization program.

In a symmetric equilibrium, all intermediate goods producers make identical decisions and the solution of (19) leads to the following equilibrium relations:

$$\frac{\pi_t}{\pi} \left(\frac{\pi_t}{\pi} - 1 \right) = \beta E_t \left\{ \frac{\lambda_{t+1}}{\lambda_t} \frac{y_{t+1}}{y_t} \left(\frac{\pi_{t+1}}{\pi} \right) \left(\frac{\pi_{t+1}}{\pi} - 1 \right) \right\} - \left(\frac{\varepsilon - 1}{\psi} \right) \left(1 - \frac{\varepsilon}{\varepsilon - 1} \frac{w_t}{z_t s_t} \right) \quad (20)$$

and

$$\frac{\partial s_t}{\partial w_t} \frac{w_t}{s_t} = 1 \quad (21)$$

Eq. (20) describes the sluggishness adjustment of inflation gross rate π_t and eq. (21) is the well-known Solow's condition.

3.3 The monetary authority

Since the focus is on the effects of technological shocks, the monetary authority is assumed to ensure constant money growth $M_t = \mu M_{t-1}$ (the newly created money is given to households in the form of a transfer).

3.4 Equilibrium

I present the log-linearized equilibrium conditions around a balanced growth steady state. Let $\bar{x}_t = x_t g^t$ be the stationarized value of growing variable x_t and $\widehat{x}_t = \log(\bar{x}_t/\bar{x})$ the logdeviation of this variable from its steady state value \bar{x} (the bar is omitted for stationary variables). Endogenous variables $\{m_t, w_t, w_t^s, n_t, \pi_t\}$ satisfy the following five equations:

$$\left(\widehat{w}_t - \widehat{w}_t^s + g_t\right) \frac{\delta_s}{\delta_a} - \widehat{n}_t = 0 \quad (22)$$

$$\rho_s \bar{w} \widehat{w}_t + (1 - \rho_s) \frac{\bar{w}^s}{g} \left(\widehat{w}_t^s - g_t\right) - \bar{w}^s \widehat{w}_{t+1}^s = 0 \quad (23)$$

$$\widehat{m}_t + g_t + \widehat{\pi}_t - \widehat{m}_{t-1} = 0 \quad (24)$$

$$\widehat{n}_t - \left(1 - \frac{\beta}{g}\right) \widehat{m}_t - \frac{\beta}{g} \text{E}_t(\widehat{n}_{t+1} + g_{t+1}) = 1 \quad (25)$$

$$\beta \text{E}_t\{\widehat{\pi}_{t+1}\} + \left(\frac{\varepsilon - 1}{\psi}\right) \widehat{w}_t - \widehat{\pi}_t = 0 \quad (26)$$

where g_t represents innovation to the productivity process as defined by Eq. (17).

Eq. (22) expresses the labor market equilibrium condition: the current value of (the logdeviation of) employment is a function of the wage, the wage norm, and labor productivity growth. Eq. (23) describes the law of motion of the wage norm. Eq. (24) and (25) concern the supply and demand for money. Finally, Eq. (26) is the Phillips curve.

4 Results

I first present the calibration and estimation procedures and then describe the results. Uhlig's (1999) method is used to solve and simulate the model.

4.1 Calibration and estimation of parameters

To assign quantitative values to the parameters, I follow Wen (1998) and adopt a strategy that combines calibration and estimation procedures to minimize the distance between theoretical and empirical spectra. The estimated parameters are those for which there is little empirical evidence: real rigidities on the labor market (the weight and persistence parameters in the effort function: δ_s and ρ_s), nominal rigidities on the goods market (the degree of sluggishness of price adjustment measured by ψ), and the variance of shock (σ_ζ). The remaining parameters are calibrated as described below. The values of all parameters are reported in Table 3.

The calibration procedure is based on several constraints. The steady-state values of unemployment, the (gross) quarterly rate of labor productivity growth, and the (gross) quarterly rate of inflation are set to their empirical mean value in the data sample (hence, $n = 0.9435$, $g = 1.0054$, and $\pi = 1.0088$). Parameters ε and β are chosen according to conventional estimates. The value of ε implies a realistic mark-up rate of 10% (see Basu and Fernald, 1997). The value of β implies an 6.9% annual interest rate as suggested by King and Rebelo (1999).

For the parameters of the effort function, the calibration and estimation procedures are combined. It must be noticed that only the ratio δ_s/δ_a matters in the dynamic system and that one steady-state restriction remains free (namely the labor market equilibrium condition). δ_s is estimated and δ_a is set to 0.90 as in Danthine and Donaldson (1990) and Collard and de la Croix (2000). Finally, the remaining steady-state restriction is used for calibrating scale parameter δ_c . The effort function's parameters δ_s and ρ_s are estimated.

The parameter of the prices stickiness ψ is estimated. Since the model is based on price adjustment costs, ψ is a scale parameter that is not easily interpreted. Nevertheless, as pointed out by Ireland (2000) amongst others, there is a relation between this parameter and the probability that a producer can revise its price in a model *à la* Calvo (1983).²¹ To facilitate

²¹The two New Phillips Curves are equivalent when $\psi = \theta(\varepsilon - 1) / [(1 - \beta\theta)(1 - \theta)]$, where $(1 - \theta)$ is the probability of revising prices in a Calvo (1983) model. Parameters ψ , ε and β are defined in Section 3.

comparisons with the literature, I report the average duration of price fixity associated with the estimate for ψ . Finally, the standard deviation of shock σ_ζ is also estimated.

The estimation method is very close to that of Wen (1998). The parameters are estimated to reproduce the spectra of unemployment and labor productivity growth. The empirical spectral density matrix is denoted $\mathcal{S}(\omega)$. The theoretical spectral density matrix, denoted $\mathcal{T}(\omega, \boldsymbol{\xi})$, depends on the vector of structural parameters $\boldsymbol{\xi} = [\sigma_\zeta, \delta_s, \rho_s, \psi]$. A simple criterion for selecting the parameter values is to minimize the distance between the spectral density matrices of the data and the model. Over frequency band Ω , the objective is to find $\boldsymbol{\xi}$ so it minimizes metric $\Delta = \text{tr}(\mathcal{W} \cdot a(\boldsymbol{\xi}))$ with the following definitions:

$$a(\boldsymbol{\xi}) = \int_{\Omega} \Gamma(\omega) \odot |\mathcal{T}(\omega, \boldsymbol{\xi}) - \mathcal{S}(\omega)| d\omega \quad (27)$$

where \odot is an element by element multiplication operator and $\Gamma(\omega)$ a frequency weighting function which determines the weight attached to each frequency. Like Wen (1998), I give each frequency a weight proportional to the percentage contribution of that frequency to the data's total variance:

$$\Gamma(\omega) = \mathcal{S}(\omega) \ominus \int_0^\pi \mathcal{S}(\omega') d\omega' \quad (28)$$

where \ominus is an element by element division operator. Finally, weight matrix \mathcal{W} is chosen to give an equal weight to the two spectra:

$$\mathcal{W} = \begin{bmatrix} \tilde{\mathcal{S}}_g(\Omega)^{-1} & 0 \\ 0 & \tilde{\mathcal{S}}_u(\Omega)^{-1} \end{bmatrix}, \text{ with } \Omega = [0, \pi] \quad (29)$$

The results of the estimation over frequency band $\Omega = [0, \pi]$ are reported in Table 3. Parameter ψ is slightly higher than the conventional value retained for aggregate data (the average fixity of price is 4.8 quarters instead of 4 quarters as suggested by King and Wollman, 1996). For the effort function, the values differ from those of Collard and de la Croix (2000). The estimate for ρ_s is 0.032, which is lower than the 0.100 value retained by the authors. For this parameter, the estimation appears to be rather close to (but still higher than) Ball and Moffitt (2002) who suggest a value for ρ_s equal to 0.050. So, this estimation describes a

strong persevering process for the reference index of past wages. Nevertheless, it also indicates that the reference index of past wages has a modest weight in the effort function: the 0.440 estimated value for δ_s is notably lower than the Collard and de la Croix's (2000) 2.450 value.

For both rigidities it is worth noting the usual difficulty in reconciling macroeconomic results with microeconomic evidence. The estimation based on macroeconomic data induces an excessively slow adjustment path for both nominal prices and workers' aspirations. While this configuration is well known for nominal rigidity as shown by Bils and Klenow (2004), Hogan (2004) provides evidence based on individual panel data which indicates a quicker adjustment of wages than considered here and in Ball and Moffit (2001).

4.2 Model evaluation

Once the values of the parameters are obtained, I can compute the theoretical spectral density matrix and compare it with the empirical density matrix. In order to assess the performances for the measures of co-movements, I must check first that the model performs well for the spectra (it has been estimated to reproduce them).

Figure 5 depicts the spectra of labor productivity growth and unemployment for the model and the data. The model perfectly fits the empirical spectrum of unemployment for it puts the main part of its variance at low frequencies. Moreover, the model's spectrum lies within the empirical CI for the major part of the frequencies considered. The results are also satisfactory for labor productivity growth. As this variable has been modeled as a white noise, its spectrum is unsurprisingly flat: each frequency has the same contribution to the variance of labor productivity growth. The model cannot naturally reproduce the rich dynamics observed in the data, notably the presence of peaks. However, the model reproduces the main empirical fact: the three frequency bands contribute almost identically to the variance of labor productivity growth. In addition, except for a small band of frequencies (near $\pi/16$), the theoretical spectrum lies within the empirical CI.

The theoretical co-spectrum depicted in Figure 6 exhibits a pattern similar to its empirical counterpart. First, it is concentrated in the low and medium-frequency bands rather than

in the high-frequency band. Second, the co-spectrum is negative for the zero frequency; it increases to reach a peak and then decreases within the medium-frequency band to converge toward a small positive value in the high-frequency band. Nevertheless, there are two failures. First, a shift toward the low frequencies appears when compared with the empirical co-spectrum. The frequencies for which the theoretical co-spectrum crosses the zero line and reaches its peak are lower than their empirical equivalents. The theoretical co-spectrum even lies outside empirical CI at these frequencies. Second, for the high-frequency band, the model overestimates the co-spectrum's value. Although the model predicts positive co-movements, empirical co-movements are negative (and significantly different from zero). To conclude, the model efficiently reproduces the pattern of the co-spectrum at medium and low frequencies (especially the shift in the sign of the co-movements), but does not account for the short-term co-movements. This conclusion is also confirmed when applying the alternative measure of co-movements presented in Section 2.

Table 4 reports the values of dynamic correlation for the model. If all frequencies are considered, the model clearly overestimates the correlation between growth and unemployment (0.307 for the model against 0.037 for the data). The breakdown of the correlation by frequency band indicates that the overestimation mainly comes from the high-frequency band. For this frequency band the theoretical correlation is close to 1 whereas results are empirically negative. For the other frequency bands, the model performs better. Even if it does not replicate the values, it correctly reproduces the sign of the co-movements.

4.3 IRFs and models' comparison

In order to understand the model's behavior, I study the IRFs and consider two alternative versions of the model. In the first version, prices are flexible (that is the parameter ψ is simply set to zero). In the second version, the fair-wage hypothesis is abandoned in favor of the model of labor supply with preferences *à la* Hansen (1985). In this case, the utility function defined by eq. (7) becomes $v(n_t) = hn_t$ (where h represents the constant hours worked per worker) and the production function defined by eq (16) becomes $y_t(i) = z_t[h \times n_t(i)]$. Parameter h

is set to the equilibrium value of the effort at work with the fair-wage hypothesis. Figures 7 and 8 report the IRFs and the co-spectrum of the models, respectively, and Table 4 reports the values of dynamic correlation.

Because there is only one shock in the model, inspecting the IRFs in the time domain is particularly useful in understanding the results previously described in the frequency domain. In the model, the rates of unemployment and labor productivity growth co-move positively in the short and medium run because prices are sticky. Blanchard (1989), Blanchard and Quah (1989), and more recently Basu et al. (2004) and Gali (1999) describe the underlying mechanism that explains the instantaneous negative effects of productivity shocks on the use of labor input. When the shock hits the economy, aggregate demand is partially fixed because of nominal rigidities. To satisfy their demand, producers need less labor due to the improvement in labor productivity. This effect vanishes when price adjustment has been completed.

The rates of unemployment and labor productivity growth co-move negatively in the long run for two reasons. The first reason is that job satisfaction depends on wage growth as shown in Collard and de la Croix (2000), de la Croix et al. (2000), Ball and Moffitt (2002), and Danthine and Kurmann (2004). In the model considered here, the equilibrium value of effort at work is constant. A given effort level entails a compensation between the intertemporal term (which depends on wage growth) and the intratemporal term (which depends on unemployment). Hence, the higher is the wage growth, the weaker is the unemployment rate required. The second reason is that the reference index of past wages adjusts very slowly over time. Due to the habit-formation assumption, a current wage increase will be compared to a large set of past wages and subsequently lead to a sustained decline in unemployment.

I have presumed that the sticky-price hypothesis explains the economy's behavior in the short and medium run whereas the fair-wage hypothesis explains it in the long run. The comparisons of the theoretical co-movements for the three models confirm this assertion. The real rigidity model's co-spectrum and dynamic correlation are negative at all frequencies studied and those of the nominal rigidity model always positive. Consequently, to explain

long-term co-movements only, one can use the model with fair wages and flexible prices. In the same manner, to explain the co-movements over the business cycle only, one can consider the model with sticky prices and indivisible labor. Conversely, to explain co-movements in the long run and over the business cycle, both fair wages and sticky prices are necessary. Finally, none of these models provides a satisfactory explanation for the short-term co-movements.

4.4 Prediction for VAR forecast errors

Results are less satisfying for the measure of co-movements based on forecast errors, see Figure 9.²² The model overestimates the correlation of forecast errors for all forecast horizons and produces a strong overestimation of the unconditional correlation coefficient, which is again due to the model's failure in the short run. To highlight this point, I studied the covariance of the updates of forecast errors for different forecast horizons. The model predicts a strong and positive co-movement for the first forecast horizon, whereas it is empirically significantly negative. For higher forecast horizons, the covariance of the updates of forecast errors is zero. Since productivity growth has no persistence, its IRF is zero for horizons above one quarter, the same as for the IRFs product of productivity growth and unemployment (which is equal to the covariance of the forecast errors' updates). Like in section 2.3, there is a discrepancy between measures of co-movements based on VAR forecast errors and on frequency domain analysis.

5 Conclusion

The co-movements of unemployment and labor productivity growth for the U.S. economy were studied by means of spectral analysis. Co-movements are positive over the business cycle and negative in the short and long run. This led to a theoretical explanation based on New Keynesian mechanisms: fair wages for the labor market and sticky prices for the goods market. The combination of these two rigidities provides a satisfactory explanation

²²They are deduced from an estimated VAR using one very long simulation of the model.

for the empirical co-movements in the long run and over the business cycle, but not in the short run. Due to real rigidity on the labor market, the rates of unemployment and of labor productivity growth co-move negatively in the long run, yet because of nominal rigidity on the goods market, they co-move positively over the business cycle. In a certain sense, the articulation between real and nominal rigidities is in line with Blanchard and Quah's (1989) initial recommendations:

Nominal rigidities can explain why in response to a positive supply shock, say an increase in productivity, aggregate demand does not initially increase enough to match the increase in output needed to maintain constant unemployment; real wage rigidities can explain why increases in productivity can lead to a decline in unemployment after a few quarters which persists until real wages have caught up with the new higher level of productivity. (p. 663).

Finally, I would like to emphasize the absence of search and matching frictions in the model although they are very popular in macroeconomics, especially when studying the relations between labor market and technological progress. To explain negative co-movements between productivity and unemployment, the consequence of workers' aspirations in the fair-wage model has been given prominence over the capitalization effect that operates in the matching model of unemployment with growth. As discussed by Pissarides (2000), this effect requires strong assumptions on preferences (namely linear utility with consumption), which seem to contradict the standard macroeconomic models. To explain the positive co-movements between productivity and unemployment, the consequence of nominal rigidities on demand has been favored instead of the reallocation process associated with technological diffusion studied by Aghion and Howitt (1994). In that sense, this paper falls in a long tradition, resuscitated by the New Keynesian models that Blanchard (1989) applied to unemployment and Gali (1999) to total hours worked.

References

- Aghion, P., Howitt, P., 1994. Growth and Unemployment. *Review of Economic Studies* 61, 477-494.
- Akerlof, G., 1982. Labor contracts as partial gift exchange. *Quarterly Journal of Economics* 97, 543-569.
- Ball, L., Moffitt, R., 2002. Productivity growth and the Phillips curve. in Krueger, A., Solow, R. (Eds.), *The Roaring Nineties*. Russell Sage Foundation, New York, 61-90. (also NBER working paper #8421).
- Balmaseda, M., Dolado, J.J., Lopez-Salido, J.D., 2000. The dynamic effects of shocks to labour markets: Evidence from OECD countries, *Oxford Economic Papers* 52, 3-23.
- Basu, S., Fernald, J., 1997. Returns to scale in U.S. production: estimates and implications. *Journal of Political Economy* 105, 249-283.
- Basu, S., Fernald, J., Kimball, M., 2004. Are technology improvements contractionary? NBER Working Paper No 10592.
- Baxter, M., King, R.G., 1999. Measuring business cycles: Approximate band-pass filters for economic time series. *Review of Economics and Statistics* 81, 575-593.
- Bils, M., Klenow, P.J., 2004. Some Evidence on the Importance of Sticky Prices. *Journal of Political Economy* 112, 947-985.
- Blanchard, O., 1989. A traditional interpretation of macroeconomic fluctuations. *American Economic Review* 79, 1146-1164.
- Blanchard, O., Katz, L.F., 1999. Wage dynamics: Reconciling theory and evidence. *American Economic Review* 89, 96-74.
- Blanchard, O., Quah, D., 1989. The dynamic effects of aggregate demand and supply disturbances. *American Economic Review* 79, 655-673.
- Blanchard, O., Wolfers, J., 2000. The role of shocks and institutions in the rise of european unemployment: The aggregate evidence. *Economic Journal* 110, 1-33.
- Calvo, G., 1983. Staggered prices in a utility maximizing framework. *Journal of Monetary*

- Economics 12, 383-398.
- Christiano, L.J., Eichenbaum, M., 1992. Current real-business-cycle theories and aggregate labor-market fluctuations. *American Economic Review* 82, 430-450.
- Christiano, L.J., Eichenbaum, M., Vigufsson, R.J., 2003. What Happens After A Technology Shock? Board of Governors of the Federal Reserve System, International Finance Discussion Papers 768.
- Christiano, L.J., Eichenbaum, M., Vigufsson, R.J., 2004. The Response of Hours to A Technology Shock: Evidence Based on Direct Measures of Technology. *Journal of the European Economic Association* 2, 381-395.
- Christiano, L.J., Fitzgerald, S., 2003. The band pass filter. *International Economic Review* 44, 435-466.
- Collard, F., de la Croix, D., 2000. Gift exchange and the business cycle: the fair wage strikes back. *Review of Economic Dynamics* 3, 166-193.
- Croux, C., Forni, M., Reichlin, L., 2001. A measure of co-movement for economic indicators: theory and empirics. *Review of Economics and Statistics* 83, 232-241.
- Danthine, J-P., Donaldson, J., 1990. Efficiency wages and the real business cycles. *European Economic Review* 34, 1275-1301.
- Danthine, J-P., Kurmann, A., 2004. Fair wages in a New Keynesian model of the business cycle. *Review of Economic Dynamics* 7, 107-142.
- Daveri, F., Tabellini, G., 2000. Unemployment, growth and taxation in industrial countries, *Economic Policy* 30, 47-88.
- de la Croix, D., Palm, F., Urbain, J-P., 2000. Labor market dynamics when effort depends on wage growth comparisons. *Empirical Economics* 25, 393-420.
- den Haan, W.J, 2000. The comovement between output and prices. *Journal of Monetary Economics* 46, 3-30.
- den Haan, W.J, Sumner, S.W., 2004. The comovement between real activity and prices in the G7. *European Economic Review* 48, 1333-1347.
- Diebold, F., Ohanian, L., Berkowitz, J., 1998. Dynamic equilibrium economies: a framework

- for comparing models and data. *Review of Economic Studies* 65, 433-452.
- Edelberg, W., Eichenbaum, M., Fisher, J.D., 1999. Understanding the effects of a shock to government purchases. *Review of Economic Dynamics* 2, 166-206.
- Evans, G., 1989. Output and unemployment dynamics in the United States. *Journal of Applied Econometrics* 4, 213-237.
- Gali, J., 1999. Technology, employment, and the business cycle: do technology shocks explain aggregate fluctuations? *American Economic Review* 89, 249-271.
- Gali, J., 2004. On the Role of Technology Shocks as a Source of Business Cycles: Some New Evidence. *Journal of the European Economic Association* 2, 372-380..
- Gali, J., 2005. Trends in hours, balanced growth, and the role of technology in the business cycle. *mimeo*.
- Gali, J., Rabanal, P., 2004. Technology shocks and aggregate fluctuations: How well does the RBC model fit postwar U.S. Data? *NBER Macroeconomics Annual* 2004, 225-288.
- Hairault, J-O., Portier, F., 1993. Money, New-Keynesian macroeconomics and the business cycle, *European Economic Review* 37, 1533-1568.
- Hamilton, J., 1994. *Times Series Analysis*. Princeton University Press.
- Hansen, G., 1985. Indivisible labor and the business cycle. *Journal of Monetary Economics* 16, 309-327.
- Hansen, G., Wright, R., 1992. The labor market in real business cycle theory. *Federal Reserve Bank of Minneapolis Quarterly Review* 16, 2-12.
- Hodrick, R.J., Prescott, E.C., 1997. Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit, and Banking* 29, 1-16.
- Hogan, V., 2004. Wage aspirations and unemployment persistence. *Journal of Monetary Economics* 51, 1623-1643.
- Hoon, T.H., Phelps, E.S., 1997. Growth, wealth and the natural rate: Is Europe's jobs crisis a growth crisis? *European Economic Review* 41, 549-557.
- Ireland, P., 2000. Interest Rates, Inflation, and Federal Reserve Policy Since 1980. *Journal of Money, Credit, and Banking* 32, 417-343.

- King, R., Rebelo, S., 1999. Resuscitating real business cycles, in: Taylor, J., Woodford, M. (Eds.), *Handbook of Macroeconomics*, chap. 14 vol. 1b. North-Holland, 927-1007.
- King, R., Wolman, A., 1996. Inflation targeting in a St. Louis model of the 21th Century. *Federal Reserve Bank of St. Louis Review* 78, 83-107.
- Kydland, F., Prescott, E., 1982. Time to build and aggregate fluctuations, *Econometrica* 50 , 1345–1370.
- Long, J., Plosser, C., 1983. Real business cycles, *Journal of Political Economy* 91, 36–69.
- Mortensen, D.T., Pissarides, C.A., 1998. Technological Progress, Job Creation, and Job Destruction. *Review of Economic Dynamics* 1, 733-753.
- Neville, F., Ramey, V.A., Is the Technology-Driven Real Business Cycle Hypothesis Dead? Shocks and Aggregate Fluctuations Revisited. forthcoming *Journal of Monetary Economics*.
- Pissarides, C.A., 2000. *Equilibrium Unemployment Theory*, second edition. Cambridge, MA: MIT Press.
- Rotemberg, J., 1982. Sticky prices in the United-States. *Journal of Political Economy* 90, 1187-1211.
- Rotemberg, J., 1996. Prices, output and hours: an empirical analysis based on a sticky price model. *Journal of Monetary Economics* 37, 505-533.
- Staiger, D., Stock, J., Watson, M., 2002. Prices, wages and the U.S. NAIRU in the 1990s, in Krueger, A., Solow, R. (Eds.), *The Roaring Nineties*. Russell Sage Foundation, New York, 3-60. (also NBER working paper #8320)
- Tripier, F., 2002. The dynamic correlation between growth and unemployment. *Economics Bulletin* 5, 1-9.
- Uhlig, H., 1999. A toolkit for analyzing nonlinear dynamic stochastic models easily. *in Computational Methods for the Study of Dynamic Economies*, Ramon Marimon and Andrew Scott (editors), Oxford University Press, pp. 30-61.
- Uhlig, H., 2004. Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association* 2, 361-371.
- Vallanti, G., 2004. Unemployment and Growth: Panel Estimates, *miméo*.

Watson, M., 1993. Measures of fit for calibrated models. *Journal of Political Economy* 101, 1011-1041.

Wen, Y., 1998. Can a real business cycle model pass the Watson test? *Journal of Monetary Economics* 42, 185-203.

Table 1. Correlation between labor productivity growth and unemployment

		Frequencies			
		All	Long-term	Business cycle	Short-term
Dynamic correlation (Croux et al., 2001)					
Bivariate VAR		+0.037	-0.458	+0.515	-0.139
Large VAR		+0.050	-0.444	+0.503	-0.126
Correlation between filtered series					
Christiano and Fitzgerald (2003)		+0.061	-0.373	+0.570	-0.105
Baxter and King (1999)	$K = 12$	+0.061	-0.498	+0.501	-0.123
	$K = 36$	+0.061	-0.316	+0.575	-0.116

Table 2. Correlation between labor productivity growth and total hours worked

		Frequencies			
		All	Long-term	Business cycle	Short-term
Dynamic correlation (Croux et al., 2001)					
Bivariate VAR		+0.012	+0.373	-0.455	+0.112
Large VAR		-0.021	+0.435	-0.536	+0.114
Correlation between filtered series					
Christiano and Fitzgerald (2003)		+0.017	+0.412	-0.594	+0.114
Baxter and King (1999)	$K = 12$	+0.017	+0.475	-0.534	+0.122
	$K = 36$	+0.017	+0.432	-0.538	+0.098

Table 3. Parameter values

Effort function	$\delta_a = 0.900, \delta_s = 0.440, \delta_c = 1.460, \rho_s = 0.032$
Goods market	$\varepsilon = 10.000, \psi = 147.73$
Technology and preferences	$g = 1.005, \sigma_\zeta = 0.0086, \beta = 0.9887$

Table 4. Correlation between labor productivity growth and unemployment

	Frequencies			
	All	Long-term	Business cycle	Short-term
Empirical dynamic correlation				
Bivariate VAR	+0.037	-0.458	+0.515	-0.139
Large VAR	+0.050	-0.444	+0.503	-0.126
Dynamic correlation of models with				
Fair wage and sticky prices	+0.307	-0.117	+0.859	+0.897
Fair wage and flexible prices	-0.272	-0.547	-0.305	-0.787
Indivisible labor and sticky prices	+0.614	+0.933	+0.630	+0.835

Captions for figures

Figure 1. Spectra for the data. Panel (a): spectrum of labor productivity growth. Panel (b): unemployment spectrum. The shaded areas show confidence intervals.

Figure 2. Co-spectrum of labor productivity growth and unemployment for the data. The shaded area shows confidence intervals.

Figure 3. Correlation of forecast errors – panel (a) – and covariance of the updates of forecast errors – panel (b) – for labor productivity growth and unemployment. The shaded area shows confidence intervals.

Figure 4. Co-spectrum of labor productivity growth and total hours worked for the data. The shaded area shows confidence intervals.

Figure 5. Spectra for the data and the model. Panel (a): spectrum of labor productivity growth. Panel (b): unemployment spectrum. For both panels, the solid line refers to the model and the dotted line refers to the data. The shaded areas show confidence intervals.

Figure 6. Co-spectrum of labor productivity growth and unemployment for the data and the model. The solid line refers to the model and the dotted line refers to the data. The shaded area shows confidence intervals.

Figure 7. IRF of unemployment rate for the three models. the solid line refers to the model with sticky prices and fair wage, the dashed line refers to the model with flexible prices and fair wage, and the dashdot line refers to the model with sticky prices and indivisible labor.

Figure 8. Co-spectrum of labor productivity growth and unemployment for the data and the three models. The dotted line refers to the data, the solid line refers to the model with sticky prices and fair wage, the dashed line refers to the model with flexible prices and fair wage, and the dashdot line refers to the model with sticky prices and indivisible labor. The shaded area shows confidence intervals.

Figure 9. Correlation of forecast errors (panel a) and covariance of the updates of forecast errors (panel b) for labor productivity growth and unemployment. The shaded area shows confidence intervals and the solid lines refers to the model with serial correlation in productivity growth.

Figure 1

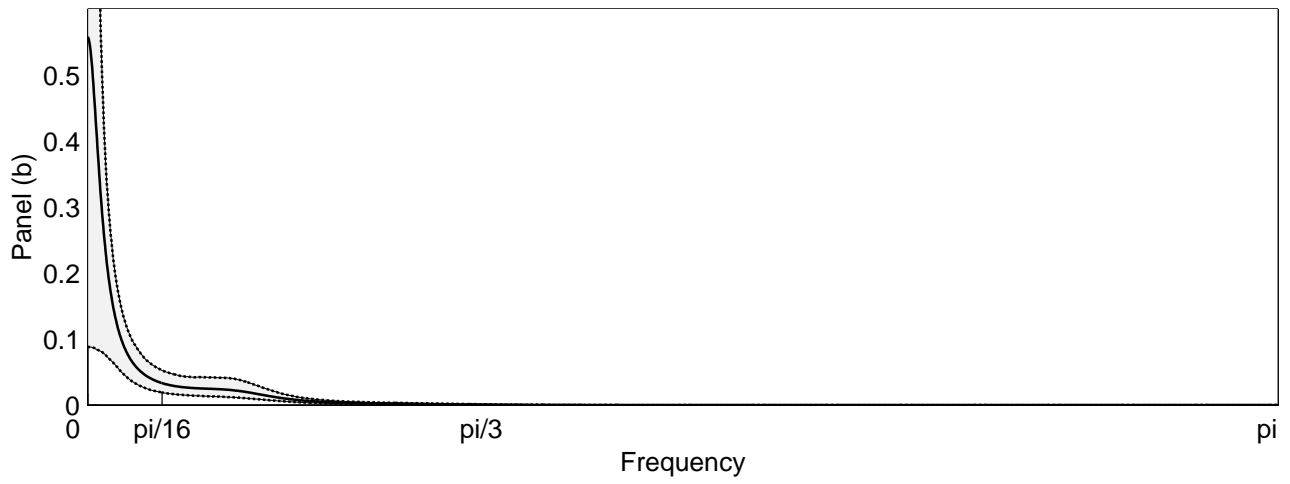
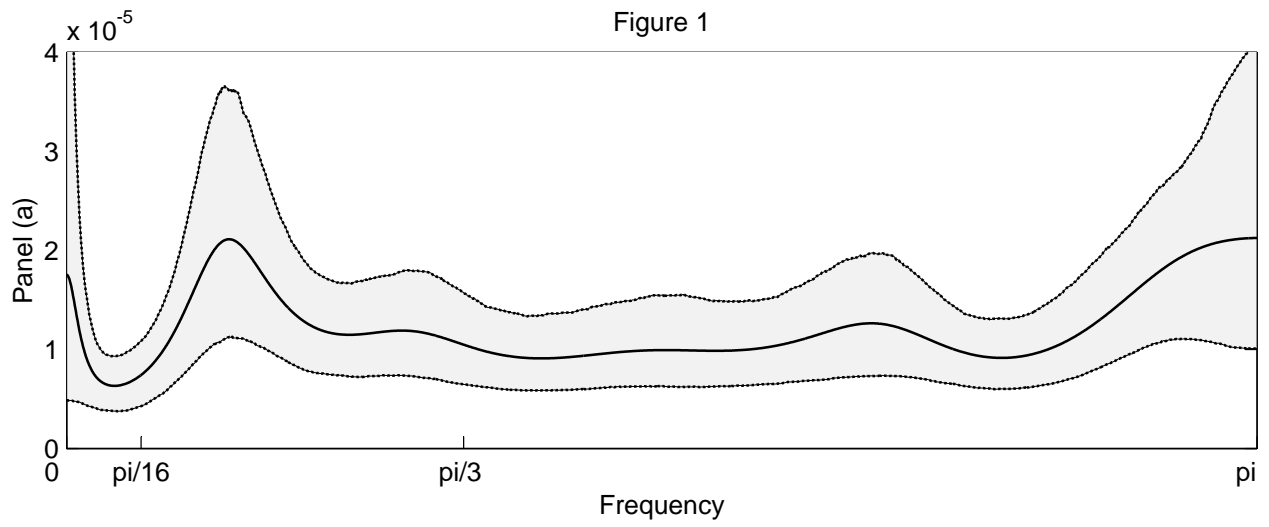


Figure 2

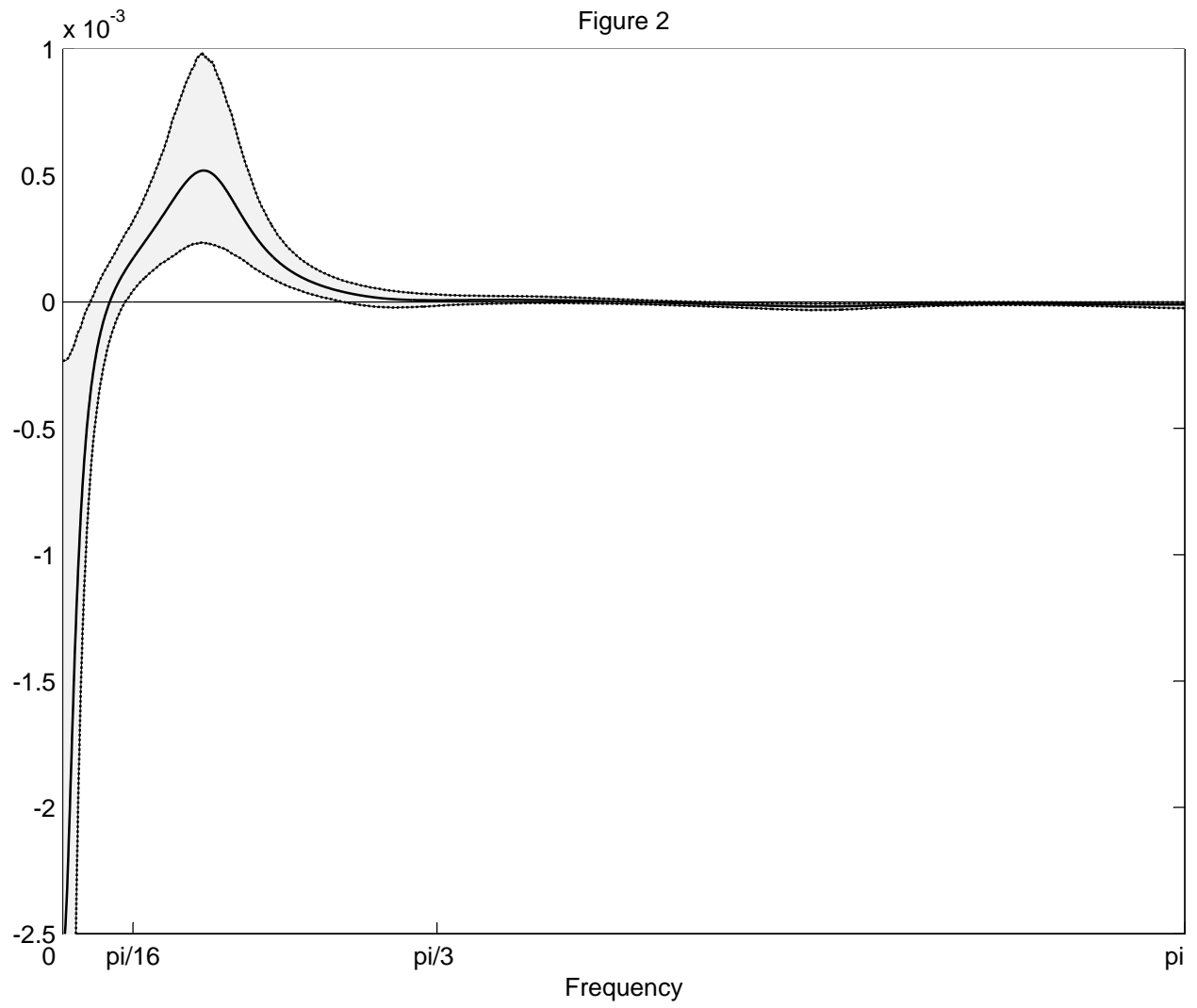


Figure 3

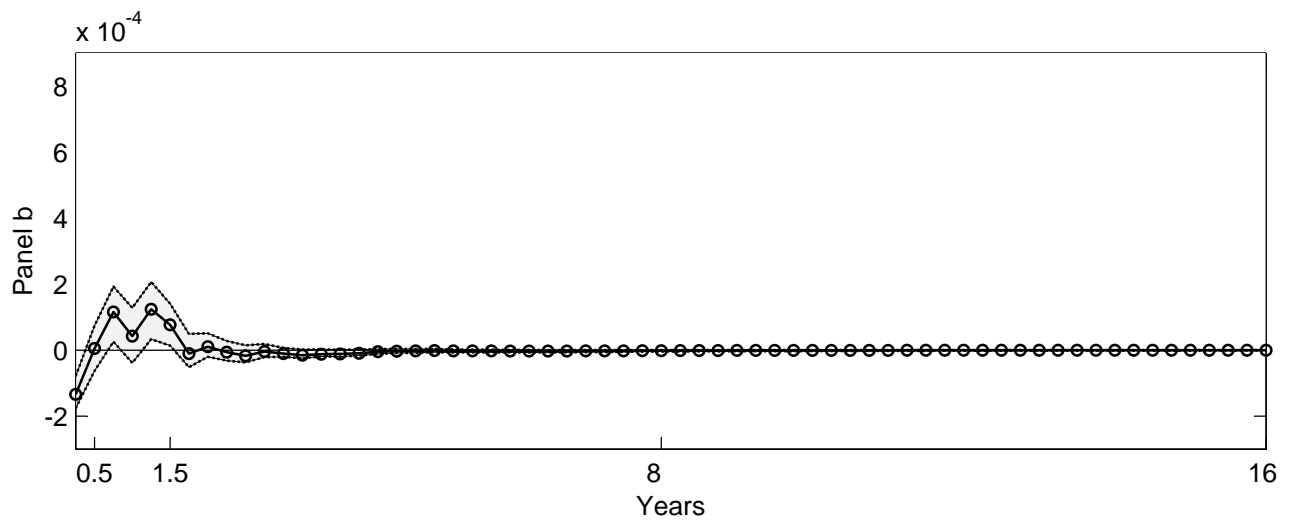
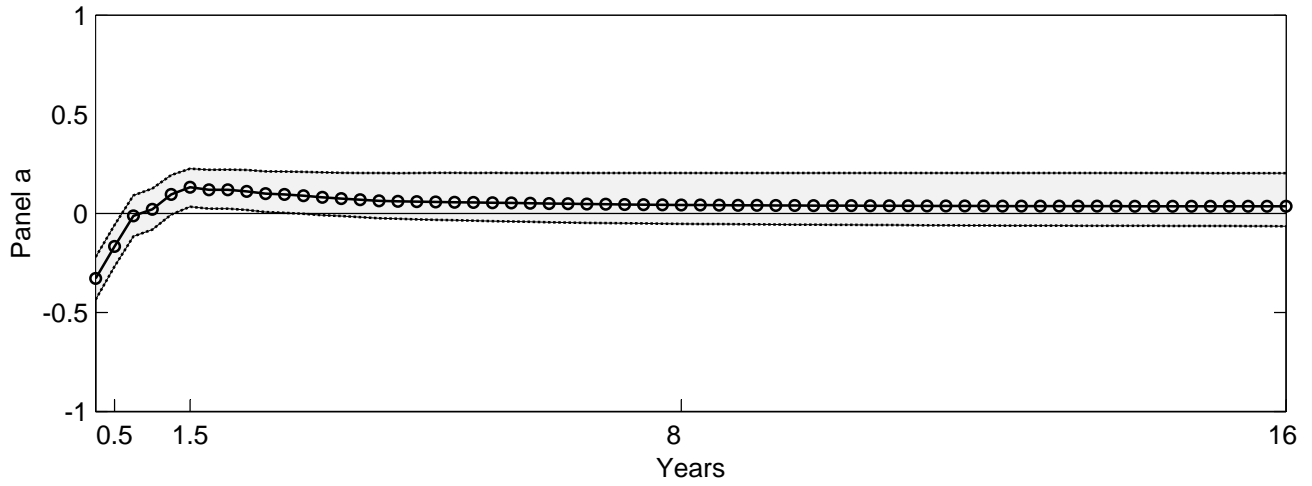


Figure 4

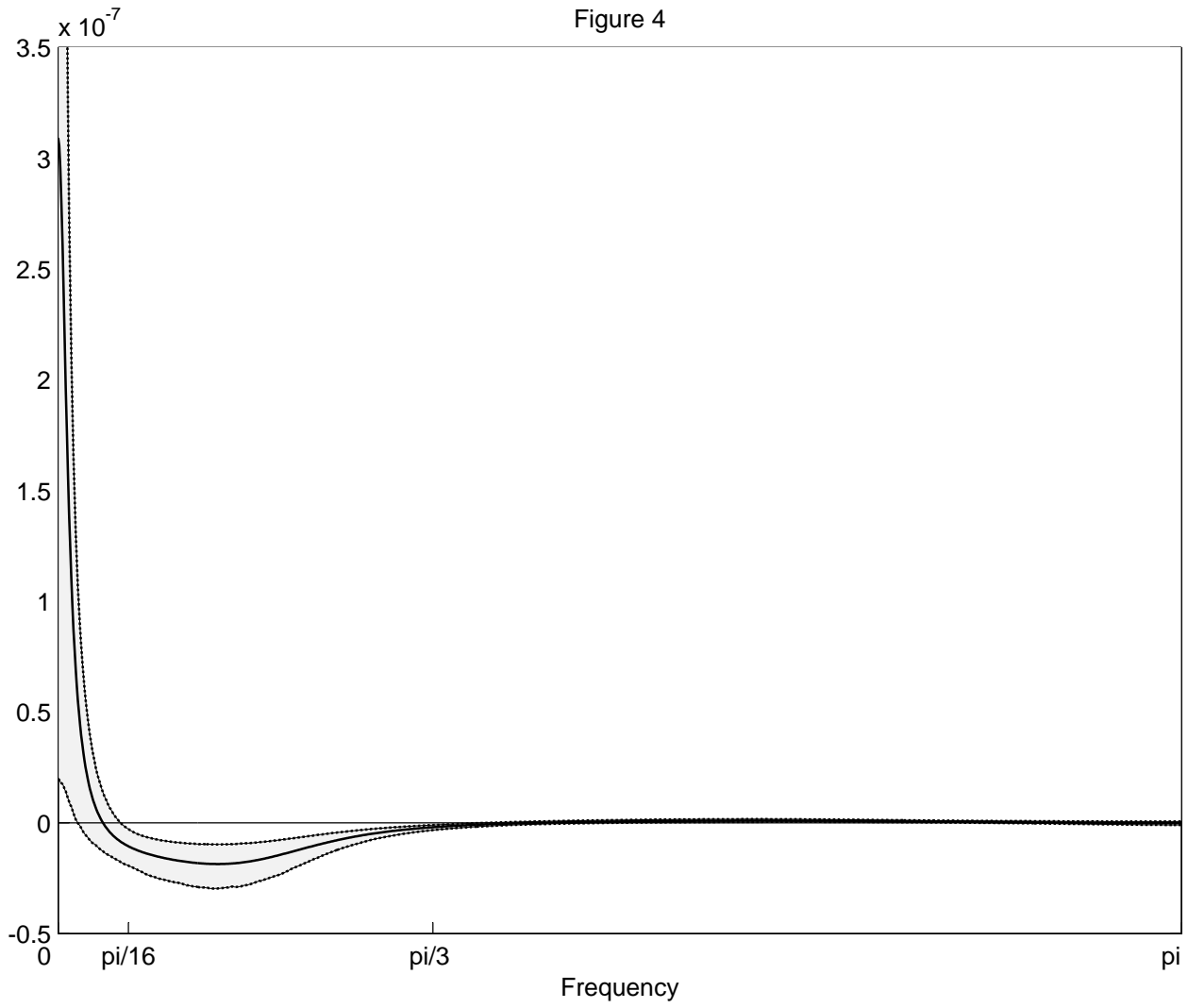


Figure 5

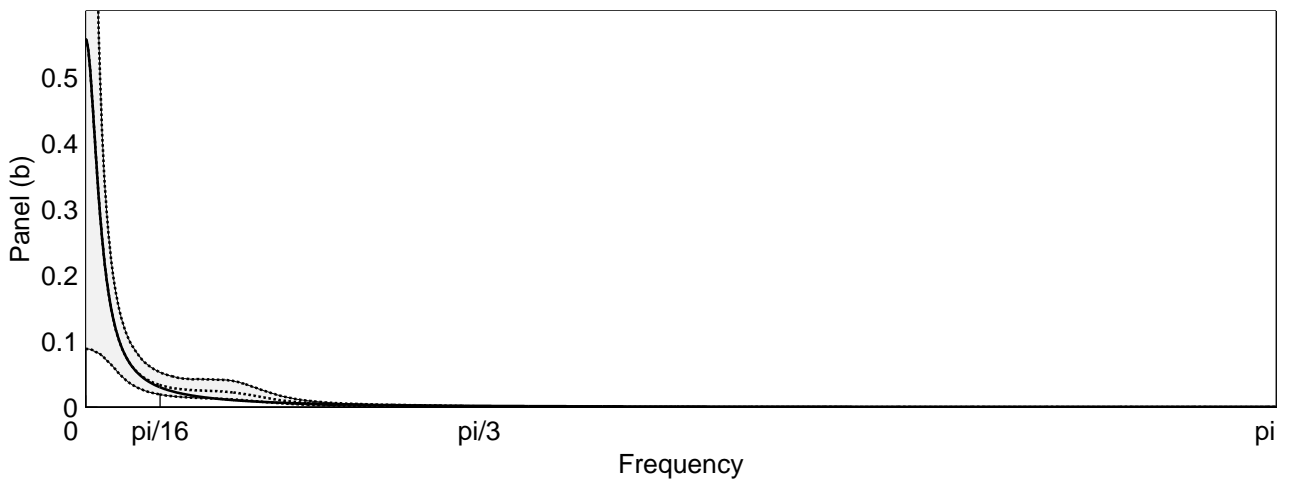
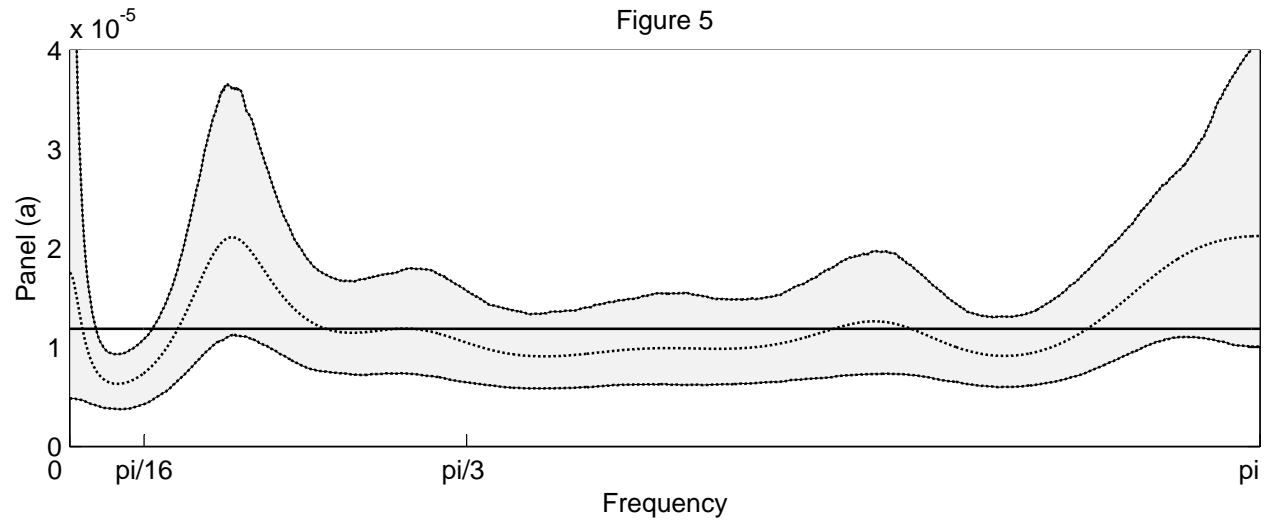


Figure 6

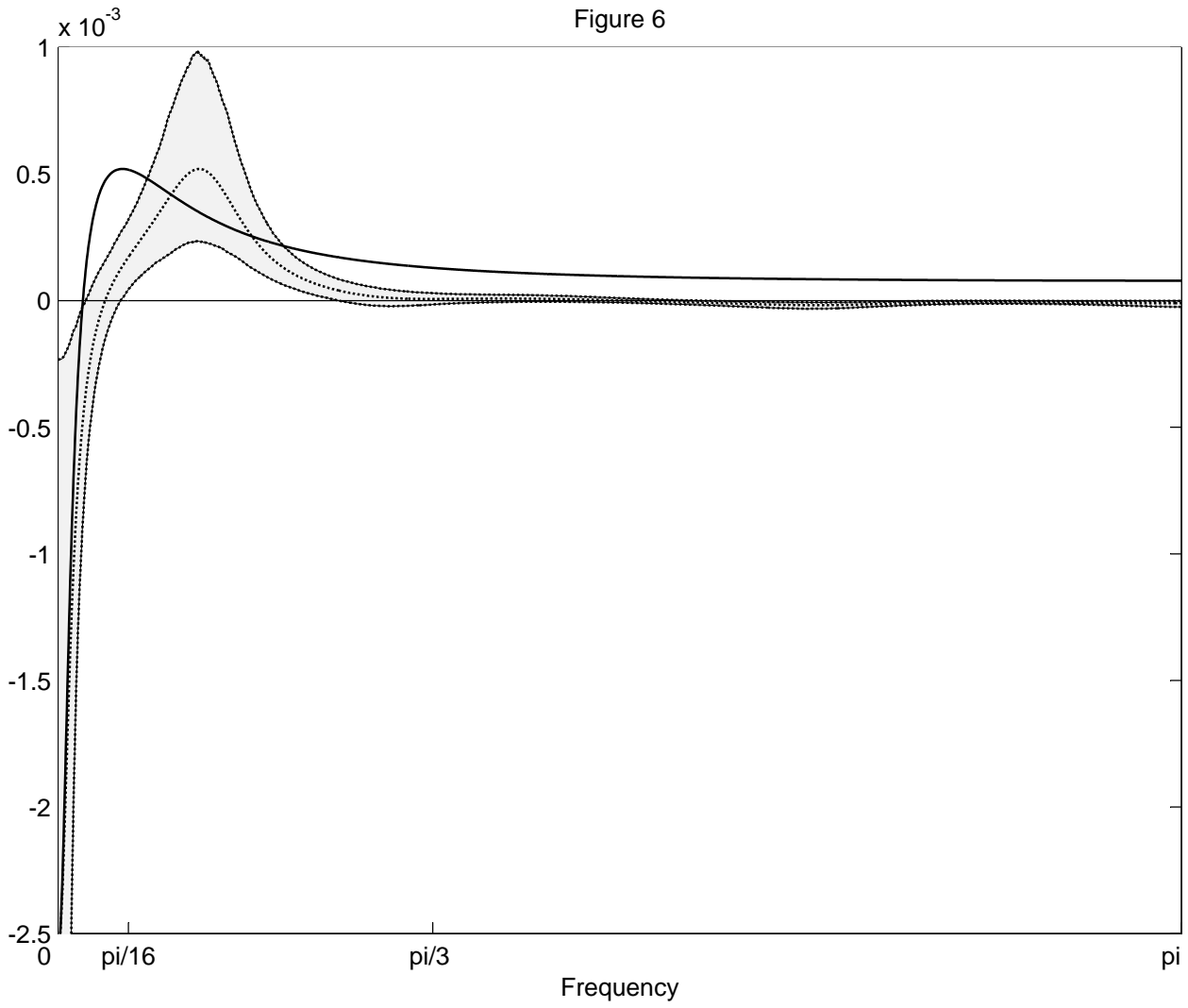


Figure 7

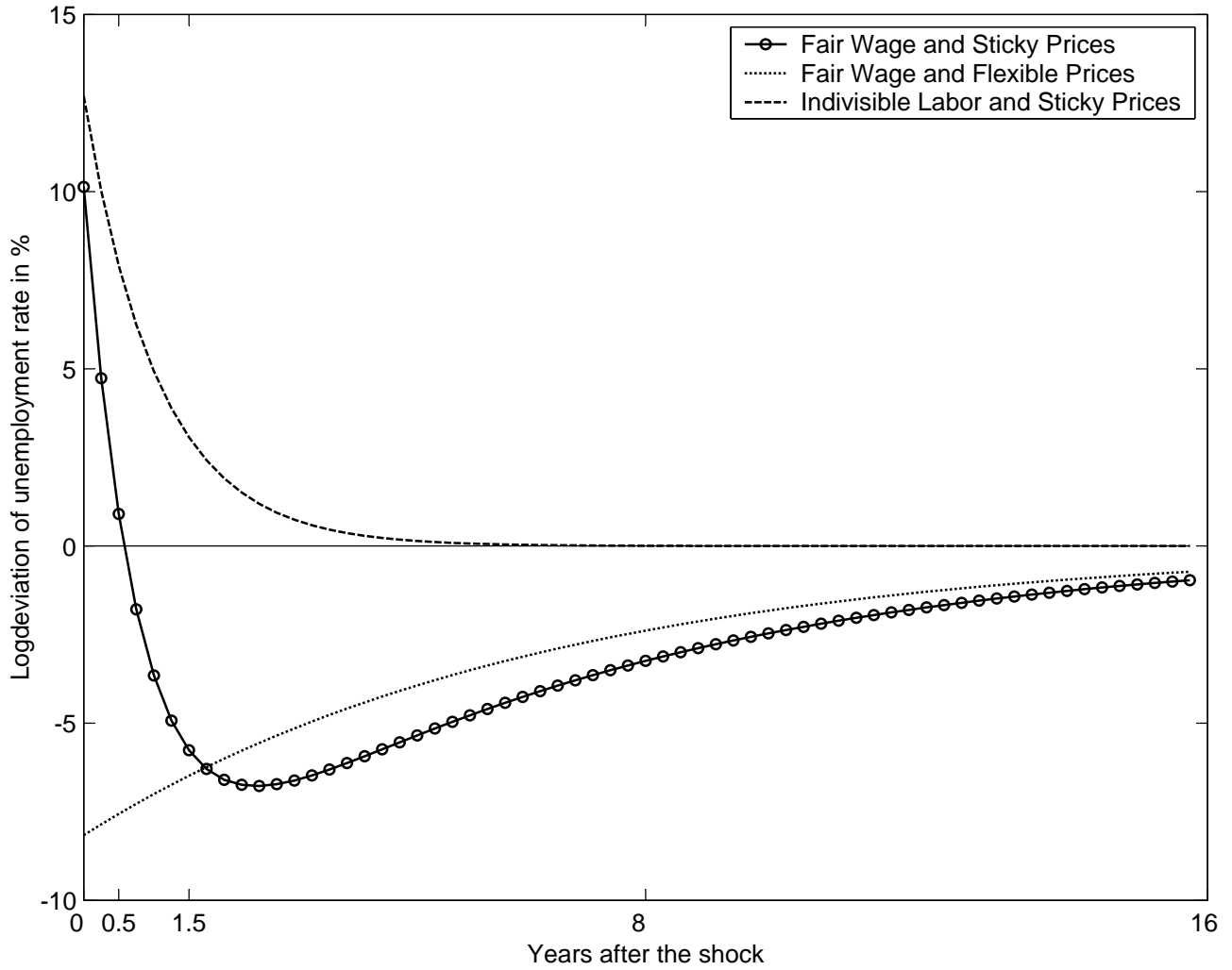


Figure 8

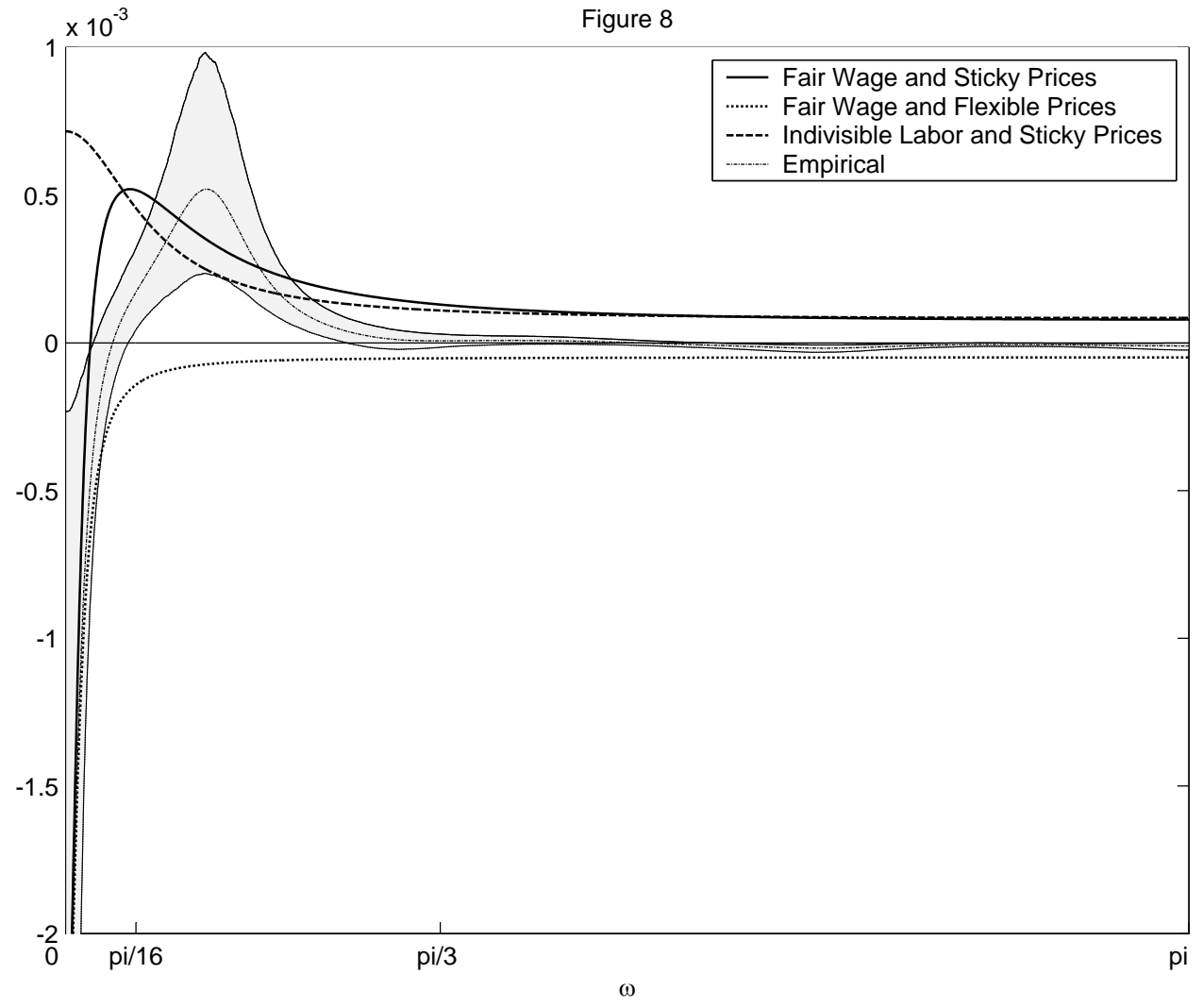


Figure 9

