CAE Working Paper #02-14

What Does it Take to Explain Procyclical Productivity

by

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October 2002

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Abstract

Labor productivity comoves strongly with output, leads output and employment, and is only weakly correlated with employment at the business-cycle frequency. Procyclical productivity is observed in virtually all countries and industries, and it is observed at both the business-cycle frequency and the seasonal frequency. Such prominent features of economic fluctuations present a litmus test for business cycle theory. The conventional explanations for procyclical labor productivity are factor hoarding (labor hoarding and capacity utilization) or increasing returns to scale. Existing equilibrium-business cycle theory explain procyclical labor productivity by technology shocks. The sheer magnitude of excess volatilities in productivity relative to employment seems to defy explanations from increasing returns alone. The technology-shock explanation, on the other hand, comes perilously close to assuming the conclusion. Furthermore, even in periods of pure demand shocks, labor productivity remains procyclical. Applying general equilibrium theory, this paper shows that neither technology shocks nor increasing returns to scale are necessary for understanding procyclical productivity. Factor hoarding is sufficient for demand shocks to induce procyclical productivity at both aggregate and disaggregate levels despite constant or even diminishing returns to scale.

1 Introduction

Many economists strongly believe that consumption demand is the primary source of short-run economic fluctuations (e.g., see Blanchard 1989 and 1993, Cochrane 1994, Evans 1992, Mankiw 1989, and Summers 1986, among others). Booms and recessions are understood also by central bankers and business people as being driven primarily by consumer spending. It is perhaps this understanding that has defined aggregate demand management as the central goal of US monetary policy.[1] After examining a wide range of possible candidates of business-cycle shocks (including technology shocks, monetary shocks, government shocks, etc.), Cochrane (1994) concludes that none of these shocks can explain the bulk of output fluctuations in the US except shocks to consumption demand. Using general equilibrium theory, Wen (2002a, 2002b) recently show that consumption demand shocks can better explain the observed international comovements puzzles (Backus, Kehoe and Kydland 1992) and aggregate inventory fluctuations (Blinder 1986) than technology shocks.

A major challenge to the demand-shock theory, however, is that measured labor productivity is procyclical. Under constant returns to scale, demand shocks tend to induce counter-cyclical productivity in standard models due to diminishing marginal product of labor, leading to less variable output than employment. Yet labor productivity, no matter how it is measured, is procyclical. The standard deviation of output, regardless industries or countries, exceeds the standard deviation of employment. In certain industries or countries, it can be more than 3 times larger than that of employment.

This procyclical productivity is a long-standing puzzle to business cycle theories based on demand shocks. According to Hall (1988), the huge differences between output and employment volatilities indicate strong monopoly power or increasing returns to scale. Hall argues that the conventional explanation - labor hoarding - is not sufficient for accounting for such a large volatility differential. Independent empirical studies, however, fail to find strong evidences supporting large monopoly power and increasing returns to scale (e.g., see Basu and Fernald, 1997).[2] One of the other possible explanations for procyclical labor

[1] Namely, "to bring the growth of aggregate demand and potential supply into better alignment." (Monetary Policy Report to the Congress, pursuant to section 2B of the Federal Reserve Act, February 13, 2001).

[2] Benhabib and Wen (2001), Harrison and Weder (2002), and Wen (1998) recently show that equilibrium business cycle models with mild increasing returns to scale and capacity utilization

productivity is technology shocks (e.g., see Kydland and Prescott 1982). The technology-shock theory, however, has been criticized by many as unconvincing because productivity remains procyclical even in periods when employment fluctuations are clearly driven by changes in aggregate demand. For example, during the Second World War (1941-1944), the average US manufacturing output level increased by 31% above trend and the average US manufacturing employment level increased only by 17% above trend. In the year of 1943, manufacturing output increased by 43% while manufacturing employment increased only by 25% with respect to their trend levels.[3] Other examples showing that strongly procyclical productivity can be a consequence of changes in aggregate demand can be found in Bernanke and Parkinson (1991) and Barsky and Miron (1989).

The most conventional and frequently invoked explanation among all for procyclical productivity is factor hoarding – labor hoarding and/or variable capacity utilization (e.g., Basu 1996, Bernanke and Parkinson 1991, Dornbusch and Fischer 1981, Lucas 1970, Sbordone 1997, and Shapiro 1993, among others). Despite the intellectual appeal of such explanations, it needs yet to be demonstrated quantitatively by models with optimizing agents that factor hoarding can indeed give rise to procyclical productivity under demand shocks, assuming constant returns to scale. The effect of factor hoarding under demand shocks is known in principle, but their quantitative importance for understanding procyclical productivity under demand shocks is unknown. This study attempts to address this question by focusing on three aspects of the productivity puzzle: 1) The variance of output exceeds the variance of employment; 2) Productivity is strongly correlated with output but only weakly correlated with employment; 3) Productivity tends to lead both output and employment.

I show that when labor is quasi-fixed due to adjustment costs (Oi, 1962), aggregate demand shocks can induce procyclical productivity under factor hoarding. Depending on the size of employment adjustment costs, a standard economic model can predict almost any degree of procyclical productivity. This is despite constant returns to scale, perfect competition, and instantaneous market clearing (i.e., flexible wages and prices). Hence the wide range of observed procyclical productivity across various industries and countries can be rationalized by demand shocks alone using standard economic theory without resorting to technology

can generate good predictions for the business cycle by using demand-side shocks.

[3]Data source: Bureau of Economic Analysis. To obtain percentage changes with respect trend level, the HP filter is applied to annual data between 1929 to 1948.

shocks, monopoly power, increasing returns, or sticky prices.[4]

The intuition can be understood using a representative-agent model. Given that firms are not able to adjust employment instantaneously and costlessly (e.g., due to contract costs, search costs, hiring and firing costs, and job training costs etc.), they opt to respond to short-run changes in demand by adjusting only the utilization rates of existing capital and labor. In general equilibrium, a positive shock to autonomous consumption spending (e.g., preferences) or government expenditure raises the marginal utility of goods (competitive price) and calls for higher output. Hence it is optimal to increase the utilization rates of capital and labor to meet the higher demand, giving rise to higher output without substantial increases in employment in the short run, resulting in higher measured labor productivity during boom periods. Conversely, firms opt to decrease the utilization rates of capital and labor when aggregate demand is low, giving rise to lower output without substantial drops in employment and resulting in apparently lower productivity in recessions. Therefore, the variance of output exceeds the variance of employment. Since employment adjustment catches up with production eventually as the boom (recession) continues, productivity falls (rises) ultimately towards the end of the boom (recession), resulting in the phenomenon that productivity leads the business cycle. In particular, due to the fact that employment lags output under adjustment costs, productivity will appear to lead employment more than it leads output, resulting in weaker contemporaneous correlations with productivity for employment than for output at the business-cycle frequency, giving rise to the Dunlop-Tarshis puzzle that labor productivity (or the real wage) does not comove strongly with employment.

The literature most closely related to this paper is Rotemberg and Summers (1990), Bernanke and Parkinson (1991), and Burnside, Eichenbaum, and Rebelo (1993). Rotemberg and Summers challenge Hall's (1988) conjecture that the observed procyclical productivity is due to strong monopoly power or increasing returns to scale. They show that if labor is quasi fixed in the short run but

[4]Ohanian (2002) recently argues that the dramatic fall of productivity during the Great Depression cannot be explained by conventional factors such as increasing returns to scale, capacity utilization, or labor hoarding. As will be shown in this paper, labor hoarding does have the potential to explain the dramatic decrease in productivity during the Great Depression. Ohanian's argument against the labor hoarding explanation is that the Great Depression lasted well over a decade. Hence it seems unlikely that firms hoarded workers because they mistakenly expected the Depression to end quickly. My model predicts that productivity will be severely depressed for a very long period of time under highly persistent adverse demand shocks despite the fact that the cost of adjusting employment remains the same as that in normal times. In other words, it is optimal to hoard labor even if the adverse demand shock is expected to be highly persistent. Hence the duration of the Great Depression does not rule out labor hoarding as a plausible explanation for procyclical productivity during the Great Depression.

the effort level can adjust instantaneously, demand shocks can explain procyclical productivity without resorting to monopoly power and increasing returns to scale. However, their model requires that goods supply be rationed and goods prices be sticky so that prices can exceed marginal costs in recessions in order to rationalize procyclical productivity by labor hoarding. I show, however, that productivity can be procyclical even when prices are flexible and always equal to marginal costs. Furthermore, their model is a static model and they do not conduct quantitative simulations to confront actual time series data. In contrast, the dynamic setup of my model allows me to conduct quantitative analysis for productivity and to yield precise predictions regarding lead-lag relationships among productivity, output and employment.

Burnside et al. (1993) set up a general equilibrium model with labor hoarding to study why the measured Solow residual may not be exogenous with respect to government spending shocks (Hall 1988). The reason, as pointed out by these authors, is that the measured Solow residual may contain movements in unobservable variables such as the utilization rate of existing capital and labor that react to government spending shocks. My model is built on their model. Their model, however, relies on technology shocks in order to generate procyclical labor productivity (since demand shocks alone will result in counter-cyclical labor productivity in their model), whereas my model does not need technology shocks in order to explain procyclical productivity. Furthermore, their model falls short in explaining the lead-and-lag relationships among productivity, output and employment.

Bernanke and Parkinson (1991) argue that technology shocks cannot possibly be a genuine explanation for procyclical productivity since productivity remains procyclical even in time periods when employment fluctuations are clearly driven by aggregate demand. They argue that procyclical productivity is consistent with the demand-shock theory with labor hoarding. However, their work is purely empirical without formal economic modeling and they incorrectly infer that refuting technology-shock theory also implies refuting equilibrium business cycle theory. Here I show that this is not the case.[5]

The rest of the paper is organized as follows. Section 2 presents stylized facts and their heuristic explanations with respect to the aforementioned three

[5]Empirical work with partial equilibrium models to explain procyclical productivity by labor hoarding and constant returns to scale can be found in Sbordone (1996). In Sbordone (1996), the importance of employment adjustment costs is clearly recognized. A weakness of such partial equilibrium studies, however, is that they cannot genuinely distinguish between technology shocks and demand shocks.

aspects of the productivity puzzle. They serve to form a perspective for further discussions in Sections 3 and 4 where a formal general equilibrium model of labor hoarding is presented and its implications for productivity are examined. Sections 5 discusses the rational behind the assumption of aggregate consumption demand shocks and their measurement issues. It is also shown that the model driven by consumption demand shocks alone is capable of explaining other features of the business cycle emphasized by the existing literature (e.g., Kydland and Prescott 1982). Section 6 uses a multi-sector version of the model to investigate the robustness of the results in the paper. It shows that consumption demand shocks to just one production sector can generate procyclical productivity for all production sectors in the economy regardless the location of industries in the production chain and returns to scale in that industry being constant or decreasing. Hence the puzzle that productivity, no matter how it is measured, is procyclical (Rotemberg and Summers 1990) is explainable by factor hoarding alone without the need to resort to technology shocks, increasing returns, monopoly power and sticky prices. Section 7 concludes the paper.

2 Stylized Facts and Heuristic Explanations

This section documents three prominent empirical features of procyclical productivity using quarterly international data. Although these stylized facts are not all new, they help form a perspective for further discussion. Table 1 reports standard deviations and contemporaneous correlations for output (y), employment (n), and productivity ($p = y - n$).[6] Table 2 reports lead and lag relationships among the three variables. Three representative groups of industrial countries from three continents are selected: The US and Canada for north America, Great Britain and Italy for Europe, and Japan for Asia.[7] The conventional perception is that institutional aspects of the labor market differ significantly across the three continents. The labor market is presumably most competitive in north America countries, less so in European countries due to strong union power, and it is presumably most rigid in Japan due to institutional and cultural reasons that give rise to strong labor hoarding behavior.

Table 1 shows that the relative standard deviation of employment with re-

[6] All data are seasonally adjusted by seasonal dummies, logged, and filtered by the Band-Pass filter (Baxyer and King 1995). The frequency band is 6 - 40 quarters per cycle, and the truncation window size is 8. Using the H-P (Hodrick and Prescott 1980) filter gives very similar results.

[7] Data are taken from OECD data bank. The time period covered for each country is respectively: US (1960:1 - 1994:4), Canada (1960:1 - 1996:2), England (1960:1 - 1996:1), Italy (1970:1 - 1996:1), and Japan (1960: - 1996:1).

spect to output declines as we move from north American countries down to Japan, confirming the conventional perception on labor market flexibility across these countries. Associated with this declining relative volatility in employment is an increasing correlation between output and productivity (column 3). This correlation is strongly positive for all countries. Although there is no clear pattern for the sign of correlations between employment and productivity among these countries, these correlations are much weaker than those between productivity and output. Table 2 reports the lead-lag relationships among productivity, output and employment. In general, three prominent features of productivity emerge from table 1 and table 2, and they can be summarized as follows:

Table 1. Contemporaneous Relationship

Country	σ_y/σ_n	$corr(p,y)$	$corr(p,n)$
US	1.23	0.63	0.25
Canada	1.32	0.66	0.17
England	1.45	0.73	-0.12
Italy	2.44	0.92	-0.22
Japan	3.45	0.96	0.31
Mean	1.98	0.78	0.08

Table 2. Lead And Lag Relationships [Correlations with Productivity]

Country		$corr(x_{t\pm j}, p_t)$								
		$t+4$	$t+3$	$t+2$	$t+1$	t	$t-1$	$t-2$	$t-3$	$t-4$
US	y	0.37	0.56	0.69	<u>0.72</u>	0.63	0.42	0.14	-0.15	-0.39
	n	0.49	<u>0.54</u>	0.52	0.41	0.25	0.04	-0.16	-0.33	-0.45
Canada	y	0.19	0.41	0.60	<u>0.71</u>	0.66	0.46	0.16	-0.15	-0.38
	n	0.26	0.33	<u>0.36</u>	0.31	0.17	-0.02	-0.22	-0.40	-0.50
England	y	0.32	0.50	0.68	<u>0.77</u>	0.73	0.53	0.23	-0.11	-0.39
	n	<u>0.46</u>	0.35	0.22	0.05	-0.12	-0.29	-0.44	-0.53	-0.57
Italy	y	-0.34	0.08	0.51	0.83	<u>0.92</u>	0.74	0.36	-0.10	-0.49
	n	<u>0.33</u>	0.26	0.12	-0.07	-0.22	-0.28	-0.26	-0.17	-0.05
Japan	y	-0.10	0.27	0.64	0.89	<u>0.96</u>	0.80	0.47	0.07	-0.27
	n	0.29	0.44	<u>0.49</u>	0.44	0.31	0.12	-0.08	-0.24	-0.32

1) (Tab. 1) The variance of output exceeds the variance of employment. For example, the ratio of standard deviations between output and employment is greater than one regardless country. This ratio is smallest for north America countries (1.23 and 1.32 respectively), and it is the largest for Japan (3.45). The sample average for all countries is 1.98.

2) (Tab. 1) Productivity is strongly positively correlated with output but only weakly (either positively or negatively) correlated with employment. The contemporaneous correlation between productivity and output is greater than 0.63, with a maximum of 0.96 (Japan) and a sample average of near 0.8; whereas the contemporaneous correlation between productivity and employment is less than 0.31 with a minimum of -0.22 (Italy) and a sample average of essentially zero (0.08).

3) (Tab. 2) Productivity tends to lead both output and employment; and it leads employment more than it leads output. For example, for north American countries, productivity leads output by one quarter and employment by two to three quarters. For England, productivity leads output also by one quarter, but it leads employment by at least 4 quarters. Although productivity does not appear to lead output significantly for Italy and Japan, it leads employment significantly

in these two countries by 2-4 quarters.[8]

These prominent features of productivity constitute three key aspects of the procyclical productivity puzzle, which any serious business cycle theory must explain. To develop insights into how to resolve this productivity puzzle, it is important to note that the three aspects of the productivity puzzle are closely related but do not imply each other. This is illustrated by Figure 1.

In Figure 1, the hypothetical employment series is generated by the function

$$n_t = \sin(\omega t); \tag{1}$$

the hypothetical output series is generated by the function

$$y_t = \lambda \sin(\omega t + \xi); \tag{2}$$

and the productivity series is defined as

$$y_t - n_t,$$

where ω determines the frequency of cycles, λ measures the gain (or returns to scale) in the production function, and ξ measures the phase shift or lead-lag relationship between output and employment. In generating Figure 1, I have set $\omega = 0.2, \lambda = 1.2$, and $\xi = 1$. First, the fact that output leads employment is captured by the assumption $\xi > 0$ in the production function (2). Since output leads employment, the difference, $y_t - n_t$, appears to lead both output and employment, and this is more so for output than for employment. Second, the fact that the variance of output exceeds the variance of employment is captured by an entirely independent assumption, $\lambda = 1.2$. Third, the sign of contemporaneous correlation between productivity and employment depends on the magnitude of the phase parameter ξ. If y leads n by too much, for example, then $y - n$ may be negatively correlated with n. This is shown in Table 3. For example, when $\xi \leq 0.6$, we have $cor(y - n, n) > 0$. When $\xi \geq 0.8$, we have $cor(y - n, n) < 0$. In any case, we always have $cor(y - n, y) > cor(y - n, n)$. This explains why in the data the correlation between productivity and employment is positive for certain

[8] Productivity does not appear to lead output significantly for Italy and Japan because employment in both Italy and Japan is too smooth relative to output (output is about 2.5 times more volatile than employment in Italy and about 3.5 times more volatile in Japan), consequently productivity move closely with output. Hence, despite that productivity is expected to lead output in these two countries, such a tendency can hardly be detected in quarterly data. Also notice that productivity leads employment by so much in the two European countries (England and Italy) such that the contemporaneous correlations between productivity and employment in these countries are negative. A consequence of this negative correlation will be discussed later.

countries but negative for others, and why this correlation is weaker than the correlation between productivity and output (the Dunlop-Tarshis puzzle).[9]

Table 3. Predicted Contemporaneous Correlations*

ξ	$corr(y,n)$	$corr(p,y)$	$corr(p,n)$	$\hat{\beta}$
0.0	1.00	1.00	1.00	1.20
0.2	0.98	0.76	0.61	1.19
0.4	0.92	0.61	0.26	1.13
0.6	0.83	0.58	0.03	1.02
0.8	0.71	0.60	−0.14	0.87
1.0	0.56	0.63	−0.29	0.69
1.2	0.40	0.67	−0.41	0.48
1.4	0.21	0.72	−0.53	0.25

*The sample size is 100.

The phase relationship shown in Figure 1 and the correlations shown in table 3 also reveal two potential pitfalls in empirical studies. First, the contemporaneous correlation between productivity (the real wage) and employment may reveal nothing about the source of shocks – namely, whether it is labor supply shocks or labor demand shocks that drive labor market fluctuations. A common argument in the literature is that if this correlation is positive, then it suggests that shocks to labor demand dominate; and if this correlation is negative, then it suggests that shocks to labor supply dominate; and if this correlation is near zero, then both demand shocks and supply shocks are equally important (e.g., see Christiano and Eichenbaum 1992). This argument is misleading because it ignores the dynamic-feedback nature of the labor market. Consider a hypothetical impulse response analysis: Regardless the source of shocks or which curve moves first, if both labor supply and labor demand curves respond to the shocks in subsequent periods, the resulting equilibrium may form a circular trajectory in the real wage and employment space. Hence the measured relationship (contemporaneous correlation) between equilibrium real wage and equilibrium employment can be either positive, negative, or zero, depending only on the relative speed and magnitude of shift of the two curves in dynamic adjustment over time, not on which curve moves first. Although there is no labor supply or demand in the

[9] It is also important to note that in order to generate procyclical productivity series, the assumption that $\lambda \geq 1$ is not needed. Namely, productivity can still appear to be positively correlated with output even if $\lambda < 1$. This is so because employment lags output. The larger the lag is, the more procyclical is the productivity.

current model, we can imagine that the productivity function $y-n$ and the employment function (n) are the equilibrium trajectories of labor supply and labor demand curves. As long as there exists a phase difference between productivity $(y-n)$ and employment (n), then the measured contemporaneous correlation between productivity and employment can have either sign. The sign depends only on the phase parameter ξ, not on the source of disturbance. This is revealed clearly by figure 1 and table 3.

Second, many empirical studies of procyclical labor productivity use the *beta* coefficient in an OLS regression,

$$y_t = \alpha + \beta n_t + a_t,$$

as an indicator to gauge the size of short-run increasing returns to labor (SRIRL) and procyclical labor productivity (PLP) (e.g., see Bernanke and Parkinson 1991). SRIRL (or PLP) is said to exist if estimated $\hat{\beta}$ exceeds one. This kind of empirical inference is misleading. This is because SRIRL and PLP can still exist (in the sense that the variance of output exceeds the variance of employment) even when the estimated beta $(\hat{\beta})$ is less than one. This can happen if the OLS residual, a_t, is negatively correlated with employment (n_t), hence $\hat{\beta}$ is biased downwards compared to the true β. To understand this, notice that a_t in the OLS regression essentially captures movements in labor productivity $(y_t - n_t)$. If output (y_t) leads employment sufficiently (which is the case for countries like England and Italy), then labor productivity $(y_t - n_t)$ or the OLS residual a_t may become negatively correlated with employment due to a sufficiently large lead between $y_t - n_t$ and n_t. Since productivity can be either positively or negatively correlated with employment depending on how much employment lags output, the estimated output elasticity of labor $(\hat{\beta})$ can be either greater than one or less than one. But $\hat{\beta}$ being less than one does not at all imply that labor productivity is not procyclical or SRIRL does not exist. This is confirmed by the last column in Table 3, where the estimated $\hat{\beta}$ becomes less than one when the correlation between $y-n$ and n becomes negative due to a large value of ξ.

This can also be confirmed using actual data. Table 4 reports the estimated beta coefficients for the countries considered previously. It shows that beta exceeds one for countries with positive correlations between productivity and employment (such as US, Canada and Japan) and that beta is less than one for countries with negative correlations between productivity and employment (such as England and Italy). But we know that the ratio of standard deviations between output and employment in England and Italy far exceeds one, suggesting strong SRIRL and PLP. This explains why Bernanke and Parkinson (1991) encounter industries with estimated labor input coefficient ($\hat{\beta}$) substantially less than one or even less than labor's income share. And they seem to incorrectly interpret these as exceptions of SRIRL and PLP. To avoid pitfalls like this, it is better to measure SRIRL or PLP by the three aspects of productivity discussed above, rather than by beta (β).

Table 4. OLS Estimates of β

Country	$\hat{\beta}$	$corr(p_t, n_t)$
US	1.12	0.25
Canada	1.12	0.17
England	0.85	-0.12
Italy	0.45	-0.22
Japan	1.92	0.31

Hence, if employment lags output, then productivity automatically leads both output and employment and the correlations with productivity is stronger for output than for employment. The challenge, however, is to explain why $\lambda > 1$ and $\xi > 0$ in the real world. That is, why does the variance of output exceeds the variance of employment and why does employment lags output? The following section shows that with employment adjustment costs, variable utilization of capital and labor is sufficient for explaining the procyclical productivity puzzle, without the need to resort to technology shocks, sticky prices, monopoly power, or increasing returns to scale.

3 The Model

The model is built on general equilibrium models of capacity utilization and labor hoarding with indivisible labor by Burnside, Eichenbaum, and Rebelo (1993) and Burnside and Eichenbaum (1996). The key difference here is that I introduce dynamic employment adjustment costs following Sargent (1978) and I focus on the effects of demand shocks on productivity. There are thus two aspects of employment adjustment costs in my model, one pertaining to an information structure and the other pertaining to intertemporal adjustment costs. The information structure assumes that employment decisions must be made one period in advance (as in Burnside et al.). Once the decisions are made, they cannot be changed after realizations of shocks (this assumption will be relaxed later). The dynamic adjustment cost takes a quadratic form, $(x_t - x_{t-1})^2$, indicating that it is costly to adjust x either up or down too fast relative to the pre-established level of x.[10] As will be shown shortly, the dynamic adjustment costs of employment is the most crucial element for allowing demand shocks to explain the observed productivity dynamics across various industries and countries at business-cycle frequencies. Without this type of adjustment costs, the model is similar to that of Burnside and Eichenbaum (1996) and it generates counter-cyclical labor productivity under demand shocks despite variable utilization rates for capital and labor.

To model aggregate consumption demand shifts, I assume that there are random shocks to agents' preferences and that these preference shocks have an aggregate component that shifts all agents' marginal utility of consumption in the same direction (for example, Christmas is such an aggregate shifter which induces synchronized consumption spending across agents). Assuming that all agents are alike and that labor supply is indivisible (Hansen, 1985 and Rogerson 1988), a representative agent in this model chooses sequences of consumption (c), probability to work (n), effort to work (e), capital utilization rate (u), and next-period capital stock (k) to solve

$$\max_{\{n_t\}} E_{t-1} \left\{ \max_{\{c_t, u_t, e_t, k_{t+1}\}} E_t \left\{ \sum_{t=0}^{\infty} \beta^t \left[\theta_t \log c_t + \tau n_t \log (T - \xi - e_t f) + \tau (1 - n_t) \log T \right] \right\} \right\}$$

subject to

$$c_t + g_t + k_{t+1} - \left(1 - \delta u_t^{\phi}\right) k_t \leq (u_t k_t)^{\alpha} (e_t n_t)^{1-\alpha} - \frac{\psi}{2} (n_t - n_{t-1})^2 k_t,$$

where T is time endowment in each period, ξ is the cost of time for going to work and f is the length of working hours per shift. Since the size of labor force is normalized to one, n also represents employment rate.[11] The E_{t-1} operator indicates that employment level is determined one period in advance based on information available in period $t-1$. The parameter ψ measures the size of dynamic adjustment costs associated with changing employment relative to its

[10] Dynamic adjustment costs of employment have long been recognized as the key for understanding firm level employment dynamics and it is widely used in empirical labor literature. See, for example, Sargent (1978), Shapiro 1986, Burgess 1988, Hamermesh 1989, Hamermesh and Pfann 1996.

[11] By assuming indivisible labor, this model does not have variable hours to work. For RBC models studying variations in both hours to work and the number of employment, see Cho and Cooley (1994).

previous level. k_t in the quadratic adjustment cost term is a way to normalize the size of dynamic adjustment costs in the steady state, it does not affect the dynamics of the model near the steady state (since its influence drops out from a first-order Taylor expansion). Hence, adjusting employment stock is costly and not instantaneous in the model, but the effort level e (or utilization rate of labor) and the utilization rate of capital can be adjusted instantaneously, reflecting the idea of factor hoarding (Burnside et al. 1993 and Burnside et. al. 1996). The rate of capital depreciation, δu_t^{ϕ}, is time dependent in this model, reflecting costs associated with capital utilization rate ($\phi > 1$, see Greenwood et al. 1988). θ_t represents aggregate impulses shifting the marginal utilities of agents' consumption by creating urges to consume. g_t is shocks to government spending. Both θ_t and g_t follow AR(1) processes:

$$\begin{aligned}\log\theta_t &= \rho_\theta \log\theta_{t-1} + \varepsilon_{\theta t}, \varepsilon_{\theta t} \sim N(0,\sigma_\theta^2);\\ \log g_t &= \rho_g \log g_t + \varepsilon_{gt}, \quad \varepsilon_{gt} \sim N(0,\sigma_g^2);\end{aligned}$$

where the two types of innovations $\{\varepsilon_{\theta t}, \varepsilon_{gt}\}$ are assumed to be othorgonal to each other.

The first-order conditions with respect to $\{n, c, u, e, k\}$ are given respectively by:

$$\begin{aligned}&E_{t-1}\left\{\tau\log T - \tau\log\left(T-\xi-e_t f\right) - (1-\alpha)\lambda_t \left(u_t k_t\right)^{\alpha} e_t^{1-\alpha} n_t^{-\alpha}\right\} \\ &= E_{t-1}\left\{\beta\lambda_{t+1}\psi\left(n_{t+1}-n_t\right)k_{t+1} - \lambda_t\psi\left(n_t - n_{t-1}\right)\right\}\end{aligned} \tag{3}$$

$$\frac{\theta_t}{c_t} = \lambda_t \tag{4}$$

$$\alpha u_t^{\alpha-1} k_t^{\alpha}\left(e_t n_t\right)^{1-\alpha} = \phi\delta u_t^{\phi-1} k_t \tag{5}$$

$$\frac{\tau f n_t}{T-\xi-e_t f} = (1-\alpha)\lambda_t\left(u_t k_t\right)^{\alpha} e_t^{-\alpha} n_t^{1-\alpha} \tag{6}$$

$$\lambda_t = \beta E_t \lambda_{t+1}\left[\alpha u_{t+1} k_{t+1}^{\alpha-1}\left(e_{t+1}n_{t+1}\right)^{1-\alpha} + 1 - \delta u_{t+1}^{\phi} - \frac{\psi}{2}\left(n_{t+1}-n_t\right)^2\right] \tag{7}$$

$$c_t + g_t + k_{t+1} - \left(1-\delta u_t^{\phi}\right)k_t = \left(u_t k_t\right)^{\alpha}\left(e_t n_t\right)^{1-\alpha} - \frac{\psi}{2}\left(n_t - n_{t-1}\right)^2 k_t. \tag{8}$$

It is worth noting that the production technology specified in the model has constant returns to scale. To see this, consider a simpler situation where the dynamic adjustment cost of employment is zero ($\psi = 0$). Then the first-order conditions (1) and (4) imply that if employment (n) is chosen contemporaneously with effort (e), then the optimal level of effort (e) is a constant and is determined by:

$$\log T - \log\left(T - \xi - e_t f\right) = \frac{f e_t}{T - \xi - e_t f}.$$

Hence the output elasticity with respect to labor is always $(1-\alpha)$, not $2(1-\alpha)$. Since a positive ψ implies extra costs on changing employment, it does not enhance returns to scale in the model.

With respect to capital utilization, equation (3) implies

$$u_t = \left(\frac{\alpha}{\phi\delta}\right)^{\frac{1}{\phi}} \left(\frac{y_t}{k_t}\right)^{\frac{1}{\phi}},$$

which can be used to substitute out u in the original production function to obtain a reduced-form production function without capital utilization:

$$y_t = A k_t^{\alpha\frac{\phi-1}{\phi-\alpha}} h_t^{(1-\alpha)\frac{\phi}{\phi-\alpha}},$$

where $h_t \equiv e_t n_t$ is the effective labor service, and A is a constant. Clearly $\alpha\frac{\phi-1}{\phi-\alpha} + (1-\alpha)\frac{\phi}{\phi-\alpha} = 1$. Hence, variable capital utilization does not enhance returns to scale either, it simply enhances the output elasticity of labor service by reducing the output elasticity of capital (since $\frac{\phi}{\phi-\alpha} > 1$ and $\frac{\phi-1}{\phi-\alpha} < 1$).[12] Therefore, procyclical labor productivity in this model, if it arises, is purely due to labor hoarding and capacity utilization, not to increasing returns.

Solution Method. Since no analytical solutions are available, I solve the model's equilibrium decision rules by log-linearizing the first-order conditions around the steady state (see King, Plosser and Rebelo 1988). Using circumflex variables to denote log deviations from steady state values, the log-linearized first-order conditions (after simplification using steady-state conditions and ignoring higher-order terms) are given by:

$$E_{t-1}\left\{-\beta\psi^*\hat{n}_{t+1} + (1+\beta)\,\hat{n}_t - \psi^*\hat{n}_{t-1}\right\} = E_{t-1}\left\{\hat{\lambda}_t + \alpha\left(\hat{u}_t + \hat{k}_t\right) - \alpha\left(\hat{e}_t + \hat{n}_t\right)\right\}$$

$$\hat{\theta}_t - \hat{c}_t = \hat{\lambda}_t$$

$$(1-\alpha)\left(\hat{e}_t + \hat{n}_t - \hat{k}_t\right) = (\phi - \alpha)\,\hat{u}_t$$

[12] See Wen (1998) for more discussions on the dynamic effects of capital utilization.

$$\pi\hat{e}_t = \hat{\lambda}_t + \alpha\left(\hat{u}_t + \hat{k}_t\right) - \alpha\left(\hat{e}_t + \hat{n}_t\right)$$

$$\hat{\lambda}_t = \hat{\lambda}_{t+1} - \eta\left(\hat{u}_{t+1} + \hat{k}_{t+1}\right) + \eta\left(\hat{e}_{t+1} + \hat{n}_{t+1}\right)$$

$$\left(1 - s_i - s_g\right)\hat{c}_t + s_g\hat{g}_t + s_i\hat{k}_{t+1} = \left(\alpha + s_i\frac{1-\bar{\delta}}{\bar{\delta}}\right)\hat{k}_t + \left(\alpha - s_i\phi\right)\hat{u}_t + \left(1-\alpha\right)\left(\hat{e}_t + \hat{n}_t\right);$$

where

$$\psi^* \equiv \tfrac{\psi}{1-\alpha}\tfrac{\bar{k}}{\bar{y}}\bar{n}^2, \pi \equiv \tfrac{\bar{e}f}{T-\xi-\bar{e}f}, \eta \equiv \left(1 - \beta\left(1-\bar{\delta}\right)\right)\left(1-\alpha\right),$$

and where s_i is the steady-state savings ratio, s_g is the steady-state government spending to output ratio, $\bar{\delta}$ is the steady-state capital depreciation rate, $\frac{\bar{k}}{\bar{y}}$ is the steady-state capital-output ratio, and $\bar{n}$ is the steady-state employment rate. The important steady-state relationships that help determine these steady-state values and the elasticity of depreciation cost (ϕ) are given by

$$\bar{\delta} = \delta\bar{u}^{\phi}, \tfrac{\bar{k}}{\bar{y}} = \tfrac{\beta\alpha}{1-\beta\left(1-\bar{\delta}\right)}, s_i = \bar{\delta}\tfrac{\bar{k}}{\bar{y}}, \phi = \tfrac{1-\beta\left(1-\bar{\delta}\right)}{\beta\bar{\delta}}.$$

Calibration. The time period is a quarter. In calibrating the parameter values for a quarterly model, I follow Burnside and Eichenbaum (1996) by setting $T = 1,369$ per quarter, $\xi = 60$, and $f = 324.8$ (implying a steady-state effort level $\bar{e} = 1$). I also set the discounting factor $\beta = 0.99$, the capital's income share $\alpha = 0.3$, the steady-state government-spending to output ratio $s_g = 0.15$,[13] the steady-state quarterly rate of capital depreciation $\bar{\delta} = 0.025$ (implying 10 percent a year and $\phi \approx 1.4$), the steady-state employment rate $\bar{n} = 0.94$ (implying an unemployment rate of 6 percent). These parameter values imply $\frac{\bar{k}}{\bar{y}} = 8.5$ and $s_i \approx 0.2$. There is no need to pin down the steady-state capital utilization rate since δ can always be chosen so that $\bar{u}$ matches the data. One of the most crucial parameter determining the behavior of labor productivity in this model is ψ. Since there is little empirical evidence regarding the size of the adjustment cost of labor, I leave ψ free for experiment and will pin it down later by matching the variance of employment relative to output between the model and the data. I also allow the persistence parameter for shocks, ρ_θ and ρ_g, to take different values for the impulse response analysis.

[13] $s_g = 0.15$ only when government shocks are considered. It is zero otherwise.

4 Predicting the Productivity Cycle

Figure 2 shows impulse responses of output, employment, and productivity to a one-standard-deviation positive shock to θ_t when the adjustment cost parameter takes different values, assuming that $\rho_\theta = 0.9$.[14] Windows on the left column show responses of output and employment for various values of ψ while windows on the right column show responses of productivity for various values of ψ. For each column, the first row pertains to the case of zero adjustment cost ($\psi = 0$), the middle row pertains to a mild adjustment cost ($\psi = 1$), and the bottom row pertains to a large adjustment cost ($\psi = 10$).

Several important features are revealed by these pictures. First, output is less volatile than employment if there is no adjustment cost (except at the impact period). However, as the adjustment cost increases from zero, output becomes more volatile than employment. For example, when $\psi = 1$, the variance of output exceeds the variance of employment for the initial 10-12 quarters after the shock; and this situation can last for 26 quarters after the shock when $\psi = 10$. Second, output appears to lead employment. Such a lead in output with respect to employment increases dramatically as ψ increases.

These effects of adjustment costs on the responses of output and employment have the following implications for productivity. First, productivity responds positively to consumption demand shocks, and the persistence of such positive responses increases dramatically as the size of the adjustment cost increases. For example, when $\psi = 0$, productivity is procyclical only at the impact period (due to the fact that employment decision is made one period in advance), then it becomes negatively correlated with output afterwards. As ψ increases, however, productivity tends to remain above the steady state for a much longer period of time, indicating stronger procyclicality of productivity. Second, productivity appears to lead both output and employment. This is the direct result of the fact that employment lags output. Evidently, the larger the adjustment cost (ψ), the more productivity tends to lead employment.

These characteristics of procyclical productivity remain intact even after relaxing the assumption that employment decisions is made one period in advance, indicating that dynamic adjustment costs of employment are the key for enabling capacity utilization and labor hoarding to generate procyclical productivity under demand shocks and constant returns to scale. The information structure of

[14] This subsection considers movements around the steady state, hence seasonal movements are absent.

the labor market, however, is important in determining the sign of contemporaneous correlations between productivity and employment since it enhances the lag between employment and output after demand shocks.

Government spending shocks have very similar effects on productivity except that the magnitudes differ. Volatilities in output and employment under government shocks, for example, are much smaller than those under preference shocks, but the shape of the impulse responses look almost identical to those in figure 2.

Using the band-pass filter (Baxter and King 1995) to isolate movements at the business cycle frequencies (6-40 quarters per cycle), table 5 reports the standard deviations of employment and productivity relative to output, their contemporaneous correlations with output as well as the beta coefficient ($\hat{\beta}$).[15] To compare the effect of the information structure on labor market dynamics, two versions of the model are considered: model A corresponds to the case where employment must be determined one period in advance; and model B corresponds to the case where employment is determined together with other variables in the model after shocks are realized. The benchmark value for the persistence parameter of shocks is $\rho_{\theta_2} = 0.9$. Predicted statistics for other values of ρ_{θ_2} are also reported (bottom panels in table 5).

Table 5 shows that in the absence of labor adjustment costs ($\psi = 0$), neither version of the model is capable of generating procyclical productivity, regardless of the persistence of shocks. Namely, when $\psi = 0$, we always have $\sigma_y/\sigma_n < 1$ and $corr(p, y) < 0$. Once adjustment costs are included, however, then both versions of the model are capable of generating procyclical productivity. As a matter of fact, both versions of the model are capable of generating virtually any degree of procyclical productivity depending on the size of the adjustment costs. For example, output can be nearly 6 times as volatile as employment when $\psi = 5$ in both versions of the model. The crucial difference between the two versions of the model, however, is that productivity is negatively correlated (contemporaneously) with employment when employment is determined one period in advance and it is positively correlated (contemporaneously) with employment when employment can respond to shocks instantaneously. This is so because the information structure induces an additional fixed lag in employment adjustment in responding to demand shocks. As discussed in figure 1 in section 2, a longer lag in employment can lead to negative correlations between productivity and employment.

[15] Numbers shown are the means of 100 simulations with sample length 140 (US data sample size). Standard errors are in parentheses.

It appears that model A captures the labor market dynamics of the two European countries very well. For example, when ψ varies from 0.5 to 1.5 in model A, we have σ_y/σ_n varies from 1.45 to 2.6, $corr(p, y)$ varies from 0.73 to 0.92, $corr(p, n)$ from -0.17 to -0.2, and $\hat{\beta}$ varies from 0.7 to 0.48. These statistics are close to those reported in table 1 for England and Italy. It also appears that model B, on the other hand, captures the labor market dynamics for the north American countries very well when ψ is small, and it captures Japan's labor market dynamics very well when ψ is large. For example, when $\psi = 0.25$ in model B, we have $\sigma_y/\sigma_n = 1.27$, $corr(p, y) = 0.62$, $corr(p, n) = 0.11$, and $\hat{\beta} = 1.08$. These statistics are very close to those reported in table 1 for America and Canada. When $\psi = 2.5$ (not reported in table 5), we have $\sigma_y/\sigma_n = 3.5$, $corr(p, y) = 0.96$, $corr(p, n) = 0.18$, and $\hat{\beta} = 1.7$. These statistics are very close to those reported in table 1 for Japan.

These predictions indicate that north American countries have smaller labor market frictions while Japan and countries in Europe have larger labor market frictions. The frictions in European countries are captured partly by the information structure of the labor market and partly by the magnitude of intertemporal adjustment costs, and the frictions in Japan are primarily captured by the large size of intertemporal adjustment costs. Therefore, depending on the information structure of the labor market and the size of the adjustment costs of employment, the general equilibrium model can explain the wide range of procyclical labor productivity experienced by various countries who are known to exhibit differences in costs of labor adjustment because of institutional reasons.[16]

[16] To have a sense on the size of the required adjustment cost, we can estimate it as follows. The ratio of the adjustment cost to output can be written as

$$\frac{\psi}{2}\left[\frac{n_t - n_{t-1}}{n_t}\right]^2 \frac{k_t}{y_t} n_t^2.$$

Assume that the steady-state annual capital-output ratio $\frac{k}{y} \approx 10$, employment rate $n \approx 0.94$, and the steady-state annual growth rate of employment $\frac{n_t - n_{t-1}}{n_t} \approx 4\%$. Then even with $\psi = 5$, the steady-state adjustment cost to output ratio is approximately 3.5% a year or 0.87% a quarter (table 5 shows that the required value of ψ to match the data is much smaller than 5). Hence the values of ψ considered in table 5 are relatively small numbers (e.g., much smaller than depreciation costs of capital) and the magnitudes are consistent with empirical estimates of employment adjustment costs (e.g., see Shapiro 1986). Despite the small adjustment cost, however, its impact on the labor market dynamics is enormous.

Table 5. Predicted Sample Moments Under Preference Shocks*

	ψ	σ_y/σ_n	$corr(y,n)$	$corr(p,y)$	$corr(p,n)$	$\hat{\beta}$
			$\rho_\theta = 0.9$			
Model A	0.00	0.88 (.004)	0.99 (.002)	-0.59 (.02)	-0.70 (.01)	0.87 (.01)
	0.25	1.17 (.04)	0.68 (.05)	0.55 (.05)	-0.24 (.02)	0.79 (.04)
	0.50	1.45 (.09)	0.52 (.06)	0.73 (.04)	-0.20 (.03)	0.75 (.06)
	1.0	2.04 (.15)	0.32 (.06)	0.87 (.02)	-0.18 (.03)	0.65 (.09)
	2.0	3.07 (.29)	0.16 (.05)	0.95 (.01)	-0.17 (.03)	0.48 (.13)
	5.0	5.76 (.65)	0.01 (.05)	0.98 (.004)	-0.17 (.03)	0.01 (.26)
Model B	0.00	0.89 (.00)	1.00 (.00)	-0.999 (.00)	-0.999 (.00)	0.89 (.00)
	0.25	1.27 (.04)	0.85 (.01)	0.62 (.04)	0.11 (.03)	1.08 (.03)
	0.50	1.57 (.10)	0.74 (.02)	0.77 (.03)	0.15 (.03)	1.17 (.05)
	1.0	2.08 (.17)	0.62 (.02)	0.88 (.02)	0.17 (.03)	1.28 (.07)
	2.0	3.08 (.28)	0.48 (.02)	0.95 (.01)	0.18 (.02)	1.50 (.11)
	5.0	5.66 (.62)	0.34 (.02)	0.98 (.004)	0.17 (.03)	1.95 (.23)
			$\rho_\theta = 0.0$			
Model A	0.5	1.16 (.10)	0.16 (.14)	0.70 (.07)	-0.58 (.04)	0.18 (.16)
Model B	0.5	1.29 (.10)	0.51 (.06)	0.67 (.06)	-0.30 (.02)	0.65 (.04)
			$\rho_\theta = 1.0$			
Model A	0.5	1.18 (.05)	0.65 (.05)	0.57 (.05)	-0.25 (.03)	0.77 (.04)
Model B	0.5	1.33 (.06)	0.81 (.02)	0.66 (.04)	0.10 (.03)	1.08 (.03)

*Numbers in the table are the means of 100 simulations (std. in parentheses).

Table 6 reports predicted lead-lag relationships among productivity, output and employment at the business cycle frequency.[17] It shows that with the information structure of the labor market, productivity tends to lead both output and employment significantly more than it does without the information structure. For example, when $\psi \in [0.25, 1.0]$, productivity leads output by one to two quarters and it leads employment by 4 quarters, and the contemporaneous correlation between productivity and employment is negative. This is consistent with experiences of England and Italy as reported in table 2 (for Italy, productivity has only a weak tendency to lead output. This is captured by the model with a larger adjustment cost, such as $\psi = 2$). Without the information structure in the labor market (Model B), productivity tends to lead output by at most one quarter and employment by at most 3 quarters, depending on the values of ψ. The contemporaneous correlations between productivity and employment are always positive in model B. These are consistent with statistics of north American countries reported in table 2. For Japan, there is no significant lead in productivity with respect to output. This is consistent with model B with a larger value of ψ (e.g., $\psi = 2$).

[17]Numbers shown are the means of 100 simulations with sample length 140 (US data sample size). Standard errors are in parentheses.

Table 6. Predicted Lead And Lag Relationships $[corr(x_{t\pm j}, y_t - n_t)]$

	x	$t+4$	$t+3$	$t+2$	$t+1$	t	$t-1$	$t-2$	$t-3$	$t-4$
						Model A				
$\psi = 0.25$	y	0.38	0.63	0.79	0.78	0.55	0.15	-0.28	-0.62	-0.77
		(.13)	(.09)	(.05)	(.04)	(.04)	(.02)	(.03)	(.05)	(.04)
	n	0.73	0.70	0.50	0.16	-0.24	-0.57	-0.75	-0.75	-0.61
		(.06)	(.06)	(.05)	(.03)	(.02)	(.04)	(.04)	(.05)	(.09)
$\psi = 0.5$	y	0.25	0.54	0.78	0.87	0.73	0.39	-0.05	-0.44	-0.67
		(.13)	(.10)	(.05)	(.04)	(.04)	(.02)	(.04)	(.06)	(.06)
	n	0.72	0.69	0.50	0.17	-0.20	-0.52	-0.70	-0.72	-0.61
		(.06)	(.06)	(.05)	(.03)	(.02)	(.04)	(.05)	(.06)	(.08)
$\psi = 1.0$	y	0.13	0.44	0.75	0.92	0.87	0.58	0.16	-0.26	-0.55
		(.13)	(.10)	(.06)	(.02)	(.02)	(.02)	(.04)	(.07)	(.07)
		0.72	0.68	0.49	0.19	-0.17	-0.48	-0.67	-0.71	-0.62
		(.07)	(.06)	(.05)	(.02)	(.03)	(.05)	(.06)	.06)	.08)
$\psi = 2.0$	y	-0.01	0.33	0.69	0.93	0.94	0.71	0.31	-0.13	-0.45
		(.15)	(.11)	(.06)	(.02)	(.01)	(.02)	(.05)	(.09)	(.10)
	n	0.71	0.68	0.49	0.19	-0.17	-0.48	-0.66	-0.70	-0.61
		(.06)	(.06)	(.05)	(.03)	(.03)	(.05)	(.06)	(.07)	(.09)
						Model B				
$\psi = 0.25$	y	0.28	0.56	0.78	0.82	0.62	0.24	-0.22	-0.59	-0.77
		(.15)	(.10)	(.05)	(.06)	(.05)	(.03)	(.03)	(.06)	(.06)
	n	0.59	0.70	0.67	0.46	0.11	-0.28	-0.60	-0.77	-0.75
		(.09)	(.07)	(.08)	(.07)	(.04)	(.03)	(.05)	(.05)	(.06)
$\psi = 0.5$	y	0.21	0.51	0.78	0.89	0.77	0.44	-0.01	-0.41	-0.67
		(.16)	(.11)	(.05)	(.03)	(.03)	(.02)	(.04)	(.07)	(.07)
	n	0.62	0.71	0.68	0.48	0.15	-0.23	-0.55	-0.73	-0.74
		(.09)	(.06)	(.06)	(.05)	(.03)	(.03)	(.05)	(.05)	(.06)
$\psi = 1.0$	y	0.07	0.39	0.72	0.92	0.88	0.60	0.17	-0.26	-0.56
		(.17)	(.13)	(.06)	(.02)	(.02)	(.02)	(.05)	(.08)	(.09)
	n	0.60	0.70	0.67	0.49	0.17	-0.20	-0.51	-0.69	-0.71
		(.09)	(.06)	(.06)	(.05)	(.03)	(.03)	(.05)	(.06)	(.07)
$\psi = 2.0$	y	-0.03	0.31	0.67	0.92	0.95	0.71	0.30	-0.13	-0.46
		(.14)	(.12)	(.07)	(.02)	(.01)	(.02)	(.06)	(.08)	(.09)
	n	0.60	0.69	0.66	0.48	0.18	-0.17	-0.48	-0.66	-0.69
		(.09)	(.07)	(.06)	(.05)	(.03)	(.03)	(.05)	(.07)	(.08)

*Numbers in the table are the means of 100 simulations (std. in parentheses).

5 Explaining other Features of the Business Cycle

This section addresses two potential concerns that may be raised regarding the model. First, in order for the model studied here to be a genuine model of the business cycle, it must also be able to explain other prominent features of the business cycle emphasized by the RBC literature, such as the positive comovements among consumption, output, employment, and investment; the smooth consumption path and volatile investment path relative to output; the hump-shaped impulse responses of output to demand shocks; the typical spectral shape of growth rates; and the forecastable comovements of changes in output, consumption, employment, and investment.

Second, in order to use consumption demand shocks to explain these features of the business cycle, one particular issue involved is how likely it is for individuals' preference shocks to be coordinated across the entire economy? Holiday seasons such as Christmas are good coordination devices, but presumably they have more to do with seasonal cycles than with the business cycle.[18] Another issue involved is how to measure such aggregate consumption shocks, if they exist?

5.1 Coordination

Here I show a simple way to generate aggregate consumption demand shocks by individual preference shocks. It is to resort to the well known social behavior of "keeping up with the Joneses" (e.g., see Abel 1990). When individuals judge the utility of their own consumption by comparing it to the consumption level of others, idiosyncratic changes in preferences can have aggregate consequences. Thus, an aggregate shift in consumption demand can be the result of a herd behavior of keeping up with the Joneses. To capture this herd behavior in consumption, I modify the representative agent's utility function of consumption to

$$\theta_t \log\left(c_t - \varkappa \tilde{c}_{t-1}\right),$$

where $\tilde{c}_{t-1}$ denotes the average consumption level of the economy in period $t-1$ which the individual observes and takes as parametric, and $\varkappa \in [0,1)$ measures the propensity for individuals to conform to social norm. Other than this modification on the utility function (to justify the concept of coordinated preferences shocks), everything else in the model remains the same.

This herd behavior of "keeping up with the Joneses" also has the effect of propagating the impact of θ_t on the economy intertemporally. It is well known that consumption shocks tend to have a crowding-out effect on private investment, generating counter-cyclical investment with respect to output. But it will be shown that as long as the effects of preferences shocks on consumption demand are persistent enough, either due to the shocks themselves being persistent or due to endogenous propagation mechanisms that render the effects of shocks persistent (such as "keep up with the Joneses"), then standard equilibrium models can predict positive comovements between investment and consumption, output,

[18] Wen (2002c) shows that seasonal shocks (e.g., due to uncertainty associated with Christmas demand) can trigger the business cycle. But here I pursue the question under the assumption that stochastic seasonal shocks do not exist.

and employment, as well as relatively smooth consumption and relatively volatile investment with respect to output.[19]

5.2 Calibration of Aggregate Preference Shocks

Like technology shocks, preference shocks are unobservable. The existing literature estimates technology shocks (the Solow residual) using specified production functions. In a similar spirit, Baxter and King (1991) and Stockman and Tesar (1995) estimate preference shocks using the model's first-order Euler conditions derived from specified utility functions.[20] Since preferences are time-nonseparable in my model, it is difficult to use the Euler equations in the model. Instead, I choose to use the University of Michigan Index for Consumer Sentiment as a proxy for representative consumer's preferences shifts. I estimate an AR(1) model for the Michigan Index and obtain the following result:

$$\log MI_t = 0.33(0.13) + 0.92(0.03)\log MI_{t-1} + v_t,$$

where MI denotes the log of the Michigan Index and the numbers in parentheses are standard errors. The estimated standard deviation of the residual is $\sigma_v^2 = 0.0685$.

Since only the US data will be used here and since the model without the information structure captures the US labor market dynamics better than the model with information structure, I choose to use the model without the information structure. Namely, employment decisions are made after the shocks are realized. Table 7 reports standard business-cycle statistics for two versions of the model, one with $\varkappa = 0$ (Model I) and another with $\varkappa = 0.95$ (Model II).[21] In model I the persistence parameter for preference shocks is set at $\rho_\theta = 0.99$ and in model II this parameter is set at the estimated value $\rho_\theta = 0.92$ according to the University of Michigan Index. The purpose of reporting both versions of the model is to show the effects of "keeping up with the Joneses". The adjustment cost parameter for both versions of the model is $\psi = 0.5$.[22]

Table 7 shows that both versions of the model predict employment and productivity dynamics very well, but with model II outperforming model I with

[19] This point has also been made recently by Wen (2002a, 2002b).

[20] Similarly, Burnside and Eichenbaum (1996) deduce capacity utilization rate using the model's first-order conditions relating capacity utilization to the output-capital ratio.

[21] There are few empirical estimates on $\varkappa$ available. Since its effect is similar to habit formation, I adopt the estimates of habit formation parameter from Constantinides (1990) here.

[22] Both the data time series and the model generated time series are filtered by the Band-Pass filter with truncation window size equal to 8 and the frequency band equal to 6-40 quarters per cycle.

regard to consumption and investment dynamics. While model I (without the dynamic effect of "keeping up with the Joneses") is fully capable of explaining the observed positive comovements and high serial correlations for consumption and investment, it over-predicts the volatility of consumption relative to output and under-predict the volatility of investment relative to output. In the US data, consumption is about 30% less volatile than output and investment is about 3 times more volatile than output. Model I predicts consumption to be equally volatile to output and investment to be only 1.7 times more volatile than output. Model II can predict these relative volatility ratios almost exactly. Model II also improves the predictions of model I along other dimensions. For example, in the US data the contemporaneous correlation with output is 0.93 for investment 0.87 for consumption. Model I predicts this correlation to be 0.65 for investment and 0.94 for consumption, whereas model II predicts this correlation to be 0.90 for investment and 0.84 for consumption. This is a significant improvement.

Table 7. Predicted Business-Cycle Statistics (Demand)

	x	σ_x/σ_y	$cor(x_t, y_t)$	$cor(x_t, x_{t-1})$
Data	y	–	–	0.90
(60:1 - 94:4)	c	0.77	0.87	0.91
	i	3.10	0.93	0.91
	n	0.76	0.86	0.91
	$y-n$	0.53	0.66	0.83
Model I	y	–	–	0.90 (.02)
($\varkappa = 0$)	c	1.03 (.04)	0.94 (.00)	0.87 (.02)
($\rho_\theta = 0.99$)	i	1.71 (.09)	0.65 (.05)	0.93 (.02)
	n	0.74 (.04)	0.81 (.02)	0.93 (.02)
	$y-n$	0.59 (.03)	0.68 (.05)	0.86 (.02)
Model II	y	–	–	0.90 (.02)
($\varkappa = .95$)	c	0.65 (.03)	0.84 (.02)	0.94 (.02)
($\rho_\theta = 0.92$)	i	3.04 (.12)	0.90 (.01)	0.88 (.02)
	n	0.76 (.03)	0.84 (.02)	0.94 (.02)
	$y-n$	0.54 (.03)	0.66 (.04)	0.87 (.02)

*Numbers in the middle and lower panels are the means of 100 simulations (std. in parentheses).

If technology shocks are assumed to be the primary force of the business cycle, then the predictions of the model are worsened along a number of dimensions, especially with respect to employment volatility. Table 8 reports predicted statistics for 5 different versions of the model under technology shocks with respect to different values of 3 key parameters of the model, including the persistence of technology shocks ρ_a, the size of adjustment costs ψ, and the effect of "keeping up with the Joneses". The first version (Model a) corresponds to $\{\varkappa = 0, \rho_a = 0.9, \psi = 0.5\}$, the second version (model b) corresponds to $\{\varkappa = 0.95, \rho_a = 0.9, \psi = 0.5\}$, the third and fourth versions (Models c and d) correspond to random-walk technology shocks$\{\varkappa = 0,\ \rho_a = 1.0,\ \psi = 0.5\}$ and $\{\varkappa = 095,\ \rho_a = 1.0,\ \psi = 0.5\}$, and the last version corresponds to the case without adjustment costs $\{\text{b}\varkappa = 0, \rho_a = 1.0, \psi = 0.0\}$.

Table 8. Predicted Business-Cycle Statistics (Technology)

	x	σ_x/σ_y	$cor(x_t, y_t)$	$cor(x_t, x_{t-1})$
Model a	y	1.00	1.00	87 (.02)
($\varkappa = 0$)	c	0.14 (.00)	0.92 (.02)	89 (.02)
($\rho_a = 0.9$)	i	4.20 (.00)	1.00 (.00)	87 (.02)
($\psi = 0.5$)	n	0.28 (.02)	0.72 (.03)	92 (.02)
	$y - n$	0.82 (.02)	0.97 (.00)	86 (.02)
Model b	y	1.00	1.00	0.87 (.02)
($\varkappa = 0.95$)	c	0.03 (.01)	-0.04 (.04)	0.96 (.02)
($\rho_a = 0.9$)	i	4.71 (.01)	1.00 (.00)	0.87 (.02)
($\psi = 0.5$)	n	0.26 (.02)	0.73 (.02)	0.92 (.02)
	$y - n$	0.83 (.02)	0.98 (.00)	0.86 (.02)
Model c	y	1.00	1.00	87 (.02)
($\varkappa = 0$)	c	0.63 (.00)	1.00 (.00)	87 (.02)
($\rho_a = 1.0$)	i	2.42 (.02)	1.00 (.00)	88 (.02)
($\psi = 0.5$)	n	0.18 (.01)	0.68 (.03)	93 (.02)
	$y - n$	0.89 (.01)	0.99 (.00)	86 (.02)
Model d	y	1.00	1.00	87 (.02)
($\varkappa = 0.95$)	c	0.19 (.02)	0.26 (.03)	94 (.02)
($\rho_a = 1.0$)	i	4.49 (.02)	0.99 (.00)	87 (.02)
($\psi = 0.5$)	n	0.19 (.01)	-0.50 (.02)	93 (.02)
	$y - n$	1.11 (.01)	0.99 (.00)	87 (.02)
Model e	y	1.00	1.00	0.87 (.02)
($\varkappa = 0$)	c	0.50 (.00)	0.99 (.00)	0.87 (.02)
($\rho_a = 1.0$)	i	2.94 (.01)	1.00 (.00)	0.87 (.02)
($\psi = 0$)	n	0.51 (.00)	0.99 (.00)	0.87 (.02)
	$y - n$	0.50 (.00)	0.99 (.00)	0.87 (.02)

*Numbers in the table are the means of 100 simulations (std. in parentheses).

Several important implications of technology shocks are revealed in Table 8. First, consumption is simply too smooth relative to output under the effect of "keeping up with the Joneses" (model b). This holds even under permanent technology shocks (model d). Second, models with permanent technology shocks perform better than models with stationary technology shocks, especially with respect to consumption volatility and investment volatility. With or without the "keeping up with the Joneses" effect, transitory technology shocks tend to generate a consumption series that is too smooth relative to output and an investment series that is too volatile relative to output.

Third, all 5 versions of the model substantially underestimate employment volatility relative to output. In the US data, the ratio of standard deviations between employment and output is 0.76. The predicted ratios, however are far below the data, ranging from 0.18 to 0.26 for the first 4 models with adjustment costs. The model without adjustment costs (model e) performs the best in this regard, with the predicted ratio to be 0.51.[23] However, even this predicted ratio lies significantly below the US data. This holds despite the assumption of indivisible labor, which can substantially increase employment volatility (Hansen 1985). Notice that without the adjustment costs (model e), it is then impossible for the model to explain the lead-lag relationships among output, employment and productivity as explained previously. On the other hand, the predictions of technology shocks on employment dynamics deteriorate significantly if employment adjustment costs are included (see model c).

Fourth, although model e seems to perform the best on almost all accounts, it is clearly dominated by the demand-shock driven model (model II in table 7) in terms of overall performance in explaining the US business cycle. Thus, even without considering why productivity is procyclical during periods of demand shocks in the US history, this analysis alone would suggest that technology shocks are less attractive than demand shocks as a possible explanation for the business cycle, especially with regard to labor market fluctuations in general and the three aspects of procyclical productivity in particular.

The intuition that consumption shocks can explain some of the most prominent features of the business cycle (which are traditionally explained only by technology shocks in general equilibrium) is simple. With standard time-separable preferences, although transitory changes in consumption demand tend to have a strong crowding-out effect on investment (which results in negative movement

[23]This predicted ratio is further decreased if employment decision must be made in advance, hence incapable of responding to current shocks.

in investment), persistent shocks to consumption demand can nevertheless result in positive changes in investment. This is because the only way to sustain a persistent increase in consumption demand in a representative-agent model is to build up future capital stock by investing more today. This not only renders investment positively correlated with consumption but also reinforces the initial increase in aggregate demand, giving rise to a multiplier effect on output and resulting in higher utilization rate of capital and labor. Consequently, standard equilibrium theory predicts that domestic consumption, investment, output and employment are positively correlated under persistent consumption demand shocks. The social behavior of "keeping up with the Joneses" has the effect of enhancing the persistence of individual preference shocks (similar to habit formation), reinforcing these dynamic effects and resulting in smoother aggregate consumption and more volatile aggregate investment.

6 Robustness

Labor productivity, no matter how it is measured and where it is measured or at what aggregate level it is measured, is procyclical. This raises a question as to whether consumption demand shocks can explain procyclical productivity for firms that produce only intermediate goods and hence are not directly subject to consumption demand shocks, as well as for firms that may have diminishing returns to scale.[24] This section addresses this problem.

Using a multi-sector version of the above model with intermediate goods producing firms, this section shows that even under diminishing returns to scale, factor hoarding is capable of generating procyclical productivity for all production sectors under sector-specific consumption demand shocks alone, regardless location of firms in the chain of production.

The Model: The model is a modified version of the multi-sector model of Long and Plosser (1983). In this model economy there are many identical households, each consisting of $j > 1$ workers working for j different industries. Assuming that labor supply is indivisible and that all workers are alike ex anti, a representative household in this model chooses sequences of household consumption (c), probability to work (n_j) for each worker j, effort to work (e_j) for worker j, and the amount of intermediate goods (x_{ij}) that are produced by industry j but are

[24]According to Basu and Fernald (1997), the estimated returns to scale are less than one for many manufacturing nondurable goods industries.

to be used as inputs for industry i to solve

$$\max_{\{c_t, e_{jt}, n_{jt}, x_{ijt}\}} E_t \left\{ \sum_{t=0}^{\infty} \beta^t \left[\theta_t \log c_t + \tau \sum_{j=1}^{M} [n_{jt} \log (T - \xi - e_{jt} f) + (1 - n_{jt}) \log T] \right] \right\}$$

subject to

$$c_j + \sum_{i=1}^{M} x_{ijt} \leq (e_{jt} n_{jt})^{b_j} \prod_{i=1}^{M} x_{jit-1}^{a_{ji}} - \frac{\psi_j}{2} (n_{jt} - n_{jt-1})^2 k_{jt},$$

for $j = 1, 2, ..., M$; where $b_j + \sum_i a_{ji} \leq 1$ measures returns to scale for industry j, and $k_{jt} \equiv 10 (e_{jt} n_{jt})^{b_j} \prod_{i=1}^{M} x_{jit-1}^{a_{ji}}$ is a way to normalize the adjustment costs of labor for industry j. All sectors are subject to employment adjustment costs with $\psi_j \geq 0$. As in Long and Plosser (1983), I assume that there are no durable capital goods in the model. Hence the effort level in each industry is the only source for factor hoarding.

Calibration: To simplify the analysis without loss of generality, I assume $c_j = 0$ for $j \neq 1$ and $M = 2$, so the source of uncertainty for industry 1 is consumption demand and that for industry 2 is demand for intermediate goods from industry 1. The time period is a quarter, the time discounting factor $\beta = 0.99$, the persistence of preference shocks $\rho_\theta = 0.9$, labor's share in each industry $b_j \leq 1 - \sum_i a_{ji}$ $(i, j = 1, 2)$, where the share parameters of intermediate goods $a_{ii} = 0.4$ and $a_{ij} = 0.1$ $(j \neq i)$. These input-output coefficients (a_{ij}) are consistent with the input-output patterns of the US economy where most output produced in an industry is used as input in that industry, hence the diagonal elements a_{ii} is larger than the off diagonal elements a_{ij} $(j \neq i)$ in the input-output table (e.g., see Long and Plosser 1983). Note that industry j has decreasing returns to scale if $b_j + \sum_i a_{ji} < 1$. The adjustment cost parameter in each sector is assumed to be $\psi_1 = \psi_2 = 1$, implying that about 0.8% sectorial output is lost each year due to the adjustment costs (assuming 4% annual employment growth rate).

Predictions: Figure 3 shows the impulse responses of output, employment and productivity in both production sectors to a one standard deviation shock to θ_t. Several prominent features of figure 1 are worth noticing. First, all variables in the two sectors are strongly synchronized. In particular, output, employment, and productivity in the first sector strongly comove with their counter parts in the second sector, despite the fact that the preference shock has only a direct impact on goods demand in sector 1. Second, productivity in each sector is procyclical with respect to that sector's output and these sectorial productivity comove with aggregate output. Third, productivity leads output and employment in each sector. These predictions are consistent with stylized empirical facts (e.g., see Sbordone 1996).

These results are robust to returns to scale. For example, even when $b_j + \sum_i a_{ij} = 0.7$ for $j = 1, 2$, productivity remains procyclical in both sectors as long as ψ is large enough.[25] These results are summarized in table 9 where model 1 has constant returns to scale in both sectors and models 2 and 3 have decreasing returns to scale in both sectors. It is assumed that all three models have $a_{ii} = 0.4, a_{ij} = 0.1$ $(i \neq j)$, but model 1 has $b_1 = b_2 = 0.5$, model 1 has $b_1 = b_2 = 0.4$, and model 3 has $b_1 = b_2 = 0.2$. Also, model 1 and model 2 have $\psi = 0.25$, and model 3 has $\psi = 0.5$. It is seen from table 9 that productivity, no matter how it is measured, is procyclical. Namely, regardless of location in the production chain and returns to scale, the variance of output exceeds the variance of employment and the correlation between productivity and output is positive in each sector. Since productivity is also positively correlated with employment in each sector for model 1 and model 2, the estimated beta coefficient exceeds one and labor's share (which is 0.5 for sector 1 and 0.4 for sector 2). In model 3, however, the estimated beta coefficient is less than one because the higher adjustment cost ($\psi = 0.5$) induces a larger lag in employment, resulting in negative correlations between productivity and employment.[26]

[25] Computations shows that when returns to scale is 0.7, then $\psi = 0.5$ is large enough to lead to procyclical productivity. The returns to scale can be lowered even further below 0.7 in each sector yet productivity remains procyclical as long as ψ is large enough.

[26] If the adjustment cost (ψ) is substantially large for a particular sector, then employment can become negatively correlated with productivity due to the large lag of employment behind output, rendering the estimated beta coefficient less than one. This, however, does not change the fact that productivity is procyclical. This point is discussed in section 2.

Table 9. Predicted Second Moments for 2-Sector Model*

	σ_y/σ_n	$corr(y,n)$	$corr(p,y)$	$corr(p,n)$	$\hat{\beta}$
		Model 1 (returns to scale = 1.0, $\psi = 0.25$)			
Sector 1	1.83	0.81	0.86	0.40	1.47
	(.08)	(.01)	(.02)	(.02)	(.05)
Sector 2	1.77	0.82	0.86	0.40	1.45
	(.08)	(.01)	(.02)	(.02)	(.05)
		Model 2 (returns to scale = 0.9, $\psi = 0.25$)			
Sector 1	1.59	0.77	0.79	0.21	1.22
	(.09)	(.01)	(.03)	(.04)	(.05)
Sector 2	1.51	0.78	0.76	0.18	1.18
	(.08)	(.01)	(.04)	(.03)	(.05)
		Model 3 (returns to scale = 0.7, $\psi = 0.5$)			
Sector 1	1.50	0.55	0.74	-0.14	0.82
	(.12)	(.01)	(.04)	(.05)	(.06)
Sector 2	1.24	0.56	0.63	-0.30	0.69
	(.10)	(.01)	(.06)	(.06)	(.05)

*Numbers in the table are the means of 100 simulations (std. in parentheses).

7 Conclusion

A major challenge to the theory that consumption demand shocks constitute the primary source of the business cycle is to explain why productivity is procyclical. Assuming constant returns to scale, demand shocks tend to generate counter-cyclical productivity in standard models due to diminishing marginal product of labor. Many possible explanations have been proposed to explain this long-standing productivity puzzle, including factor hoarding (labor hoarding and/or capital utilization), increasing returns to scale, and technology shocks, among others. The technology-shock story is not appealing because productivity remains procyclical even during periods of demand shocks (such as World-War II and Christmas season). The increasing-returns story is not appealing either because productivity is procyclical virtually everywhere, even in industries that may have decreasing returns to scale. This paper shows that factor hoarding due to employment adjustment costs is a powerful force for generating procyclical productivity and is sufficient for explaining the wide range of observed procyclical productivity across different industries and countries without the need to resort to technology shocks and increasing returns to scale. The analysis suggests that demand shocks, especially consumption demand shocks, should be taken seriously by equilibrium business cycle theory that has so far relied too heavily on technology shocks to understand the business cycle.

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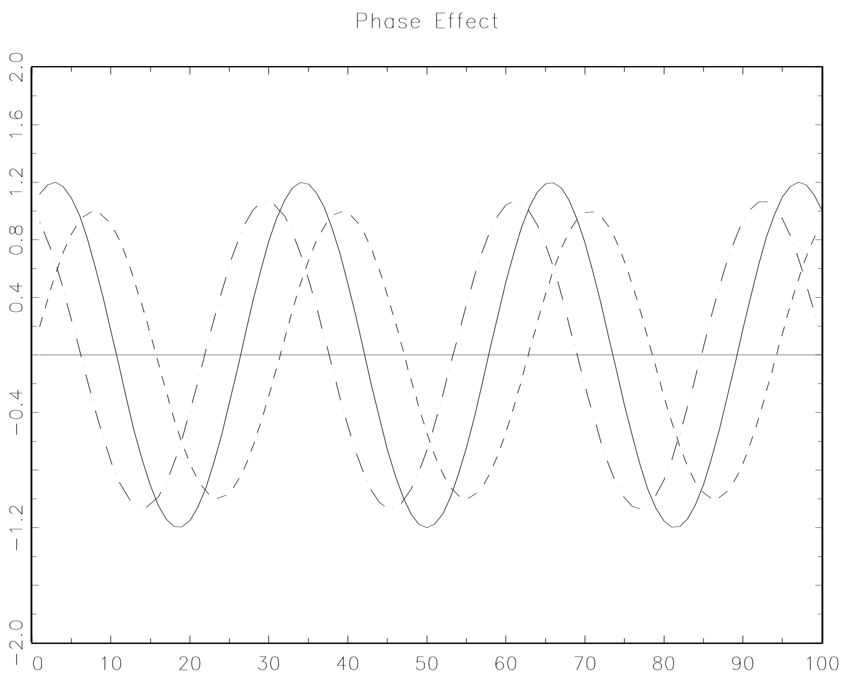

Figure 1: Lead-Lag Relations Among Output (——), Employment (- - -), And Productivity (— · —).

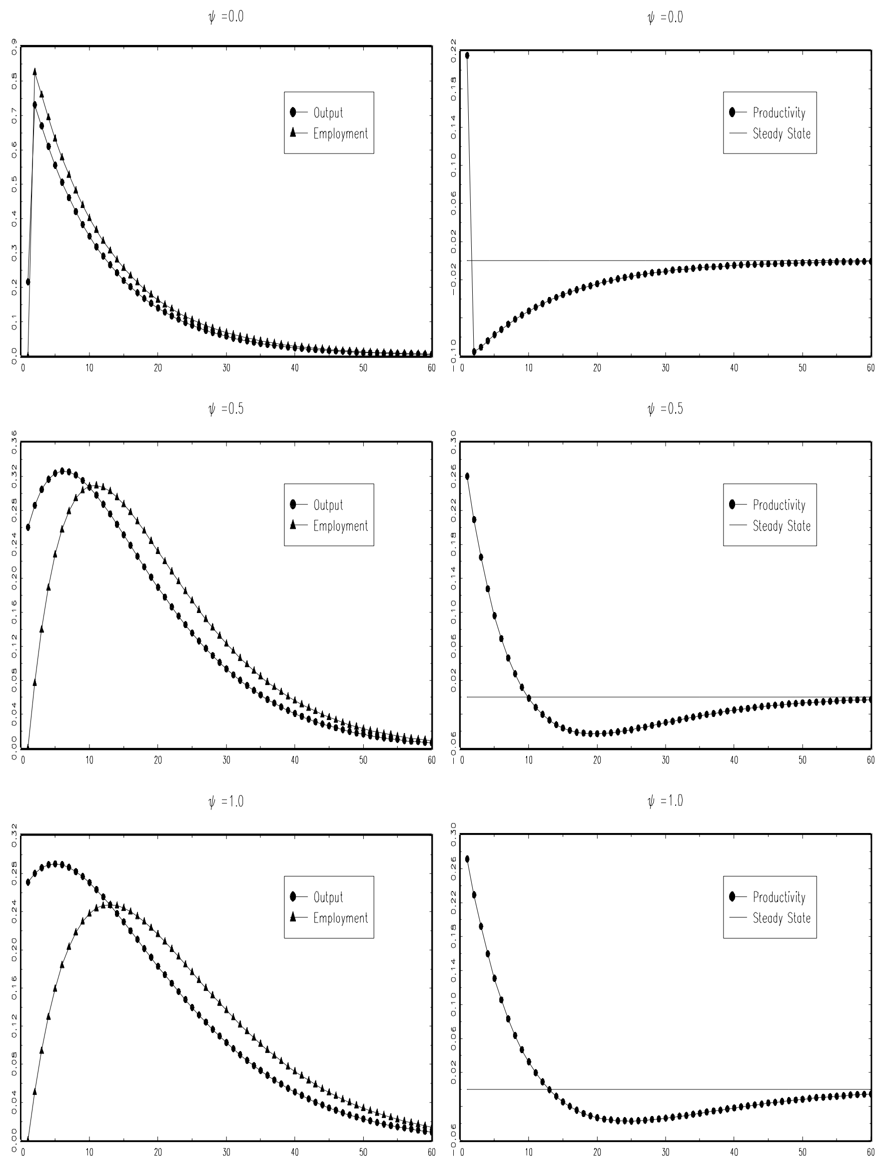

Figure 2: Impulse Responses to a Preference Shock.

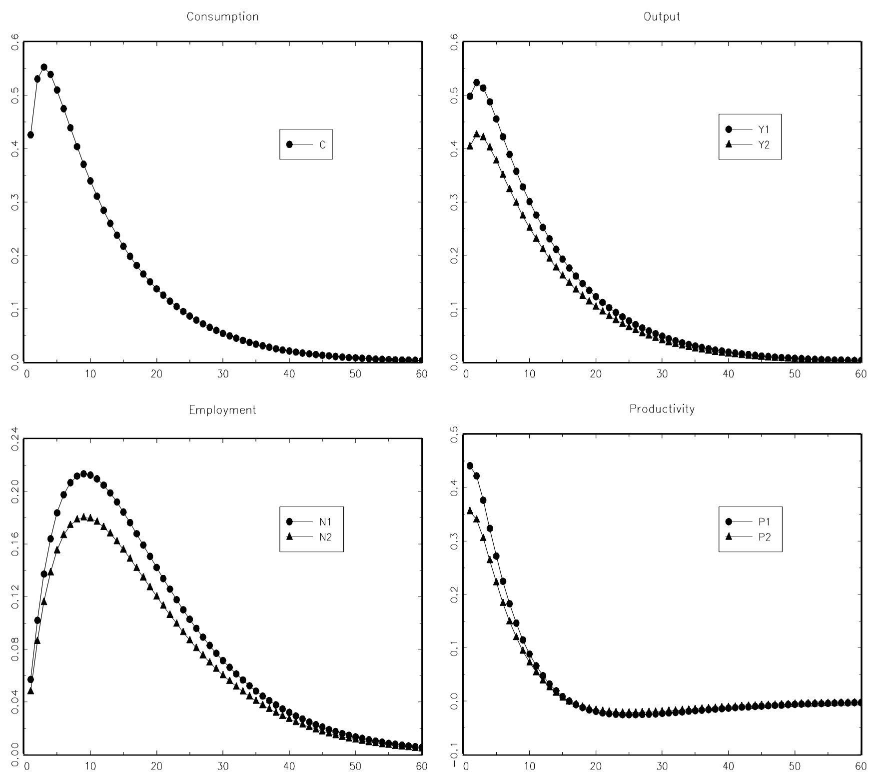

Figure 3: Impulse Responses to Demand Shock to Sector 1.