Effects of Introducing Five-Day Work Week in Korean Labor Market: A Semiparametric Vector Error Correction Approach

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Abstract

This paper uses the semiparametric error correction model (Li and Wooldridge, 2002) and investigates the dynamics of wage, employment and labor efficiency after introducing five-day work week to the Korean labor market. Efficient working hour function is obtained by nonparametric method (polynomial approximation) and the dynamics are investigated using impulse response analysis. Average derivative estimator is used to derive the impulse response function of the semiparametric error correction model. The results show that reducing working hours would not create new employment and thus it, as a labor policy, could not be a solution for unemployment. On the other hand, cutting working hours boosts labor efficiency so sharply that the efficient labor input increases. It is also shown that the Korean labor market is flexible enough to adjust the shock within a year.

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JEL Classification: C14, C32, E24, E27

1 Introduction

Introducing five-day work week is currently one of the hottest political issues concerning the Korean labor market. The proponents of the reform argue that the current working hour level in Korea is too high in comparison to other countries (see <Table 1>), and thus, reducing total working hours by regulating the standard working hours will lead to the better life quality and higher productivity for employees. Furthermore, in light of the positive effects of the past labor policies in Korea, cutting labor hours may alleviate the unemployment problem by creating new job opportunities.

Much literature has been devoted to studying the effects of reducing working hours; however, the effects and the directions of employment, wage and labor efficiency vary across model specifications or data. There is not even a consensus as to whether working hours and employments are substitutes or complements in production. For the detailed discussion, refer to Calmfors and Hoel (1988), Hamermesh (1993) and Hart and Moutos (1995) among others. Brunello (1989) also supplies a good summery of these arguments.

This study investigates the dynamics after introducing five-day work week in the Korean labor market. This new labor policy is interpreted as reducing working hours. The result shows that the Korean labor market is flexible enough to adjust the shock within a year. Moreover, cutting labor hour increases efficient labor input and real wage per hour, but decreases employment. This finding is contrary to the conventional economic wisdom that reducing labor hour creates new employment, i.e., the work sharing.

This study offers new perspectives in three major ways. In economic theory, we try to find the efficient working hour function, and consider the efficient labor in the labor demand to investigate relationship among labor hour, wage and employment. In econometric theory, we employ the semiparametric error correction model in Li and Wooldridge (2002) for more flexible dynamic specification. Whereas conventional analyses limit the error correction term to be adjusted linearly only, we allow it to be adjusted nonparametrically to the dynamics. Moreover, the impact of reducing working hours is studied though impulse response analysis. To derive the impulse response function of semiparametric error correction model, we adopt average derivative estimator in Härdel and Stocker (1989) and in Powell et al. (1989). Concerning the Korean economic policy, we compare the impact of this new labor policy with the effect of the old policies. The major difference is found on the dynamics of employment, which predicts that employment will shrink. We also look at the adjustment speed of the Korean labor market.

This paper is organized as follows. Section 2 describes the underlying economics model and econometric machineries used in this study. It starts with deriving a partial labor demand function to find the long-run relationship among wage, employment, working hours and approximating the unknown efficient working hour function. Then it introduces semiparametric error correction model and its impulse response function. Section 3 provides the empirical results, and Section 4 concludes our study.

Table 1: Yearly working hours of OECD countries in 1999

Australia	1,864	Iceland	1,873	Norway	1,395
Canada	1,785	Italy	1,625	Spain	1,827
Czech	2,088	Japan	1,810	Sweden	1,634
Finland	1,765	Korea	2,497	Switzerland	1,597
France	1,596	Mexico	1,921	U.K.	1,720
Germany	1,496	New Zealand	1,842	U.S.	1,846

Source: OECD, Employment Outlook, 2000 (Including part time works)

2 The Model

2.1 Economic model and efficient working hours

In order to evaluate the implications of five-day work week policy, we first lay out a simple model in which the firm chooses both the working hours of its own workers and the number of workers. We assume that the homogeneous labor input L is a function of the number of workers N and the average (nominal) working hours per worker H. In general,

$$L = L(N, H) = NG(H),$$

where the unknown function $G : \mathbf{R}_+^1 \to \mathbf{R}_+^1$ represents effective or efficient average working hours per worker. It is following that $G(H)/H$ represents the labor efficiency rate per working hour and per worker. We assume that the efficient working hour function $G(\cdot)$ is continuous in H and nonnegative with $G(0) = 0$. Moreover, it increases up to some optimal working hour point H^* but decreases after H^*. This assumption can be justified by the fact that accumulated fatigue of workers lowers productivity or labor efficiency, and once the marginal productivity per hour becomes negative, efficient working hour correspondingly decreases. Such a specification is well established in the standard labor demand theory, e.g., Hamermesh (1993) or Hart and Moutos (1995).

We consider a more general Cobb-Douglas type production function given by[1]

$$Q = F\left(\bar{K}, L\right) = Af\left(\bar{K}\right) N^{\theta} G\left(H\right) = AN^{\theta} G\left(H\right), \tag{1}$$

where Q is real output and A and θ are parameters such that $\theta > 0$ and $A > 0$. For the sake of simplicity, we consider a short-run model and let the capital input fixed, $\bar{K}$. We further normalize $f\left(\bar{K}\right)$ as one since both A and $f\left(\bar{K}\right)$ cannot be identified from each other. We thus only consider labor input in this model without imposing any assumption on the returns to scale in labor productivity. Each firm faces the optimization problem

$$\max_{N,H} \pi = Q - WNH \tag{2}$$

$$\text{such that } 0 < H < \overline{H} \;\text{ and }\; N > 0,$$

which maximizes the short-run profit π, where W is per-hour real wage and $\overline{H}$ is the physical upper bound of working hours. The necessary conditions for an interior solution to this problem are

$$\theta AN^{\theta-1} G\left(H\right) = WH, \tag{3}$$

$$AN^{\theta} \dot{G}\left(H\right) = WN, \tag{4}$$

where $\dot{G} = dG/dH$. Therefore, the long-run steady state is described by

$$\log W + \log H = \log \theta A + (\theta - 1) \log N + \log G\left(H\right) \tag{5}$$

after taking log on equation (3). Notice that if all of the variables, $\log W_t$, $\log N_t$ and $\log H_t$, are integrated (i.e., unit-root) processes for $t = 1, \cdots, T$, equation (5) can be interpreted as a nonlinear cointegrating equation. To make it estimable, however, we need further specifications.

We first approximate the unknown function $G\left(H\right)$ with polynomials as

$$G\left(H\right) \approx \exp\left(\sum_{j=0}^{p} \gamma_j \left(\log H\right)^j\right).$$

As $p \to \infty$, it is assumed that $\exp\left(\sum_{j=0}^{p} \gamma_j \left(\log H\right)^j\right) \to G\left(H\right)$ for each H. Moreover, we allow A to be time-varying and let it capture the deterministic trend in the cointegrating equation (5). More precisely, we assume

$$\log A_t = \delta_0 + \delta_1 t$$

and if there presents a structural break at $t = \tau$ in the deterministic trend, we can alternatively assume

$$\log A_t = \begin{cases} \delta_{01} + \delta_{11} t & \text{if } t \leq \tau; \\ \delta_{02} + \delta_{12} t & \text{if } t > \tau. \end{cases}$$

Then, the equation (5) becomes

$$\log W_t = \log A_t + \gamma_0 + \log \theta + (\theta - 1) \log N_t + (\gamma_1 - 1) \log H_t + \sum_{j=2}^{p} \gamma_j \left(\log H_t\right)^j \tag{6}$$

[1] If θ is the labor share, we can redefine $G\left(\cdot\right)$ as $G\left(\cdot\right)^{\theta}$ without loss of generality. This is because $G\left(\cdot\right)$ is an unknown function and it can be rescaled freely.

for $t = 1, \cdots, T$. Notice that γ_0 and the constant term in $\log A_t$ cannot be identified and need some normalization restriction. We thus assume that $\delta_0 = 0$ and $\delta_{01} = 0$.

Equation (6) represents the long-run equilibrium in labor demand, which can be interpreted as a nonlinear cointegrating relation among $(\log W_t, \log N_t, \log H_t)$ when all three variables are unit-root processes. Regular working hours are regarded to be exogenously determined by law or labor negotiation, whereas total working hours H and employment N are decided by the profit maximization of each firm. Notice that equation (6) is not a wage equation but just represents the long-run equilibrium among the integrated processes $(\log W_t, \log N_t, \log H_t)$. Therefore, we do not need to consider any endogeneity or selection issues here.

Once we estimate the cointegrating regression model (6), we obtain the efficient working hour estimate as

$$\widehat{G}(H) = \exp\left(\sum_{j=0}^{p} \hat{\gamma}_j (\log H)^j\right).$$

For the notational simplicity, we denote $w = \log W$, $n = \log N$, $h = \log H$ and $g = \log \widehat{G}(H)$ throughout the paper.[2]

We can consider a more general model. Notice that total working hours H consists of regular working hours H_r and overtime hours H_o. Similarly, total per-hour wage W is a sum of regular per-hour wage W_r, overtime per-hour wage W_o and special wage W_s such as bonus. More precisely, we assume

$$\begin{aligned} H &= H_r + H_o, \\ W &= W_r + W_o + W_s, \end{aligned} \tag{7}$$

and

$$\begin{aligned} G(H) &= G(H_r, H_o) = G_r(H_r) + G_o(H_o), \\ WH &= W_r H_r + W_o H_o + W_s. \end{aligned} \tag{8}$$

We still impose the homogeneous labor but we allow different working hour efficiency functions $G_r : \mathbf{R}^1_+ \to \mathbf{R}^1_+$ and $G_o : \mathbf{R}^1_+ \to \mathbf{R}^1_+$. The production function thus can be rewritten as

$$Q = AN^{\theta}(G_r(H_r) + G_o(H_o))$$

and the profit maximization problem becomes

$$\max_{N, H_r, H_o} Q - (W_r H_r + W_o H_o + W_s) N.$$

[2] In this study, we ignore the errors in variable problem with g. In fact, it is not a harmful simplification when we are considering a cointegrating regression since cointegrating regression estimators are super-consistent, i.e., T-consistent. We can verify it by looking at the following example. For a cointegrating regression $y_t = x_t\beta + u_t$, where $x_t = x_{t-1} + v_t$, we observe $x_t^* = x_t + \varepsilon_t$ instead of the true process x_t. To simplify the argument, we assume u_t, v_t and ε_t are mutually independent stationary process satisfying $T^{-1/2}\sum_{t=1}^{[Tr]} u_t \to_d B_u(r)$, $T^{-1/2}\sum_{t=1}^{[Tr]} v_t \to_d B_v(r)$ and $T^{-1/2}\sum_{t=1}^{[Tr]} \varepsilon_t \to_d B_\varepsilon(r)$, where B_u, B_v and B_ε are Brownian motions. If we further assume that x_t and ε_t are independent, then

$$\hat{\beta} - \beta = \frac{\sum x_t^* y_t - \sum (x_t^*)^2 \beta}{\sum (x_t^*)^2} = \frac{\sum (x_t + \varepsilon_t)(u_t - \varepsilon_t \beta)}{\sum (x_t + \varepsilon_t)^2} = \frac{\sum x_t u_t + \sum \varepsilon_t u_t - \sum x_t \varepsilon_t \beta - \sum \varepsilon_t^2 \beta}{\sum x_t^2 + 2\sum x_t \varepsilon_t + \sum \varepsilon_t^2},$$

so $\hat{\beta} - \beta = O_p(T^{-1})$ since $n^{-1}\sum x_t u_t \to_d \int_0^1 B_v dB_u$, $n^{-1}\sum x_t \varepsilon_t \to_d \int_0^1 B_v dB_\varepsilon$, $n^{-2}\sum x_t^2 \to_d \int_0^1 B_v^2$, $n^{-1}\sum \varepsilon_t u_t \to_p \mathbf{E}\varepsilon_t u_t = 0$ and $n^{-1}\sum \varepsilon_t^2 \to_p \mathbf{E}\varepsilon_t^2 = \sigma^2$. $\to_p$ and $\to_d$ denote convergence in probability and convergence in distribution respectively. Therefore, it is still consistent even when the asymptotic distribution is biased. For the technical details, refer Phillips and Durlauf (1986).

Therefore, from the following first order conditions

$$\begin{aligned}\theta A N^{\theta-1} G(H) &= WH, \\ A N^{\theta} \dot{G}_r(H_r) &= W_r N, \\ A N^{\theta} \dot{G}_o(H_o) &= W_o N,\end{aligned}$$

we have the long-run relationship given by

$$\log W_t + \log H_t = \log \theta A_t + (\theta - 1) \log N_t + \log \left(G_r(H_{rt}) + G_o(H_{ot}) \right)$$

which is identical with (5) if we apply the conditions (7) and (8).

2.2 Semiparametric error correction models

After we obtain an estimate of the unknown function $G(\cdot)$, we can define a 4-dimensional vector $I(1)$ process $y_t = (h_t, g_t, n_t, w_t)'$, i.e., Δy_t is a stationary vector process. We consider an error correction model given by

$$\Delta y_{it} = m_i(v_{t-1}) + \sum_{s=1}^{k} \rho_{is}' \Delta y_{t-s} + u_{it} \quad \text{for } i = 1, \cdots, 4, \tag{9}$$

where $m_i : \mathbf{R}^1 \to \mathbf{R}^1$ is an unknown function for each i, ρ_{it} is a 4×1 coefficient vector, and $u_t = (u_{1t}, \cdots, u_{4t})'$ is a stationary vector process with zero mean and positive definite variance Σ_u. v_{t-1} is determined in the cointegrating regression given by

$$h_t = \beta_{0t} + \beta_1 g_t + \beta_2 n_t + \beta_3 w_t + v_t, \tag{10}$$

where β_{0t} is a deterministic trend. If m_i is given by a linear function such as

$$m_i(v) = \varphi_i v \quad \text{for } i = 1, \cdots, 4,$$

where φ_i is a scalar parameter, then equation (9) is a conventional error correction model with one cointegrating relation (10). However, we allow more general error correction mechanism by letting $m_i(\cdot)$ be any nonlinear function.

To estimate the semiparametric error correction model (9), we adopt the semiparametric estimation procedure of Robinson (1988). Notice that our model is somewhat different from the Robinson's assumption since the variable v_{t-1} in the unknown function m_i is unobservable and thus needs to be estimated *a priori*. The estimation procedure, however, is identical if we have an estimate of v_{t-1}. The details are discussed in Li and Wooldridge (2002). We begin estimating (9) by observing

$$\mathbf{E}(\Delta y_{it} | v_{t-1}) = m_i(v_{t-1}) + \sum_{s=1}^{k} \rho_{is}' \mathbf{E}(\Delta y_{t-s} | v_{t-1}) \tag{11}$$

for each i, and we have

$$\Delta y_{it} - \mathbf{E}(\Delta y_{it} | v_{t-1}) = \sum_{s=1}^{k} \rho_{is}' \left[\Delta y_{t-s} - \mathbf{E}(\Delta y_{t-s} | v_{t-1}) \right] + u_{it} \tag{12}$$

by subtracting (11) from (9). Following Robinson (1988), the conditional expectations are first estimated by the leave-out kernel estimators with v_{t-1} replaced by $\hat{v}_{t-1}$ which is defined as

$$\hat{v}_t = h_t - \hat{\beta}_{0t} + \hat{\beta}_1 g_t + \hat{\beta}_2 n_t + \hat{\beta}_3 w_t$$

from equation (10). More precisely, for each $i = 1, \cdots, 4$ and for all $t = 1, \cdots, T$, we estimate

$$\hat{\mathbf{E}}\left(\Delta y_{it}|\hat{v}_{t-1}\right) = \frac{\sum_{j\neq t} K\left(\frac{\hat{v}_{t-1}-\hat{v}_{j-1}}{b_T}\right)\Delta y_{is}}{\sum_{j\neq s} K\left(\frac{\hat{v}_{t-1}-\hat{v}_{j-1}}{b_T}\right)} \mathbf{1}\left\{\frac{1}{nb_T}\sum_{j\neq s} K\left(\frac{\hat{v}_{t-1}-\hat{v}_{j-1}}{b_T}\right) > c\right\},$$

for some constant $c > 0$ with $c \to 0$ as $n \to \infty$, which prevents the denominator from being too small. Note that b_T is a bandwidth parameter and $K(\cdot)$ is a 4-dimensional kernel function. We consequently define

$$\hat{\mathbf{E}}\left(\Delta y_{t-s}|\hat{v}_{t-1}\right) = \left[\hat{\mathbf{E}}\left(\Delta y_{1,t-s}|\hat{v}_{t-1}\right), \cdots, \hat{\mathbf{E}}\left(\Delta y_{4,t-s}|\hat{v}_{t-1}\right)\right]'$$

for each $s = 1, \cdots, k$. Then, (ρ_{is}) are estimated by least squares regression on equation (12) if we replace the conditional expectations with the above kernel estimators. Note that Li and Wooldridge (2002) prove that $(\hat{\rho}_{is})$ are $\sqrt{T}$-consistent and asymptotically normal under proper conditions. Finally, we can estimate m_i from equation (11), *viz.*,

$$\hat{m}_i\left(\hat{v}_{t-1}\right) = \hat{\mathbf{E}}\left(\Delta y_{it}|\hat{v}_{t-1}\right) - \sum_{s=1}^{k} \hat{\rho}'_{is}\hat{\mathbf{E}}\left(\Delta y_{t-s}|\hat{v}_{t-1}\right).$$

2.3 Impulse response functions

Once we obtain the error correction representation (9), we can investigate the responses of each process from an exogenous shock. Conventionally, the impulse response analysis of nonstationary system is conducted without considering cointegrating relationship. For example, the impulse response function is obtained from the level vector autoregressive (VAR) model or the first-differenced VAR model. However, Park (1990) indicates that using the level VAR model leads to the erroneous conclusion that all the shocks have only transitory effects. On the other hand, using the first-differenced VAR leads to the conclusion that all the shocks have permanent effects. In this study, we look at how to derive the impulse response function in the presence of cointegration in a system, i.e., for an error correction model. More discussion can be found in Lütkepohl and Reimers (1992) and Phillips (1998).

To derive the impulse response function, we first regard a parametric linear error correction model given by

$$\Delta y_t = \mu + \varphi\beta' y_{t-1} + \sum_{s=1}^{k} \rho'_s \Delta y_{t-s} + u_t,$$

where the cointegrating relation in vector y_t is give by β. We can rewrite this equation into a $VAR(k+1)$ model such as

$$y_t = \mu + \Phi_1 y_{t-1} + \cdots + \Phi_{k+1} y_{t-k-1} + u_t, \tag{13}$$

where

$$\begin{cases} \Phi_1 = I + \varphi\beta' + \rho'_1; \\ \Phi_j = \rho'_{j+1} - \rho'_j \qquad \text{(for } 2 \leq j \leq k); \\ \Phi_{k+1} = -\rho'_k. \end{cases} \tag{14}$$

We cannot derive the MA representation of this VAR model since y_t is a nonstationary process. However, Lütkepohl and Reimers (1992) show that even for the nonstationary case, we can recursively obtain the impulse response function $(\Psi_p)_{p\geq 1}$ as

$$\Psi_p = ({}_p\psi_{ab}) = \sum_{j=1}^{p} \Psi_{p-j}\Phi_j,$$

where $\Psi_0 = I$ and $\Phi_j = 0$ for $j > (k+1)$. ${}_p\psi_{ab}$ is the (a,b)-th element of Ψ_p, which represents the response of variable $y_{a,t}$ to a unit shock in variable $y_{b,t-p}$, p periods ago. We also define orthogonal impulse responses as $\Psi_p P$, where $PP' = \Sigma_u$. A unit orthogonal impulse has size one standard deviation in this case. Notice that the procedure is identical with the stationary case.

Now we consider a semiparametric error correction model given by

$$\Delta y_{it} = m_i\left(\beta' y_{t-1}\right) + \sum_{s=1}^{k} \rho_{is}' \Delta y_{t-s} + u_{it} \qquad \text{for } i = 1, \cdots, 4.$$

Since we cannot directly obtain $\varphi\beta'$ matrix as the linear case (14), the VAR representation as (13) is not straightforward. To obtain a proxy of $\varphi\beta'$ matrix, however, we linearly approximate $m_i\left(\beta' y_{t-1}\right)$ by applying the average derivative estimation (ADE) method. The ADE method, suggested by Härdel and Stocker (1989) and Powell et al. (1989), defines the average derivative of a smooth function $m_i(\cdot)$ as

$$\phi_i = \mathbf{E}\left(\frac{\partial m_i}{\partial y_{t-1}}\right) = \mathbf{E}\left(\dot{m}_i\left(\beta' y_{t-1}\right)\right)\beta \qquad \text{for all } i = 1, \cdots, 4,$$

where $\dot{m}_i(v) = dm_i/dv$. We then approximate $m_i\left(\beta' y_{t-1}\right)$ by a linear function $\mu + \phi_i' y_{t-1}$ for each i. Note that μ is an appropriate constant term, which could be time varying. Through these approximation procedures, we can also rewrite the semiparametric error correction model into a $VAR(k+1)$ model (13), where

$$\begin{cases} \Phi_1 = I + \phi' + \rho_1' & \text{with } \phi = \left(\phi_1', \cdots, \phi_4'\right)'; \\ \Phi_j = \rho_{j+1}' - \rho_j' & (\text{for } 2 \leq j \leq k); \\ \Phi_{k+1} = -\rho_k'. & \end{cases}$$

The average derivative ϕ_i can be estimated as follows. First we estimate β and ρ by the least squares method, then we can rewrite the semiparametric error correction model into a single index model given by

$$x_{it} = m_i\left(\hat{\beta}' y_{t-1}\right) + \xi_{it}$$

for each i, where $x_{it} = \Delta y_{it} - \sum_{s=1}^{k} \hat{\rho}_{is}' \Delta y_{t-s}$. Härdel and Stocker (1989) suggest that

$$\hat{\phi}_i = \hat{\beta} \cdot \frac{1}{T} \sum_{t=1}^{T} x_{it} \hat{s}_i\left(\hat{\beta}' y_{t-1}\right) \mathbf{1}\left\{\hat{f}\left(\hat{\beta}' y_{t-1}\right) > c\right\},$$

and Powell et al. (1989) suggest the density weighted ADE given by

$$\hat{\phi}_i = -\hat{\beta} \cdot \frac{2}{T} \sum_{t=1}^{T} x_{it} \widehat{\dot{f}}_i\left(\hat{\beta}' y_{t-1}\right),$$

where

$$\hat{s}_i\left(\hat{\beta}' y_{t-1}\right) = -\frac{\widehat{\dot{f}}_i\left(\hat{\beta}' y_{t-1}\right)}{\hat{f}\left(\hat{\beta}' y_{t-1}\right)} = -\frac{\frac{1}{T \cdot b_T^5} \sum_{j \neq t} \dot{K}_i\left(\frac{\hat{\beta}'(y_{t-1} - y_{j-1})}{b_T}\right)}{\frac{1}{T \cdot b_T^4} \sum_{j \neq t} K\left(\frac{\hat{\beta}'(y_{t-1} - y_{j-1})}{b_T}\right)}$$

with a bandwidth parameter b_T and a 4-dimensional kernel function $K(\cdot)$ with its partial derivatives $\dot{K}_i(\cdot)$. Note that $c > 0$ is a trimming parameter such that $c \to 0$ as $T \to \infty$. This is to prevent the problem that $\hat{s}_i\left(\hat{\beta}' y_{t-1}\right)$ may not be well-behaved when the denominator $f_i\left(\hat{\beta}' y_{t-1}\right)$ is too small. The average derivative estimator ϕ_i can be also obtained using other methods such as

$$\text{(Direct ADE)} \quad : \quad \hat{\beta} \cdot \frac{1}{T} \sum_t \widehat{\nabla m_i}\left(\hat{\beta}' y_{t-1}\right);$$

$$\text{(Indirect IV ADE)} \quad : \quad \hat{\beta} \cdot \left[\frac{1}{T} \sum_t \hat{s}_i\left(\hat{\beta}' y_{t-1}\right)(y_{t-1} - \bar{y})' \hat{\beta}'\right]^{-1} \frac{1}{T} \sum_t \hat{s}_i\left(\hat{\beta}' y_{t-1}\right)(x_{it} - \bar{x}_i),$$

where $\bar{y}$ and $\bar{x}_i$ are the empirical means of (y_{t-1}) and of (x_{it}) respectively. In both cases, we also need to trim each summand properly in order to get rid of the small denominator problem. $\widehat{\nabla m_i}$ is the derivative estimator of $m_i = m_{1i}/m_{2i}$ given by

$$\widehat{\nabla m_i}(v) = \frac{\widehat{\dot{m}}_{1i}(v) - \widehat{\dot{m}}_{2i}(v)\,\widehat{m}_i(v)}{\widehat{m}_{2i}(v)},$$

where

$$\widehat{\dot{m}}_{1i}(v_t) = -\frac{1}{Tb_T^2} \sum_{j \neq t} \dot{K}_i\left(\frac{v_t - v_j}{b_T}\right) x_{it} \quad \text{and} \quad \widehat{\dot{m}}_{2i}(v_t) = -\frac{1}{Tb_T^2} \sum_{j \neq t} \dot{K}_i\left(\frac{v_t - v_j}{b_T}\right).$$

3 Empirical Results

3.1 Data

We collect monthly Korean labor and macroeconomic data from July 1982 to May 2003. $(T = 251)$ The data set consists of consumer price index (CPI), average nominal monthly wage $\left(W^0 : 1,000\ Korean\ won\right)$, average monthly working hours (H), and total employment $(N : million)$. CPI is based on 2000 price, i.e., in 2000 the index is set to be 100. Wage W^0 is a sum of regular wage, overtime wage, and special wage. The per-hour real wage W is obtained by dividing W^0 by both H and $CPI/100$. Each worker's total working hour H is a sum of regular working hours and overtime hours. <Figure 1> shows time plots of $\log W$, $\log N$ and $\log H$ respectively. Each process is seasonally adjusted by applying the U.S. Census X-12 method (additive) on the log transformed series. Note that the original time series imposes strong seasonality since each series is a monthly data. We can also observe a structural break in January 1998 when the Asian financial crisis accelerated in Korea, and throughout the analysis, we will consider this structural break.

The data before 1999 are collected from KLIDB (Korea Labor Institute Data Base) CD-ROM Version 2.5. The most up-to-date labor data including working hours and wage are collected from the KLI web DB[3]. Other macroeconomic data including CPI and employment are from the KOSIS (Korean Statistical Information System) web DB[4].

We first conduct unit root tests for each log transformed process, $w_t = \log W_t$, $n_t = \log N_t$, $h_t = \log H_t$ and $g_t = \log \widehat{G}(H_t)$. As shown in <Table 2> both Augmented Dickey-Fuller test (ADF) and KPSS test strongly support the existence of unit root in

[3] www.kli.re.kr

[4] kosis.nso.go.kr

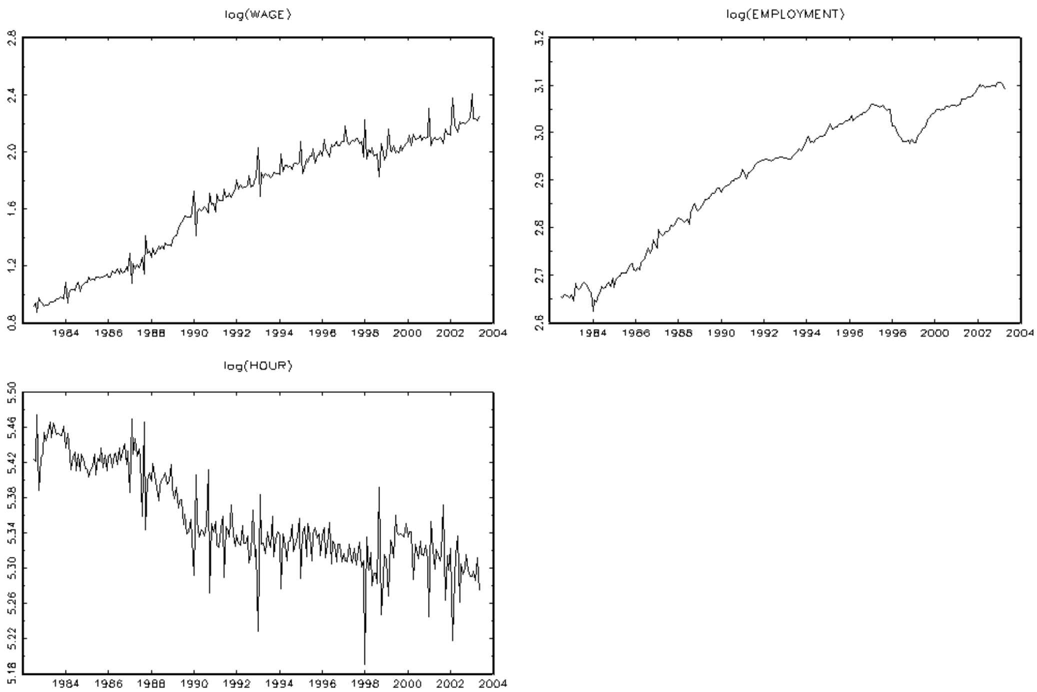

Figure 1: Data (July 1982 - May 2003)

every process. The optimal lag k^* for ADF test is determined by minimizing Schwartz Information Criterion (SC, or Bayesian Information Criterion: BIC), *viz.*,

$$k^* = \arg\min_k \left\{ \log \left| \hat{\Sigma}(k) \right| + (\log T)\, j(k)/T \right\},$$

where $\hat{\Sigma}(k)$ is the variance-covariance matrix estimate and $j(k)$ is the number of parameters for each specification of lag k. All tests on the levels include a constant and a linear time trend term, so the KPSS tests on levels have the null hypothesis of trend stationary. On the other hand, all tests on the first differences only include a constant, so the KPSS tests on levels have the null hypothesis of level stationary. Further details and the critical values of the KPSS test can be found in Kwiatkowski et al. (1992).

Table 2: Unit root tests

	lag	ADF	$\text{ADF}_S^\dagger$	KPSS		lag	ADF	$\text{ADF}_S^\dagger$	KPSS
w_t	3	-1.254	-1.518	1.345*	Δw_t	2	-17.171*	-16.844*	0.046
n_t	1	-0.979	-1.500	2.525*	Δn_t	0	-18.902*	-5.749*	0.000
h_t	3	-2.944	-2.468	0.906*	Δh_t	3	-13.853*	-5.445*	0.015
g_t	3	-2.695	-2.605	0.952*	Δg_t	2	-18.310*	-11.151*	0.012

(*): Significant at 1% level.

(†): ADF_S includes a structural break at Jan.1998.

Table 3: Cointegration analysis

Johansen Test			Cointegrating Regression			
$H_0 : r$ cointegrations	λ_{trace}	$\lambda_{\max}$			estimate	t-value
$r = 0$	170.60*	91.32*	$const_1$	(α_{01})	-214.219	-0.006
$r \leq 1$	79.28	35.09	$trend_1$	(α_{02})	0.004	2.535
$r \leq 2$	44.19	24.04	$const_2$	(α_{11})	0.140	0.488
$r \leq 3$	20.15	10.15	$trend_2$	(α_{12})	-0.001	-1.074
$r \leq 4$	10.00	7.78	n_t	(α_2)	0.566	0.794
$r \leq 5$	2.22	2.22	h_t	(α_3)	-239.123	-0.009
			h_t^2	(α_4)	179.646	0.023
optimal lag = 9			h_t^3	(α_5)	-36.446	-0.037
			h_t^4	(α_6)	2.359	0.051
			Residual based cointegration test			
(*): Significant at 1% level.						-5.415

3.2 Efficient working hour function

We first estimate the efficient working hour function $G(H)$ from the cointegrating regression (6). More precisely, we assume a deterministic trend with a structural break[5] for $\log A_t$ and fourth-order polynomial for $\log G(\cdot)$ after several simple specification tests. We thus have

$$w_t = \alpha_{01} + \alpha_{11}t + (\alpha_{02} + \alpha_{12}t) D_{\tau t} + \alpha_2 n_t + \alpha_3 h_t + \alpha_4 h_t^2 + \alpha_5 h_t^3 + \alpha_6 h_t^4,$$

where $D_{\tau t}$ is a structural break dummy defined as $D_{\tau t} = \mathbf{1}\{t > \tau : \tau = (\text{Jan.,1998})\}$. The Johansen test suggests that the six $I(1)$ processes $(w_t, n_t, h_t, h_t^2, h_t^3, h_t^4)$ share one long-run equilibrium. The test result and the cointegrating regression results are given in <Table 3>. λ_{trace} tests that the number of cointegration is r versus 0, whereas $\lambda_{\max}$ tests that the number of cointegration is r versus $r+1$. We use the critical values presented in Johansen (1995). We also conduct unit root tests on the fitted residual, which yield the residual based cointegration tests. The test result says that the cointegrating relation is significant at 1% level. Note that lack of considering a structural break weakens stationarity of the fitted residual.

From this first step cointegrating regression, we obtain

$$\begin{aligned} \theta &= 1.566, \\ \log A_t &= \begin{cases} 0.004t & \text{if } t \leq \tau; \\ 0.140 + 0.003t & \text{if } t > \tau, \end{cases} \end{aligned}$$

and the efficient working hour function

$$G(H) = \exp\left(-214.668 - 238.123h + 179.646h^2 - 36.446h^3 + 2.359h^4\right).$$

The efficient working hour estimate $\widehat{G}(H)$ and the labor efficiency rate estimate $\widehat{G}(H)/H$ are depicted in <Figure 2>. The two graphs in the second row shows the shape of functions

[5] We also considered other more general specifications such as polynomial, trigonometric and nonparametric time trend. But all the generalizations do not improve the result much.

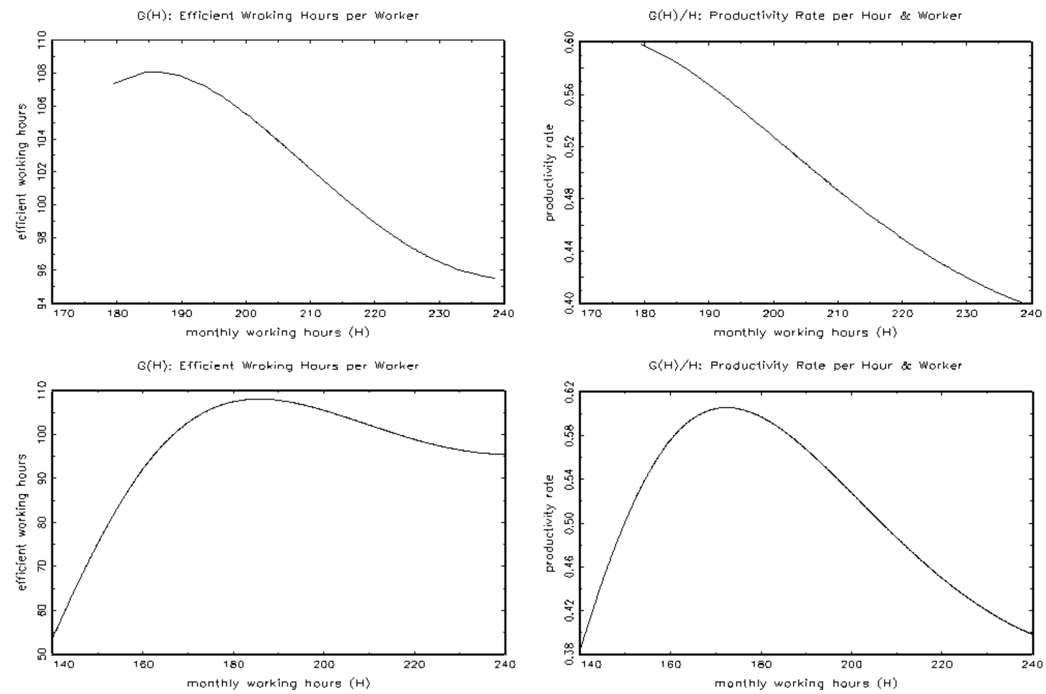

Figure 2: Efficient working hours

over a wider range of H from 140 to 240. We can see that the most efficient working hour lies between 180 and 190 in terms of $G(H)$ and the most efficient working hour is about 170 in terms of $G(H)/H$. In 2003, the monthly working hour level in Korea is around 200, so there is still room to improve.

It is worth noting that the overall scale of both $\widehat{G}(H)$ and $\widehat{G}(H)/H$ is somewhat smaller than we are expecting. It seems mainly because of two normalizations, $f\left(\bar{K}\right) = 1$ in (1) and $\delta_{01} = 0$ in (6). The shape of $G(H)$, however, is consistent since α_3, α_4, α_5 and α_6 are not affected by these normalizations. We thus can still get meaningful information from this result.

3.3 Error correction model

We use two stage error correction estimation procedure, so we first run a cointegrating regression of h_t on (g_t, n_t, w_t), *viz.*,

$$h_t = \beta_{01} + \beta_{11} t + (\beta_{02} + \beta_{12} t) D_{\tau t} + \beta_2 g_t + \beta_3 n_t + \beta_4 w_t + v_t.$$

The first stage cointegrating regression result is provided in <Table 4>. All covariates are significant except some deterministic trends and the residual based test convinces the cointegration.

To formulate the error correction model, we select the optimal lag by Hannan-Quinn Information Criterion (HQ), which minimizes $\log\left|\hat{\Sigma}(k)\right| + 2(\log\log T) j(k)/T$. HQ suggests lag 2, which is two months. Note that the Akaike Information Criterion (AIC) and BIC (or SC) suggest lag 4 and lag 0 respectively. For $y_t = (h_t, g_t, n_t, w_t)'$ we consider the

Table 4: Cointegrating regression

		estimate	t-value
$const_1$	(β_{01})	12.41991	63.647
$trend_1$	(β_{02})	-0.00010	-1.372
$const_2$	(β_{11})	-0.01712	-1.672
$trend_2$	(β_{12})	0.00006	1.195
g_t	(β_2)	-1.58615	-38.214
n_t	(β_3)	0.11897	4.852
w_t	(β_4)	-0.03529	-3.204
Residual based cointegration test			
			-12.311

following two different specifications given by

$$\Delta y_{it} = m_i\left(v_{t-1}\right) + \sum_{s=1}^{2} \rho_{is}' \Delta y_{t-s} + u_{it}, \tag{15}$$

and

$$\Delta y_{it} = \mu_{1i} + \mu_{2i} D_{\tau t} + \varphi_i v_{t-1} + \sum_{s=1}^{2} \rho_{is}' \Delta y_{t-s} + u_{it}, \tag{16}$$

for the comparison purpose. The second equation (16) is the conventional error correction model with a constant term imposing a structural break at $t = \tau$. In the semiparametric error correction model (15), we omit the constant term since it cannot not be identified from the unknown function $m_i(\cdot)$. For the nonparametric estimation, we use a third order kernel to reduce the asymptotic bias and optimal bandwidth is selected by cross-validation. The estimation results are given in Appendix, <Table A1>.

3.4 Impulse response analysis

3.4.1 Forecasting future responses

We perform a simulation showing responses from one negative standard error shock on the log of working hours, h. The results are given in <Figure 3>[6], which show the orthogonal impulse responses for 3 years. We also provide 95% confidence intervals for the impulse response functions of parametric linear error correction model (ECM) in <Figure 4>. It is clear that the impact of working hours is permanent for all variables and they reach the long-run equilibrium level in 12 periods or one year. This implies that the Korean labor market is flexible enough to adjust the policy shock on working hours in a year.

First, we look at the paths of $h = \log(\text{working hours})$, $g = \log(\text{efficient working hours})$ and $w = \log(\text{real wage per hour})$. We can see that both parametric and semiparametric results are almost identical for these three variables. At the first period, the log of working

[6] We do not provide confidence intervals for impulse responses of semiparametric ECM here. In the case of linear ECM, the confidence intervals can be obtained from asymptotic distributions with $\sqrt{T}$-order. However, we do not have the asymptotic result for the semiparametric ECM yet. We conjecture that the confidence interval should be broader in the semiparametric case since the asymptotics of confidence intervals depends on the nonparametric estimator whose order is $\sqrt{b_T T}$ and thus it is dominant in the limit. We also think of bootstrap to produce confidence intervals for impulse responses, but this procedure is still lack of proper theory and imposes problematic features as noted in Benkwitz et al. (2000).

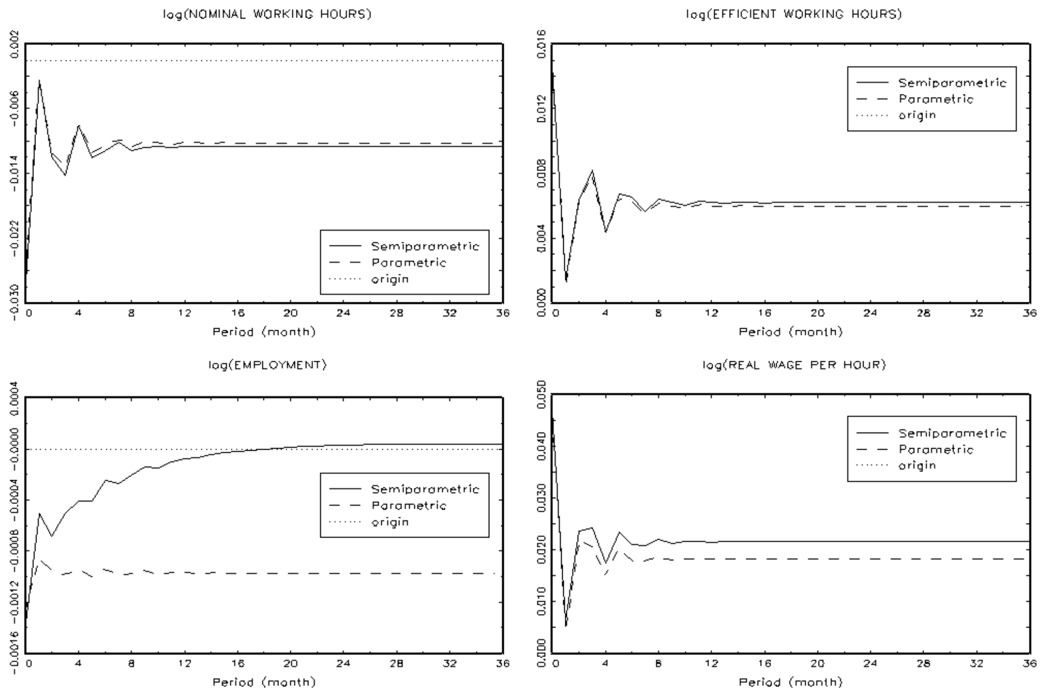

Figure 3: Impulse response functions (from negative h shock)

hours jumps up but still remains in the negative region. Accordingly both the log of efficient working hours and the log of real wage per hour decrease. The sharp pick of h in the first period might be caused from the increase of log (overtime hours). We will consider it at the end of this chapter. Reducing working hours not only boosts labor efficiency but also increases real wage per hour.

On the other hand, parametric and semiparametric specifications show different results in the long-run equilibrium level of $n = \log(\text{employment})$. The impact on the log of employment is very small, i.e., near zero, in the semiparametric error correction model (SECM) case. Notice that, however, both long-run employment levels are not significantly positive. This implies that reducing working hours will reduce or at least will not boost the number of employees. Many policy makers in Korea believe that reducing working hours by introducing five-day work week will create new employment and thus it could be a solution for unemployment. This expectation is natural because the past policies, which reduced working hours in 1989 and 1991, increased employment in Korea. Our result, however, shows that introducing five-day work week to the current Korean labor market would not create new employment and thus this policy could not be a solution for unemployment.

3.4.2 Past working hour reductions

As a matter of fact, the Korean government has decreased regular working hours several times in the past. The first reduction was from 48 to 46 hours in April 1989, the second reduction onto 44 hours was in October 1990 and the final reduction was in October

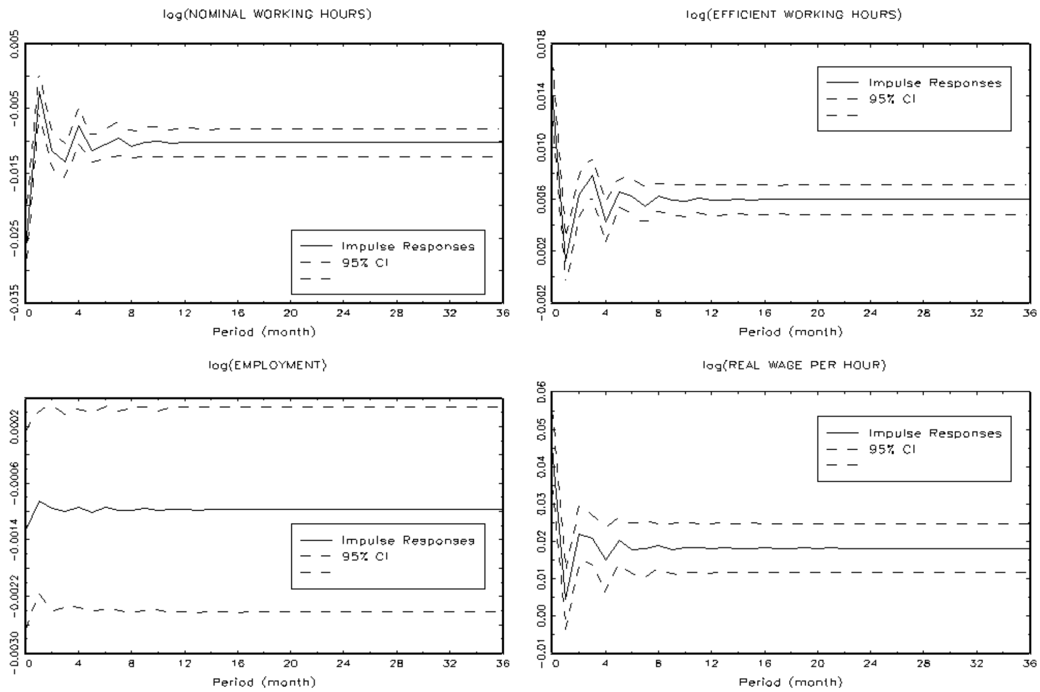

Figure 4: 95% confidence intervals for impulse response functions of parametric ECM

1991[7]. That such reductions actually created new employment in Korea in the past, is well known. In <Figure 5> the impulse response analysis with data from July 1982 to March 1989, which is just before the first working hour reduction policy, also supports this fact. The optimal lag is chosen as 5 that HQ suggests. Different from <Figure 3>, the level of n is positive in the long-run in this case, which implies that the work sharing works at this time. Reflecting on the efficient working hour function in <Figure 2>, however, the working hour efficiency level was very low in March 1989, and it is the main reason of the different results from our future forecasts in <Figure 3>. Note that in March 1989, the average monthly working hours was 222.

To investigate the discrepancy in employment between past effects in <Figure 5> and future predicted effects in <Figure 3>, we look at another result in <Table 5>. The log of physical labor input level NH $(= n + h)$ and the log of efficient labor input level $NG(H)$ $(= n + g)$ on the long-run equilibrium are calculated. We can see that the log of physical labor input shrinks for both cases, whereas the log of efficient labor input increases. However, in the current situation, i.e., working hour cut in July 2003, the increment of efficient labor input $\log NG(H)$ is much larger than the past case even though the physical labor input $\log NH$ decreases more. Such an unexpected phenomenon is possible because reducing working hours dramatically increases the labor efficiency and the efficient working hours per worker so that firms do not need more workers to keep up production levels. In addition, we can see that the real wage increment is larger in <Figure 3>. Higher wage increase elevates labor cost more, and therefore, it would more decrease the labor demand, or employment.

[7] In October 1990, the reduction was only for the firms with more than 300 employees and financial/insurance companies. In October 1991, all firms reduced weekly working hours onto 44.

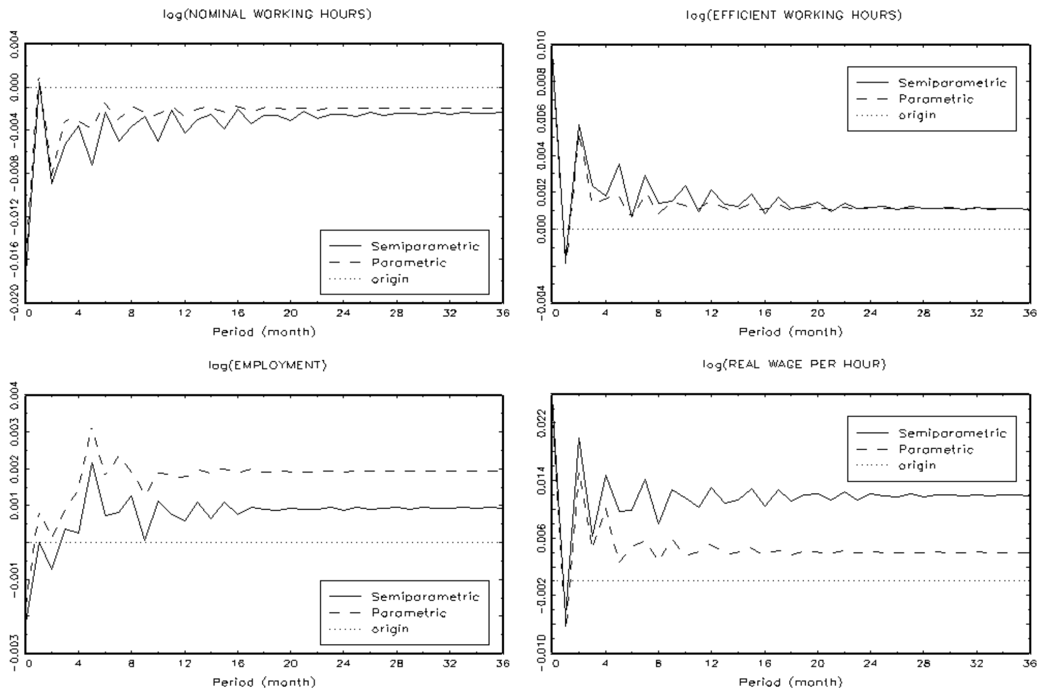

Figure 5: Impulse response functions (from negative h shock)

Table 5: Physical labor input $\log NH$ *versus* efficient labor input $\log NG(H)$

	SECM		ECM	
Working Hour Cut	$\log NH$	$\log NG(H)$	$\log NH$	$\log NG(H)$
in 2003.6	-0.01065	0.00616	-0.01122	0.00501
in 1989.4	-0.00139	0.00201	-0.00003	0.00306

3.4.3 Considering overtime hours

For comparison purposes, we finally conduct a similar analysis with a different variable set $y_t = (h_{rt}, h_{ot}, g_t, n_t, w_t)'$, where h_{rt} and h_{ot} are log of regular and overtime working hours respectively. The impulse response function from the negative unit shock on regular working hours h_{rt} is given in <Figure 6>. HQ suggests the optimal lag 1.

From this result, we can see that each parametric and semiparametric specification produces distinct responses of overtime hour and average real wage. The semiparametric model says that the log of overtime hours h_o will increase and at the same time the log of real wage w will also increase. So, the decrease of total working hours is mainly from the regular working hour reduction. On the other hand, the parametric model says that the log of overtime hours will decrease and the log of real wage will also go down. We thus can see that the average wage rather moves together with overtime working hours, which suggests that the change of overtime work premium is a main determinant of the average wage fluctuation in Korea. Note that traditionally quite a few people work overtime in Korea. Moreover, from this analysis we can also see that employment will decrease in any model specification. The reaction of the overtime hours, however, is somewhat ambiguous.

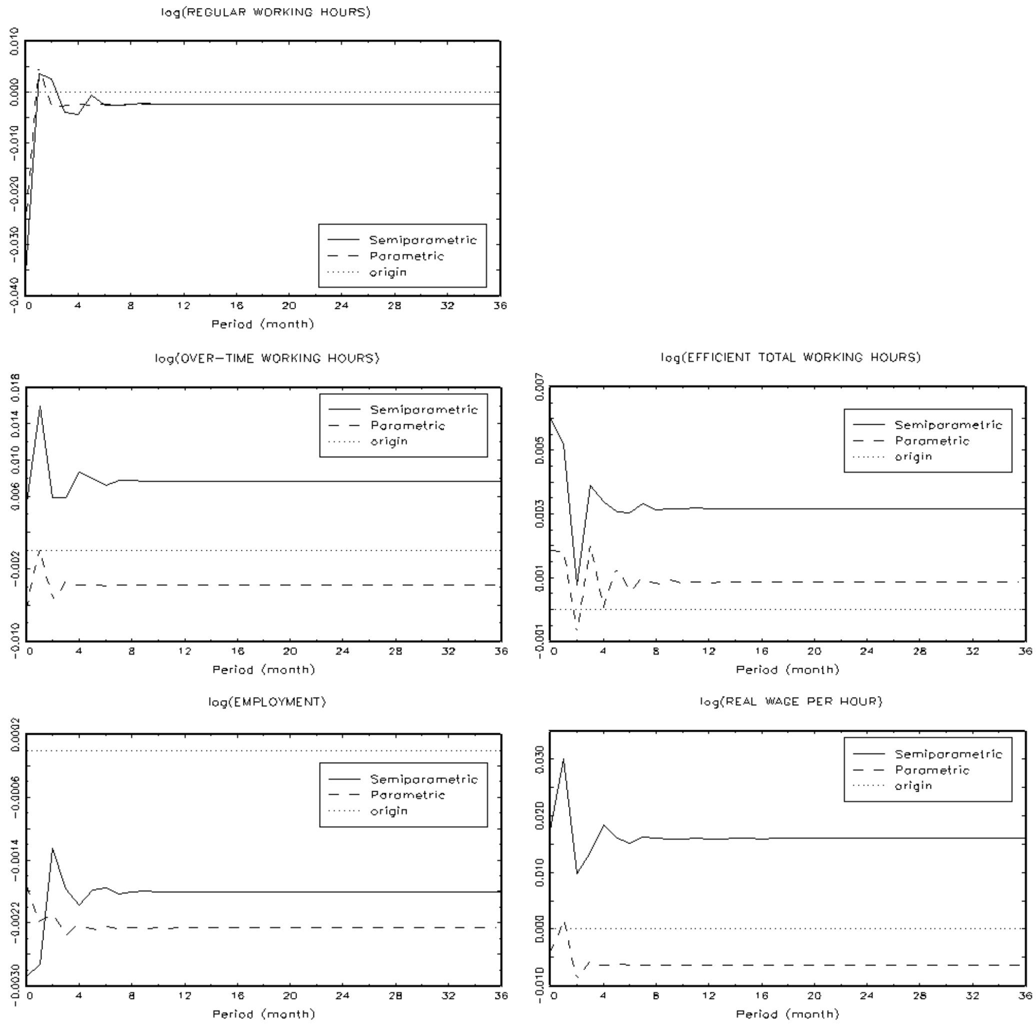

Figure 6: Impulse response functions (from negative h_r shock)

4 Conclusion

By investigating the labor demand, this study shows that introducing five-day work week to Koran labor market is not effective in creating new employment. Even though the result is not that different from parametric model, the semiparametric error correction model and its impulse response analysis show that employment will shrink because of the sharp increase in efficient labor input. This result seems plausible when we look at the high unemployment rates in developed countries. Moreover, we find that the Korean labor market is flexible enough to adjust the policy shock in a year.

This study has the defect that introducing five-day work week to the Korean labor market has more impact in terms of reducing working days than in terms of reducing working hours, and it could have unexpected effects to the labor market, of course. Future research should consider the effect of working day reduction on the labor demand. This could be done by measuring the utility of employees on weekly working days and by weighing working hours differently. Moreover, we could conduct a similar study with more specific data and compare the differences across groups. For example, we can use male/female data, industry-level data, firm-size data, wage-level data, or education-level data. Interesting results are expected with the industry-level data, especially with the manufacturing sector *versus* service/entertainment sector, because work-day reduction will alter the weekend leisure pattern.

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6 Appendix: ECM estimation results

Table A1: ECM estimation results

	Semiparametric ECM				Parametric ECM			
	Δh_t	Δg_t	Δn_t	Δw_t	Δh_t	Δg_t	Δn_t	Δw_t
$const$	–	–	–	–	0.001	0.000	0.001	0.004
					0.264	-0.147	1.231	0.518
$D_{\tau t}$	–	–	–	–	-0.002	0.001	0.001	0.005
					-0.421	0.340	0.750	0.567
v_{t-1}	–	–	–	–	-0.742	0.051	0.027	0.998
					-1.975	0.243	0.256	1.249
Δh_{t-1}	-0.763	0.184	0.047	0.148	-0.432	0.183	0.014	-0.205
	-2.916	1.255	0.618	0.263	-1.283	0.970	0.154	-0.286
Δg_{t-1}	0.118	-0.580	0.031	0.032	0.710	-0.616	-0.027	-0.612
	0.286	-2.524	0.260	0.037	1.340	-2.070	-0.180	-0.542
Δn_{t-1}	-0.204	0.040	-0.182	0.979	-0.205	0.040	-0.179	1.021
	-0.908	0.319	-2.814	2.025	-0.866	0.302	-2.718	2.025
Δw_{t-1}	0.022	0.007	0.023	-0.766	0.016	0.015	0.022	-0.757
	0.466	0.279	1.694	-7.477	0.334	0.572	1.650	-7.390
Δh_{t-2}	-0.124	-0.080	0.051	-0.061	0.060	-0.083	0.054	-0.335
	-0.493	-0.570	0.698	-0.113	0.217	-0.537	0.698	-0.571
Δg_{t-2}	0.494	-0.615	0.009	-0.140	0.782	-0.616	0.012	-0.545
	1.249	-2.777	0.081	-0.164	1.814	-2.546	0.100	-0.595
Δn_{t-2}	-0.420	0.178	0.067	0.788	-0.517	0.240	0.006	1.250
	-1.824	1.383	1.007	1.592	-2.156	1.782	0.092	2.451
Δw_{t-2}	0.020	0.000	0.032	-0.349	0.022	0.003	0.032	-0.358
	0.417	0.010	2.346	-3.403	0.456	0.123	2.421	-3.526

Note: Numbers in small font represent t-values.