Estimating a dynamic labour demand equation using small, unbalanced panels: An application to Italian manufacturing sectors

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Abstract

We estimate a dynamic labour demand equation using a small unbalanced panel data-set of italian manufacturing sectors.There are 31 sectors with an average group size of 24 time observations. The estimator adopted is the Least Squares Dummy Variable estimator corrected for the finite-sample bias (LSDVC) using the bias approximations derived in Bruno (2005a), which extend Bun and Kiviet's (2003) to unbalanced panels. It is implemented in Stata using Bruno's (2005b) code XTLSDVC (available from the SSC archive at http://ideas.repec.org/c/boc/bocode/s450101.html) The estimated long-run and short-run labour demand elasticities are in line with the ranges indicated in Hamermesh (2000). In addition, their magnitudes are not positively affected by measures of sectoral international exposure, which rejects the Rodrick's (1997) conjecture for Italy. This confirms the results in Bruno, Falzoni, Helg (2004) obtained using a balanced data set.

JEL classification: F16, J23.

Keywords: within estimator; bias approximations; international exposure; dynamic labor demand equation; labour demand elasticities.

1. Introduction

This paper estimates a dynamic labour demand equation for Italy using an unbalanced panel data of manufacturing sectors, in an attempt to test for the joint presence of sectoral international exposure (globalization) effects and output generated external economies.

Following Bruno, Falzoni and Helg (2004), the model specification accommodates the presence of employment adjustment costs and allows for two types of globalization effects. First, a possible direct effect of globalization on labour productivity may emerge as formulated in Greenaway *et al.* (1999). Secondly, as emphasized by Dani Rodrik in his book "*Has globalization gone too far?*"(1997), the role played by international exposure in the labour market is not (or not only) that of a labour demand shifter, but rather of a force boosting the responsiveness of labour demand to changes in labour prices "regardless of economic structure and the identity of the trade partners" (Rodrik, 1997, 26). Our specification will permit to test both effects in a unique estimation run by treating the globalization variable as a shifter for both the labour demand equation and the labour elasticity[1]. Also, by conditioning on a measure of sectoral output we can test for the presence of output generated external economies.

Three important econometric issues emerge in the empirical analysis, which need a solution. First, as is well known the within (or LSDV) estimator for dynamic panel data models is not consistent for T fixed and N large (Nickell (1981)). Second, the cross-sectional dimension of our panel is small (there are 31 manufacturing sectors with an average group size of 24 years), so that N-consistent GMM estimators -a by now standard alternative to the within estimator for dynamic panel data models- may be affected by a potentially severe small sample bias (Kiviet (1995)). Finally, the unbalanced nature of our panel does not permit to correct the within estimator by applying the bias approximation formulae derived in Kiviet (1995), (1999) and Bun and Kiviet (2003), only valid for balanced panels. The adoption of those formulae as they are would in fact require discarding the cross-sections (or time-series) causing unbalancedness with a potentially high loss of information. This has been the strategy followed in Bruno, Falzoni and Helg (2004), which has led to the sacrifice of the sector "Radio, TV & Communication Equipment".

[1] As opposed to the two-stage approach followed by Slaughter (2001), who first estimates labour demand elasticities and then regress the estimated elasticities on a set of globalization measures.

In the view of the above considerations, our estimation strategy will employ a bias corrected LSDV estimator using the recent LSDV bias approximation formulae derived in Bruno (2005a), which extends Kiviet's (1999) and Bun and Kiviet's (2003) to (possibly) unbalanced panels.

The received empirical literature on the labour market effects of globalization is not conclusive. Bruno, Falzoni and Helg (2004) carry out a comparative study on OECD countries, including Italy, using a specification similar to that adopted in this paper, but on a balanced version of the data and with a restricted choice of bias approximations, to find support for the Rodrik's conjecture only in the cases of France and the UK.

Slaughter (2001), adopting a two-stage approach on an industry-year panel from 1961 through 1991 for the United States, provides mixed support to the view that trade contributed to increased elasticities. In the first stage, Slaughter finds that demand for production labour has become more elastic in manufacturing overall and in five of eight industries within manufacturing; the same is not true for non-production labour. In the second stage, when estimated elasticities are regressed on a set of trade variables and industry dummies are included, Slaughter finds many significant coefficients, with the expected sign. However, in a number of cases, these predicted effects disappear when time dummies are introduced. For production workers as well as for non production workers, time results to be a very strong predictor of elasticity pattern. In sum, there appears to be a large unexplained residual for changing factor demand elasticities[2].

The experience of dramatic changes in trade regimes in a number of developing countries might be thought as the appropriate context to investigate the theoretical link between openness and labour demand elasticities. This approach is in fact been followed by Krishna *et al.* (2001) and Fajnzylber and Maloney (2001), finding however no support to the conjecture of more-elastic labour demand in response to trade liberalization. Using Turkish plant-level data, Krishna *et al.* (2001) estimates a labour demand equation in which the wage variable is interacted with a liberalization dummy, capturing the effect of changes in trade policy. Overall, the results show that labour demand elasticities seem to be unresponsive to openness. Only very mixed support and no consistent patterns for the idea that trade liberalization has an impact on own wage elasticities also emerges in the study by Fajnzylber and Maloney (2001). They use dynamic panel techniques to estimate labour demand functions for manufacturing establishments in Chile,

[2] Applying a similar methodology, Faini *et al.* (1999) find some support to the hypothesis that greater globalisation is associated with larger elasticities for Italy during the period 1985-1995.

Colombia and Mexico.

Finally, Greenaway *et al.* (1999) evaluate the impact of trade volumes on employment through induced productivity changes. Adopting a dynamic labour demand framework for the UK, they find that increases in trade volumes, both in terms of imports and exports, cause reductions in the level of derived labour demand, consistently with the view that increased openness serves to increase the efficiency with which labour is utilized in the firm. Greenaway *et al.* also analyses the impact of trade changes on the slope of the derived labour demand introducing a term corresponding to interactions between the wage rate and import and export volumes. They find a positive effect of trade volumes on the labour demand elasticity but this impact is not significant[3].

Our emprical results are as follows. First, all testable regularity conditions implied by cost minimising behaviour are always satisfied, with the estimated labour demand elasticities, both short-run and long-run, being always significantly negative and within the empirical ranges documented in Hamermesh (2000). Second, results for the bias-corrected LSDV estimators are robust to changes in the order of the bias approximations and to different choices of the N-consistent estimator used to initialize the bias correction. Third, the Rodrik's conjecture is decidedly rejected for all estimators used (bias-corrected and GMM), which confirms the results for Italy in Bruno, Falzoni and Helg (2004). Fourth, the direct effect of globalization on labour demand is never found significant. Finally, we find robust evidence in favour of output generated external economies.

The structure of the paper is as follow. The next section explains the bias correction strategy. Section 3 set up the theoretical framework. Section 4 describes the data. Estimation results are contained in Section 5.

2. Bias corrected LSDV estimators

In this section we review the existing results on the LSDV bias approximations for dynamic panels with N and T small, or only moderately large, and and their use to implement bias-corrected LSDV estimators. Consider the standard dynamic panel data model

$$y_{it} = \gamma y_{i,t-1} + x'_{it}\beta + \eta_i + \epsilon_{it}; \quad |\gamma| < 1; \; i = 1, ..., N \text{ and } t = 1, ..., T, \qquad (2.1)$$

[3] Adopting a different methodology and focusing on the intersectoral dimension of the *scale effect*, Jean (2000) finds, for France, that trade openness can indeed have a significant effect on labour demand elasticities.

where y_{it} is the dependent variable; x_{it} is the $((k-1)\times 1)$ vector of strictly exogenous explanatory variables; η_i is an unobserved individual effect; and ϵ_{it} is an unobserved white noise disturbance. Collecting observations over time and across individuals gives

$$y = D\eta + W\delta + \epsilon,$$

where y and $W = \left[y_{-1} \vdots X \right]$ are the $(NT \times 1)$ and $(NT \times k)$ matrices of stacked observations; $D = I_N \otimes \iota_T$ is the $(NT \times N)$ matrix of individual dummies, (ι_T is the $(T \times 1)$ vector of all unity elements); η is the $(N \times 1)$ vector of individual effects; ϵ is the $(NT \times 1)$ vector of disturbances; and $\delta = \left[\gamma \vdots \beta' \right]'$ is the $(k \times 1)$ vector of coefficients.

It has been long recognized that the LSDV estimator for model (2.1) is not consistent for finite T. Nickell (1981) derives an expression for the inconsistency for $N \to +\infty$, which is $O\left(T^{-1}\right)$. Kiviet (1995) obtains a bias approximation that contains terms of higher order than T^{-1}. In Kiviet (1999) a more accurate bias approximation is derived. Bun and Kiviet (2003) reformulate the approximation in Kiviet (1999) with simpler formulae for each term.

All foregoing bias approximations are derived for balanced panels. As such they are useless in our case, unless we balance our panel at the cost of time or sector observations. This waste of information can be avoided, however, by using the bias approximations in Bruno (2005a) extending Bun and Kiviet's (2003) formulae to unbalanced panels with a strictly exogenous selection rule. Bruno (2005a) defines the static selection indicator z_{it} such that $z_{it} = 1$ if (y_{it}, x_{it}) is observed and $z_{it} = 0$ otherwise. From this he also defines the dynamic selection rule $s\left(r_{it}, r_{i,t-1}\right)$ selecting only the observations that are usable for the dynamic model, namely those for which both current values and one-time lagged values are observable:

$$s_{it} = \begin{cases} 1 & \text{if } (z_{i,t}, z_{i,t-1}) = (1,1) \\ 0 & \text{otherwise} \end{cases} \qquad i = 1, ..., N \text{ and } t = 1, ..., T.$$

Thus, for any i the number of usable observations is given by $T_i = \sum_{t=1}^{T} s_{it}$. The total number of usable observations is given by $n = \sum_{i=1}^{N} T_i$; and $\overline{T} = n/N$ denotes the average group size. For each i define the $(T \times 1)$-vector $s_i = [s_{i1} ..., s_{iT}]'$ and the $(T \times T)$ diagonal matrix S_i having the vector s_i on its diagonal. Define also the $(NT \times NT)$ block-diagonal matrix $S = diag\left(S_i\right)$. The (possibly) unbalanced dynamic model can then be written as

$$Sy = SD\eta + SW\delta + S\epsilon. \tag{2.2}$$

The LSDV estimator is given by

$$\delta_{LSDV} = \left(W'M_sW\right)^{-1} W'M_sy,$$

where

$$M_s = S\left(I - D\left(D'SD\right)^{-1} D'\right) S$$

is the symmetric and idempotent $(NT \times NT)$ matrix wiping out individual means and selecting usable observations.

Bruno's (2005a) bias approximation terms for unbalanced panels are then the following

$$c_1\left(\overline{T}^{-1}\right) = \sigma_\epsilon^2 tr\left(\Pi\right) q_1; \tag{2.3}$$

$$\begin{aligned} c_2\left(N^{-1}\overline{T}^{-1}\right) &= -\sigma_\epsilon^2 \left[Q\overline{W}'\Pi M_s\overline{W} + tr\left(Q\overline{W}'\Pi M_s\overline{W}\right) I_{k+1} + \right. \\ & \left. 2\sigma_\epsilon^2 q_{11} tr\left(\Pi'\Pi\Pi\right) I_{k+1}\right] q_1; \end{aligned}$$

$$\begin{aligned} c_3\left(N^{-1}\overline{T}^{-2}\right) &= \sigma_\epsilon^4 tr\left(\Pi\right)\left\{2q_{11}Q\overline{W}'\Pi\Pi'\overline{W}q_1 + \left[\left(q_1'\overline{W}'\Pi\Pi'\overline{W}q_1\right) + \right.\right. \\ & \left.\left. q_{11} tr\left(Q\overline{W}'\Pi\Pi'\overline{W}\right) + 2tr\left(\Pi'\Pi\Pi'\Pi\right) q_{11}^2\right] q_1\right\}; \end{aligned}$$

where $Q = \left[E\left(W'M_sW\right)\right]^{-1} = \left[\overline{W}'M_s\overline{W} + \sigma_\epsilon^2 tr\left(\Pi'\Pi\right) e_1 e_1'\right]^{-1}$; $\overline{W} = E\left(W\right)$; $e_1 = (1, 0, ..., 0)'$ is a $(k \times 1)$ vector; $q_1 = Qe_1$; $q_{11} = e_1'q_1$; L_T is the $(T \times T)$ matrix with unit first lower subdiagonal and all other elements equal to zero; $L = I_N \otimes L_T$; $\Gamma_T = \left(I_T - \gamma L_T\right)^{-1}$; $\Gamma = I_N \otimes \Gamma_T$; and $\Pi = M_s L\Gamma$. Clearly, in any balanced design $S \equiv I_{NT}$, so $M_s = I - D\left(D'D\right)^{-1} D'$, and the above terms reduce to Bun and Kiviet's (2003).

With an increasing level of accuracy, the following three possible bias approximations emerge

$$B_1 = c_1\left(\overline{T}^{-1}\right);\ B_2 = B_1 + c_2\left(N^{-1}\overline{T}^{-1}\right);\ B_3 = B_2 + c_3\left(N^{-1}\overline{T}^{-2}\right). \tag{2.4}$$

Approximations (2.4) depend upon the unknown parameters σ_ϵ^2 and γ, so they are unfeasible for bias correction. The bias corrected LSDV estimator is then implemented using the two-step procedure suggested by Kiviet (1995) and Bruno (2005b). The first step obtains estimates for σ_ϵ^2 and γ from some $N-$consistent estimator. The second step performs bias correction by depuring the LSDV estimator from the bias approximation of choice evaluated at the estimated σ_ϵ^2 and γ, $\widehat{B}_i$, as follows:

$$LSDVC_i = LSDV - \widehat{B}_i, \; i = 1, \; 2 \text{ and } 3. \tag{2.5}$$

Possible consistent estimators for γ are Anderson and Hsiao (AH) and Arellano and Bond (AB). Depending on the estimator of choice for γ, say h, a consistent estimator for σ_ϵ^2 is then given by

$$\widehat{\sigma}_h^2 = \frac{e_h' M_s e_h}{(N - k - T)}, \tag{2.6}$$

where $e_h = y - W\delta_h$, and $h = AH, \; AB$. Monte Carlo analysis in Bruno (2005b) demonstrates that for sample sizes comparable to ours all possible forms of LSDVC outperforms LSDV and GMM estimators.

3. The Model

The theoretical model on which we base our empirical analysis has the feature of producing labour demand elasticities in one stage. We consider a sector in the economy with a large number of firms using the same technology. There are two domestic production inputs, domestic labour l and capital k producing output q, with w and r being the compensations for l and k, respectively. The market for production factors is perfectly competitive, whereas no assumption is made on the form of the output market.

We allow for two distinct sources of external economies at the firm level. Those generated by the sectoral production ; and those generated by the sectoral international exposure. Sectoral international exposure may foster technology advancement and productivity growth through several channels, such as technology advancement embodied in imported capital goods and intermediate inputs, technology transfers accompanying foreign direct investment, learning-by-exporting effects, etc. The empirical literature on these issues is vast. A number of empirical works have resorted to firm and plant-level panel data to see whether the predicted gains from trade liberalization have materialized in some recent episodes of drastic trade reform in the developing world and/or to see whether productivity growth has been a result of increasing international integration and exposure in developed countries. Most of these studies find that trade reform in developing countries was indeed accompanied by productivity growth, technology advancement, falling mark-ups and a reshuffling of resources toward the more efficient firms, although in some cases the evidence may fail to convince because of the hurdles involved in the methodology used in these studies (see, among others, Tybout (2003) which reviews the plant-level evidence in the light of the new trade theory, Bernard and Jensen (1999), Clerides, Lach and Tybout (1998), Pavcnik (2002)).

With this in mind, we suppose that the firm technology exhibits constant returns to scale with external economies generated by sectoral international exposure g and also by sectoral output y. We also allow for exogenous technical change captured by a time trend t :

$$q = f\left(k, l; y, g, t\right), \tag{3.1}$$

Given the property of constant returns to scale at the firm level, the sectoral production function is just the firm production function f with the aggregate sectoral variables as arguments and it is implicitely defined by

$$y = f\left(k, l; y, g, t\right) \tag{3.2}$$

(see Bruno (2004) and the references threin). We suppose that f is invertible in y so that an equivalent form of the sectoral production function in (3.2) is the following

$$y = F\left(k, l; g, t\right).$$

We also suppose F homothetic.

For given g and y the optimal aggregate input demands l^* and k^* must satisfy the following cost minimisation problem:

$$\min_{l,k}\left[wl + rk : y = F\left(k, l; g, t\right)\right] \tag{3.3}$$

We assume that the following labour demand equation emerges as a solution of problem (3.3).

$$\ln l = \left(\beta_w + \beta_{wg}\ln g + \beta_{wt}\ln t\right)\ln\left(w/r\right) + \beta_y \ln y + \beta_g \ln g + u + \epsilon, \tag{3.4}$$

where β_y, β_w, β_{wg}, β_{wt}, β_g and β_x are constant parameters. The parameter β_g measures the impact of g as a demand shifter, whereas β_{wg} and β_{wt} measure the impact of g and the time trend t on the relative wage elasticity of the labour demand function, which is given by

$$\varepsilon_{lw} \equiv \frac{\partial \ln l}{\partial \ln w} = \beta_w + \beta_{wg} \ln g + \beta_{wt} \ln t. \tag{3.5}$$

In equilibrium, sectoral international exposure g may influence labour's own price elasticity, as well as bring about a direct effect on labour demand acting as a demand shifter.

To correctly interpret parameter estimates it is important to establish the exact relationship between the parameters of the labour demand equation (3.4) and those of the underlying production function. Details on the recovering of the production function from (3.4) are shown in appendix. Basically, we first retrieve the underlying cost function by integrating (3.4), and then we obtain the following production function from the cost function by duality:

$$y = \left(\frac{1}{e^{u+\epsilon} g^{\beta_g}}\right)^{\frac{1}{\beta_y}} \left(\frac{-\varepsilon_{lw}}{1+\varepsilon_{lw}}\right)^{\frac{\varepsilon_{lw}}{\beta_y}} (k)^{-\frac{\varepsilon_{lw}}{\beta_y}} (l)^{\frac{1+\varepsilon_{lw}}{\beta_y}}. \tag{3.6}$$

From (3.6) it is clear that for equation (3.4) to be theoretically consistent with both cost minimizing behaviour (requiring a downward sloping labour demand curve) and a regular production function (requiring a non negative labour marginal productivity) the regularity condition $\varepsilon_{lw} \in [-1, 0]$ must hold.

Function (3.6) is homothetic of degree $1/\beta_y$ and has a restricted translog form, with a variable technical efficiency given by

$$A = \left(\frac{1}{e^{u+\epsilon} g^{\beta_g}}\right)^{\frac{1}{\beta_y}} \left(\frac{-\varepsilon_{lw}}{1+\varepsilon_{lw}}\right)^{\frac{\varepsilon_{lw}}{\beta_y}}. \tag{3.7}$$

A depends on international exposure g, the stochastic shock ϵ, and labour demand elasticity ε_{lw}. If $\beta_{wg} = 0$, then A reduces to the expression for technical efficiency in Greenaway et al. (1999).

Implementing this model empirically we can test for the presence of globalization effects in the labour demand equation as broken down into 1) the Rodrik's conjecture that $\beta_{wg} < 0$, that is international exposure has a positive impact on $|\varepsilon_{lw}|$; and 2) a globalization's direct effect on labour demand as measured by β_g (Greenaway et al., 1999). We can also test for the presence of output generated scale economies, which implies $0 < \beta_y < 1$.

4. Data Description

Our panel data set comes from the STAN database, a data set compiled by the OECD and containing internationally comparable data. The industries are grouped using the standard ISIC Revision 2 classification[4]. The data set originally covered a panel of 40 manufacturing industries in the period 1970-1997 across countries. Missing observations for some of the regression variables along with the loss of the first observation when taking lags, however, make the estimation sample unbalanced, reducing to $N = 31$ sectors (we lose Drugs; Chemicals; Office & Computing Machinery; Machinery & Equipment; Electrical Apparatus; Railroad Equipment; Motorcycles & Bicycles; Transport Equipment) with an average group size of $\overline{T} = 24$. Unbalancedness is not severe, as evidenced from the computation of the Ahrens and Pincus index of unbalancedness $\omega = 0.99$, where

$$\omega = N / \left[\overline{T} \sum_{i=1}^{N} (1/T_i) \right],$$

with $0 < \omega \leq 1$ and $\omega = 1$ when the panel is balanced (see Bruno (2005)). Nevertheless, balancing the data would have caused the loss of one further cross-section, namely Radio, TV & Communication Equipment, which we can avoid by using the appropriate estimation techniques.

The variables used in the empirical work are the following[5]. Our dependent variable l is measured as "number engaged" (NE). The output variable y is proxied by Value Added in constant 1990 prices (VA90). Relative wage of domestic labour w is constructed as follows: 1) we obtain average remuneration of labour by taking the ratio of total labour cost to number engaged; 2) we divide this variable by the price of capital p which is proxied by the value added deflator. As a proxy for international integration, g, we utilize the share of import over value added[6]. The choice of this proxy to measure international integration is motivated by our focus on the substitution effect's component of the labour demand elasticity. In fact, import penetration might well represent, at the same time, a measure of substitution possibilities in production due to the availability of a larger variety

[4]Details concerning the industry description and the ISIC rev.2 code are given in Table 1.

[5]Table 2 provides definitions for the variables of the STAN database that have been used in the empirical implementation as given in the OECD STAN database manual, as well as the variable codes used in the regression analysis.

[6]Further details regarding the construction of these variables are given in Table 3.

of inputs and a measure of the competitive pressure coming from the international markets.

Figures 1 and 2 taken from Bruno, Falzoni and Helg (2004) provide a first picture of the issue under analysis for some OECD countries. In the last decades a generalised reduction in the demand for labour paralleled the developments in the international openness. Employment in the manufacturing industry has been decreasing, in the face of an increasing integration into the world economy, although the correlation between the two phenomena is not high for Italy.

5. Estimation results

Our econometric model is based upon equation (3.4). Let N denote the number of sectors and T the largest group size in the panel. We accommodate sector heterogeneity by allowing u to vary across sectors. Since data on r are not available we proxy it by a complete set of time dummies, based on the assumption that the price of capital does not vary across sectors, as it would happen in the presence of perfect capital markets. The time trend interacted with $\ln w$ allows for autonomous variations in labour demand elasticity. Time dummies and the interacted trend should also capture the effect of exogenous technical change. Thus, our empirical baseline equation is as follows

$$\begin{aligned} z_{it} \ln l_{i,t} &= z_{it} \Big[\left(\beta_w + \beta_{wg} \ln g_{i,t} + \beta_{wt} \ln t_{i,t}\right) \ln w_{i,t} + \beta_y \ln y_{i,t} \\ &\quad + \beta_g \ln g_{i,t} + \sum_{t=1}^{T-1} \beta_t d_t + u_i + \epsilon_{i,t} \Big], \end{aligned} \tag{5.1}$$

where z_{it} is the static selection rule, $t = 1, ..., T$, $i = 1, ..., N$.

Equation (5.1) is static in nature, so it fails to incorporate labour adjustment cost. This is can be taken into account by including the lagged dependent variable into the right hand side of the baseline equation and replacing the static selection rule z_{it} with the dynamic selection rule s_{it} derived from z_{it} as in Section 2 :

$$\begin{aligned} s_{it} \ln l_{i,t} &= s_{it} \Big[\gamma \ln l_{i,t-1} + \left(\beta_w + \beta_{wg} \ln g_{i,t} + \beta_{wt} \ln t_{i,t}\right) \ln w_{i,t} \\ &\quad + \beta_y \ln y_{i,t} + \beta_g \ln g_{i,t} + \sum_{t=1}^{T-1} \beta_t d_t + u_i + \epsilon_{i,t} \Big], \end{aligned} \tag{5.2}$$

$t = 1, ..., T$, $i = 1, ..., N$.

In the empirical application our focus is on the long-run wage elasticity, which depends on $\ln g$, $\ln t$ and the long-run parameters

$$\overline{\beta}_j = \beta_j / (1-\gamma), j = w,\ wg,\ wt. \tag{5.3}$$

according to the following formula[7]:

$$\overline{\varepsilon}_{lw_{i,t}} \equiv \overline{\beta}_w + \overline{\beta}_{wg} \ln g + \overline{\beta}_{wt} \ln t.$$

The simple long-run estimator obtained by using the bias-corrected LSDV estimator for the β's into equation (5.3) is not unbiased to order $O(T^{-1})$ as pointed out by Bun (2001). Therefore, to estimate the long-run coefficients we adopt the estimator proposed by Bun (2001), based upon Pesaran and Zhao (1999), which is a more appropriate transformation of the bias-corrected LSDV short run estimator.

Finally, since analytic expressions for the standard errors of all corrected estimators typically turns out to be very inaccurate, we estimate them by using parametric bootstrap resampling schemes, as proposed in Bun and Kiviet (2001) and Bun (2001)[8].

Tables 4 to 7 present estimation results for equation (5.2). Table 4 reports results for all possible bias-corrected LSDV estimators, based on bias approximations $\widehat{B}_1$ $\widehat{B}_2$ and $\widehat{B}_3$ and initial estimators AH and AB, as explained in Section 2. For the sake of comparison, Tables 5 and 6 reports results for two different GMM estimators, respectively with strictly exogenous and predetermined regressors. In either case the number of GMM instruments is taken to a minimum to not exacerbate the small-sample bias[9]. Results for the uncorrected LSDV are reported in Table 7.

Overall, our estimates are statistically and economically satisfactory with all regularity conditions satisfied. Results for the bias-corrected LSDV estimators are robust to changes in the order of the bias approximations and to different choices

[7] To avoid that ε_{lw} become too large in absolute value when g is close to zero, the globalization index g is normalized so that $g \geq 1$.

[8] All estimation work has been carried out in STATA 9 using for the bias-corrected LSDV estimators the user-written code XTLSDVC by Bruno (2005c) downloadable from http://ideas.repec.org/c/boc/bocode/s450101.html

[9] GMM estimation has been carried out in Stata 9 using the user-written code XTABOND2 by David Roodman (2005).

of the N-consistent estimator used to initialize the bias correction. In the GMM regressions the null hypothesis of no-second order correlation in the disturbances of the first-differenced equation is never rejected at any conventional level of significance. The estimated coefficient on the one-time lagged employment level is always significantly greater than zero and smaller than unity providing evidence of significant adjustment costs. Our dynamic framework allows estimation of both short and long run constant output labour demand elasticities. Estimates are always plausible. The mean value of the long run elasticity is for all countries within the range estimates of other studies surveyed by Hamermesh (2000) and is relatively robust to changes in estimation method. Moreover, all point estimates for the various sectors are negative.

What is the role of increasing international integration? In our framework this effect can work on labour demand through two channels: the direct effect and the effect via elasticity (Rodrik's conjecture). The Rodrik's conjecture is decidedly rejected for all estimators used (bias-corrected and GMM), which confirms the results for Italy in Bruno, Falzoni and Helg (2004) and also those obtained by Slaughter (2001) for the US, by Krishna et al. (2001) for Turkey and Fajnzylber and Maloney (2001) for a group of Latin American less developed countries. Fourth, differently from what found in Bruno, Falzoni and Helg (2004) the direct effect of globalization on labour demand is never found significant. This discrepancy may be due to the neglected sector in Bruno, Falzoni and Helg (2004) where a significantly positive direct effect has been found in the bias corrected regressions. Finally, we find robust evidence in favour of output generated external economies.

6. Conclusions

This paper has estimated a dynamic labour demand equation for an unbalanced panel data set of Italian manufacturing sectors. We have used both bias-corrected LSDV estimators and GMM estimators. Our findings are substantially robust to changes in the estimator adopted. While we do not find support for either the Rodrik's conjecture or the presence of a direct globalization effect in the labour demand equation, we can provide robust evidence in favour of output generated external economies. Long run and short run estimated elasticities are always plausible in both an economics and statistics sense.

References

[1] Ahn, S.C. and P. Schimdt, (1995), “Efficient Estimation of Models for Dynamic Panel Data”, *Journal of Econometrics*, 68, 5-28.

[2] Arellano, M. and S. Bond, (1991), “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations”, *Review of Economic Studies*, 58, 277-297.

[3] Blundell, R.W. and S.R. Bond, (1998), ”Initial Conditions and Moment Restrictions in Dynamic Panel Data Models”, *Journal of Econometrics*, 87, 115-143.

[4] Bruno, G.S.F. (2005a). “Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models”. Economics Letters, 87, 361-366.

[5] Bruno, G.S.F. (2005b) “Estimation and inference in dynamic unbalanced panel data models with a small number of individuals”. CESPRI WP n.165 , Università Bocconi-CESPRI, Milan.

[6] Bruno, G.S.F. (2005c) ”XTLSDVC: Stata module to estimate bias corrected LSDV dynamic panel data models,” Statistical Software Components S450101, Boston College Department of Economics.

[7] Bruno, G.S.F. (2004). “On the Equivalence of Two Concepts of Returns to Scale”. Bulletin of Economic Research, 56, 67-80.

[8] Bruno, G.S.F., Falzoni A.M. and R. Helg (2004), “Measuring the effect of globalization on labor demand elasticity: An empirical application to some OECD countries”, w.p. CESPRI n. 153, Università Bocconi-CESPRI, Milano.

[9] Bun, M.J.G. (2001) “Bias Correction in the Dynamic Panel Data Model with a Nonscalar Disturbance Covariance Matrix” Tinbergen Institute Discussion Paper TI 2001-007/4.

[10] Bun, M.J.G. and J.F. Kiviet, (2001), “The accuracy of inference in small samples of dynamic data models”, Tinbergen Institute D.P. 006/4.

[11] Bun, M.J.G. and J.F Kiviet (2003) “On the diminishing returns of higher order terms in asymptotic expansions of bias” *Economics Letters*, 79, 145-152.

[12] Coe, D. and E. Helpman, (1995), "International R&D spillovers", *European Economic Review*, 39, 859-87.

[13] Faini, R., A.M. Falzoni, M. Galeotti, R. Helg and A. Turrini, (1999), "Importing jobs and exporting firms? On the wage and employment implications of Italian trade and foreign direct investment flows", *Giornale degli Economisti ed Annali di Economia*, 58 (1), 95-135.

[14] Fajnzylber, P. and W. Maloney, (2001), "Labour demand and trade reform in Latin America", World Bank Working Paper No. 2491, January.

[15] Feenstra, R. and G. Hanson, (2001), "Global production sharing and rising inequality: A survey of trade and wages", NBER W.P. 8372, July.

[16] Greenaway, D., R.C. Hine and P.Wright, (1999), "An empirical assessment of the impact of trade on employment in the United Kingdom", *European Journal of Political Economy*, 15, 485-500.

[17] Hamermesh, D.S., (1993), *Labor Demand*, Princeton University Press, Princeton.

[18] Hamermesh, D.S., (2000), Demand for labor, in International Encyclopaedia of the Social & Behavioural Sciences

[19] Harris, M.N., and L. Matyas, (2000), "A comparative analysis of different estimators for dynamic panel data models", mimeo.

[20] Jean, S., (2000), "The effect of international trade on labour-demand elasticities: intersectoral matters", *Review of International Economics*, 8(3), 504-516.

[21] Kiviet, J.F., (1995), "On bias, inconsistency and efficiency of various estimators in dynamic panel data models", *Journal of Econometrics, 68, 53-78.*

[22] Kiviet, J.F. (1999), "Expectation of Expansions for Estimators in a Dynamic Panel Data Model; Some Results for Weakly Exogenous Regressors" in C. Hsiao, K. Lahiri, L-F Lee and M.H. Pesaran (eds.), *Analysis of Panel Data and Limited Dependent Variables,* Cambridge University Press, Cambridge.

[23] Krishna, P., D. Mitra and S. Chinoy, (2001), "Trade liberalization and labour demand elasticities: evidence from Turkey", *Journal of International Economics,* 55, 391-409.

[24] Nickell, S.J., (1981), "Biases in Dynamic Models with Fixed Effects", *Econometrica*, 49, 1417-1426.

[25] Panagariya, A., (1999), Trade openness: consequences for the elasticity of demand for labor and wage outcomes, mimeo.

[26] Pesaran, M.H. and Z. Zhao (1999), "Bias Reduction in Estimating Long-run Relationships from Dynamic Heterogeneous Panels" in C. Hsiao, K. Lahiri, L-F Lee and M.H. Pesaran (eds.), *Analysis of Panel Data and Limited Dependent Variables,* Cambridge University Press, Cambridge.

[27] Rauch, J.E. and V. Trindade, (2003), "Information, International Substitutability and Globalisation", *American Economic Review*, 93, 775-791.

[28] Rodrik, D., (1997), *Has globalisation gone too far?*, Institute for International Economics, Washington DC.

[29] Roodman, D. (2003). "XTABOND2: Stata module to extend xtabond dynamic panel data estimator," Statistical Software Components S435901, Boston College Department of Economics, revised 22 Apr 2005.

[30] Slaughter, M.J., (2001), "International trade and labor-demand elasticities", *Journal of International Economics*, 54, 27-56.

Appendix A

Basically, we first retrieve the underlying cost function by integrating (3.4), and then we obtain the production function from the cost function by duality. For simplicity, we limit to a specification with no time trend in the labour demand equation and let $r = 1$.

The first step of the derivation is straightforward. From Shephard's Lemma and (3.4) we have

$$\frac{\partial C}{\partial w} = l = e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g} w^{\beta_w + \beta_{wg} \ln g},$$

and so the (normalized) cost function must have the following restricted translog form:

$$C = \int_0^w e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g} \omega^{\beta_w + \beta_{wg} \ln g} d\omega = \frac{e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g}}{\beta_w + \beta_{wg} \ln g + 1} w^{\beta_w + \beta_{wg} \ln g + 1}. \quad (6.1)$$

It is a restricted form in that the interaction term between output and wage and the squared wage do not enter the cost function specification.

The second step goes as follows. Singling out w in

$$l = e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g} w^{\beta_w + \beta_{wg} \ln g}.$$

yields

$$w = \left(\frac{l}{e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g}} \right)^{1/(\beta_w + \beta_{wg} \ln g)}. \quad (6.2)$$

Since C is a normalized cost function, we can write

$$C = wl + k. \quad (6.3)$$

Thus, substituting for C from (6.1) and for w from (6.2) into (6.3) gives

$$\left(\frac{l}{e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g}} \right)^{1/(\beta_w + \beta_{wg} \ln g)} l + k = \frac{e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g}}{\beta_w + \beta_{wg} \ln g + 1} \left(\frac{l}{e^{u+\epsilon} y^{\beta_y} x^{\beta_x} g^{\beta_g}} \right)^{1 + \frac{1}{\beta_w + \beta_{wg} \ln g}}, \quad (6.4)$$

which, after rearrangement and substituting for $\beta_w + \beta_{wg} \ln g$ from (3.5), gives the desired production function.

$$y = \left(\frac{1}{e^{u+\epsilon} x^{\beta_x} g^{\beta_g}} \right)^{\frac{1}{\beta_y}} \left(\frac{-\varepsilon_{lw}}{1 + \varepsilon_{lw}} \right)^{\frac{\varepsilon_{lw}}{\beta_y}} (k)^{-\frac{\varepsilon_{lw}}{\beta_y}} (l)^{\frac{1+\varepsilon_{lw}}{\beta_y}}.$$

By taking equation (3.7) in logarithms and then differentiating it with respect to $\ln g$, we obtain the elasticity of A with respect to g

$$\varepsilon_{Ag} = -\frac{\beta_g}{\beta_y} + \frac{\beta_{wg}}{\beta_y}\left[\ln\left(\frac{-\varepsilon_{lw}}{\varepsilon_{lw}+1}\right) + \frac{1}{\varepsilon_{lw}+1}\right]. \tag{6.5}$$

In Greenaway's case of $\beta_{wg} = 0$, ε_{Ag} reduces to the constant parameter $-\beta_g/\beta_y$, with g acting on the isoquant mapping as Hicks-neutral technical change. Thus, in our formulation (6.5) ε_{Ag} must be thought of as generalized technical efficiency effect. Unlike β_y and ε_{lw}, there are no theoretical restrictions on the sign of ε_{Ag}, which in turn depends on the sign of β_g and β_{wg} and the size and sign of ε_{lw}.

Notice that the presence of β_g ensures enough flexibility to cover all possible relevant economic instances. For example, should we restrict ourselves to $\beta_g = 0$, then in the presence of a negative impact of g on ε_{lw} ($\beta_{wg} \leq 0$), a positive impact of g on technical efficiency ($\varepsilon_{Ag} \geq 0$) would be possible only for $|\varepsilon_{lw}| \in [0, 1/2]$. On the other hand, if β_g is free to assume any value, then $\beta_{wg} \leq 0$ and $\varepsilon_{Ag} \geq 0$, as well as any other combination of signs, can be compatible with any plausible $|\varepsilon_{lw}|$.

The economic interpretation of β_g parallels that of β_w, in that β_g is the intercept of the labour elasticity with respect to g. In fact

$$\varepsilon_{\mathrm{lg}} \equiv \frac{\partial \ln l}{\partial \ln g} = \beta_g + \beta_{wg} \ln w.$$

As such, β_g measures the responsiveness of labour demand to g at $w = 1$, that is when the economic rate of substitution (w) is 1.

Table 1 - Industry Codes, Definitions and Labels

ISIC Revision 2	Industry Description	Industry Labels*
311/2	Food	fod
3130	Beverages	bev
3140	Tobacco	tob
3210	Textiles	tex
3220	Wearing Apparel	wear
3230	Leather & Products	leather
3240	Footwear	foot
3310	Wood Products	wood
3320	Furniture & Fixtures	furn
3410	Paper & Products	pap
3420	Printing & Publishing	print
3510	Industrial Chemicals	indche
3520	Other Chemicals	DRUGS&CHE
3522	Drugs & Medicines	drugs
3520 less 3522	Chemical Products n.e.c.**	che
3530	Petroleum Refineries	petref
3540	Petroleum & Coal Products	petcoal
3530 and 3540	Petroleum Refineries & Products	REF&COAL
3550	Rubber Products	rub
3560	Plastic Products, n.e.c.	plas
3610	Pottery, China etc.	pot
3620	Glass & Products	glass
3690	Non-Metallic Products, n.e.c.	nmetp
3710	Iron & Steel	festeel
3720	Non-Ferrous Metals	nferm
3810	Metal Products	met
3820	Non-Electrical Machinery	OECOMP&MAEQUIP
3825	Office & Computing Machinery	ocomp
3820 less 3825	Machinery & Equipment, n.e.c.	maequi
3830	Electrical Machinery	COMM&ELEC
3832	Radio, TV & Communication Equipment	comm
3830 less 3832	Electrical Apparatus, n.e.c.	elec
3841	Ship-Building & Repairing	ship
3842	Railroad Equipment	rail
3843	Motor Vehicles	moto
3844	Motorcycles & Bicycles	mcycles
3845	Aircraft	air
3849	Transport Equipment, n.e.c.	transp
3842 and 3844 and 3849	Railroad Equipment, Motorcycles & Bicycles, Transport Equipment, n.e.c.	RAIL&MCYCLES&TRANS
3850	Professional Goods	prof
3900	Other Manufacturing, n.e.c.	other

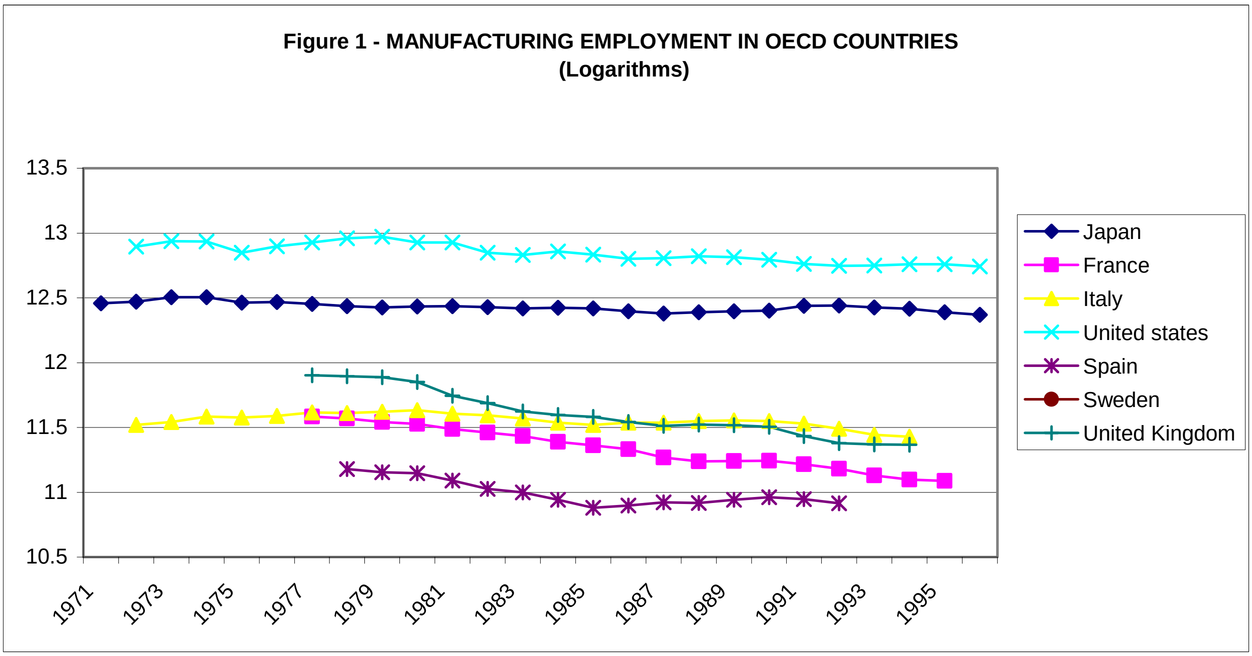
* These regression codes refer to the labels that have been attributed to the different industries in the empirical work .
** n.e.c. stands for “not elsewhere classified”.

Table 2 - STAN Variables: Definitions

Variable	Regression Code	STAN Definition
Value Added	VA	This represents the contribution of each industry to national GDP in current prices
Value Added 1990	VA90	This represents the contribution of each industry to national GDP in constant 1990 prices
Number Engaged	NE	This includes the number of employees as well as self-employed, owner proprietors, and unpaid family workers
Labour Compensation	COMP	Current price national accounts compatible labour costs which include wages as well as the costs of supplements such as employer's compulsory pension or medical payments
Imports, Exports	IMP, EXP	These represent imports and exports in current prices.

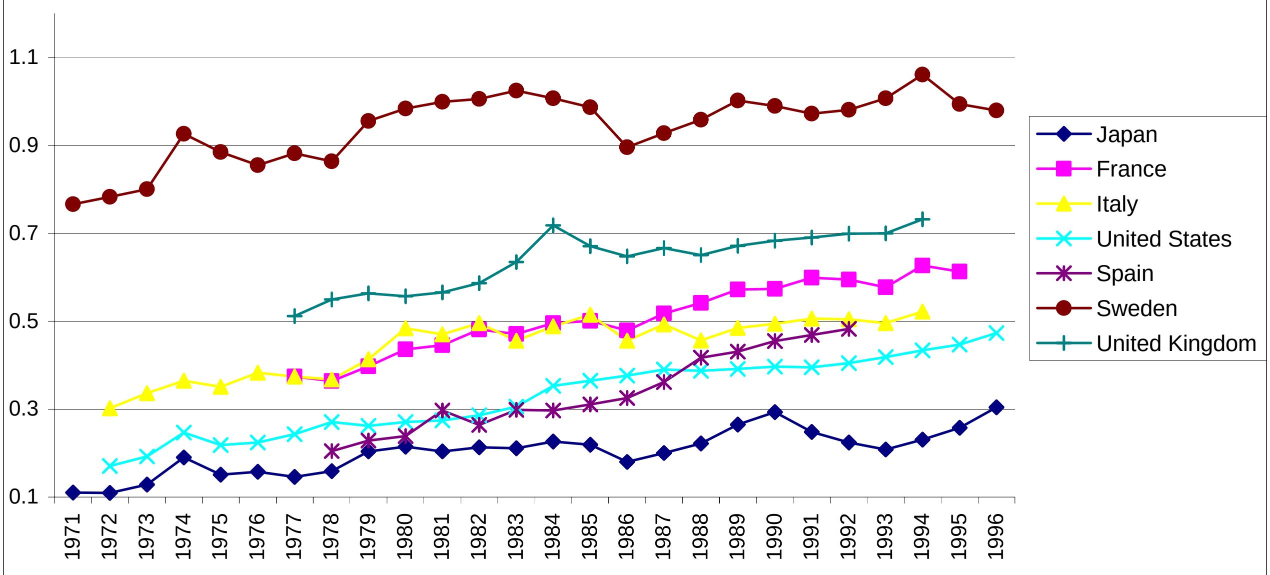
Table 3 - Variables

Variable	Description
P90, value added deflator	VA/VA90
Wnom, average remuneration of labour	COMP/NE
W90, average remuneration price index	Wnom/value taken by Wnom in 1990
w, relative remuneration of labour	W90/P90
g	IMP/VA



Source: OECD, STAN Database.

Figure 2 - IMPORT PENETRATION IN OECD COUNTRIES
(Logarithms)



Source: OECD, STAN Database.

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                                          ___  ____  ____  ____
____tm                                   /__    /   ____/   /
____/                                   ___/   /   /___/   /
/___/                                     Statistics/Data Analysis
```

TABLE 4: BIAS CORRECTED LSDV ESTIMATORS

Bias correction initialized by Anderson and Hsiao estimator
Bias correction up to order O(1/T)

LSDVC dynamic regression
(bootstrapped SE)

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
short_run						
LnNE L1.	.8106739	.0160838	50.40	0.000	.7791502	.8421975
Lnw	-37.4282	17.73478	-2.11	0.035	-72.18773	-2.66868
Lng2	.0078927	.0058922	1.34	0.180	-.0036559	.0194412
Lng2w	.0157043	.0053194	2.95	0.003	.0052784	.0261302
LnGDP90	.1383679	.0164558	8.41	0.000	.1061152	.1706206
Lnyearw	4.915498	2.33678	2.10	0.035	.3354933	9.495503
Iyear_2	.0424779	.047464	0.89	0.371	-.0505498	.1355057
Iyear_3	.0187401	.049529	0.38	0.705	-.078335	.1158152
Iyear_4	.0555018	.045633	1.22	0.224	-.0339373	.1449408
Iyear_5	.0689923	.0482524	1.43	0.153	-.0255806	.1635652
Iyear_6	.0476312	.0475623	1.00	0.317	-.0455892	.1408516
Iyear_7	.0569102	.0460109	1.24	0.216	-.0332696	.1470899
Iyear_8	.0706446	.0440672	1.60	0.109	-.0157255	.1570147
Iyear_9	.0444029	.0461517	0.96	0.336	-.0460527	.1348585
Iyear_10	.0534521	.0450789	1.19	0.236	-.0349009	.1418051
Iyear_11	.0516243	.0449347	1.15	0.251	-.0364461	.1396948
Iyear_12	.0198271	.0460805	0.43	0.667	-.070489	.1101432
Iyear_13	.0309256	.0473824	0.65	0.514	-.0619422	.1237933
Iyear_14	.0168571	.0467204	0.36	0.718	-.0747132	.1084274
Iyear_15	.0091166	.0451015	0.20	0.840	-.0792806	.0975139
Iyear_16	.022155	.0468176	0.47	0.636	-.0696058	.1139158

Iyear_17	.0431933	.0448089	0.96	0.335	-.0446305	.1310171
Iyear_18	.0272969	.0474507	0.58	0.565	-.0657049	.1202986
Iyear_19	.0379913	.0467535	0.81	0.416	-.0536438	.1296264
Iyear_20	.0262487	.0446918	0.59	0.557	-.0613456	.113843
Iyear_21	.025243	.0472039	0.53	0.593	-.067275	.1177609
Iyear_22	.01301	.0488011	0.27	0.790	-.0826384	.1086583
Iyear_23	-.0047914	.0468276	-0.10	0.919	-.0965719	.0869891
Iyear_24	-.0204272	.0476064	-0.43	0.668	-.1137341	.0728796
Iyear_25	-.0041911	.0464144	-0.09	0.928	-.0951616	.0867794
Iyear_26	.0063145	.0722471	0.09	0.930	-.1352872	.1479162
long_run						
Lnw	-196.3564	94.48479	-2.08	0.038	-381.5432	-11.1696
Lng2	.041429	.03028	1.37	0.171	-.0179188	.1007768
Lng2w	.0814084	.0267561	3.04	0.002	.0289675	.1338494
LnGDP90	.7277796	.0669652	10.87	0.000	.5965303	.859029
Lnyearw	25.78742	12.44976	2.07	0.038	1.386339	50.1885
Iyear_2	.2233931	.2340658	0.95	0.340	-.2353675	.6821536
Iyear_3	.1010697	.2467197	0.41	0.682	-.382492	.5846314
Iyear_4	.2910637	.2255012	1.29	0.197	-.1509106	.733038
Iyear_5	.360783	.2368998	1.52	0.128	-.1035321	.8250982
Iyear_6	.2520719	.2350439	1.07	0.284	-.2086056	.7127494
Iyear_7	.2993409	.2280123	1.31	0.189	-.1475549	.7462368
Iyear_8	.370555	.217913	1.70	0.089	-.0565466	.7976565
Iyear_9	.2347784	.22815	1.03	0.303	-.2123875	.6819442
Iyear_10	.2813662	.222639	1.26	0.206	-.1549983	.7177306
Iyear_11	.2716963	.2241747	1.21	0.226	-.167678	.7110706
Iyear_12	.1073947	.2290324	0.47	0.639	-.3415005	.55629
Iyear_13	.1647337	.2361492	0.70	0.485	-.2981103	.6275776
Iyear_14	.091775	.2336649	0.39	0.694	-.3661999	.5497498
Iyear_15	.0510051	.2260771	0.23	0.822	-.392098	.4941081
Iyear_16	.1180928	.2340488	0.50	0.614	-.3406344	.57682
Iyear_17	.2264222	.2230246	1.02	0.310	-.2106979	.6635423
Iyear_18	.1442769	.2370824	0.61	0.543	-.3203961	.6089499
Iyear_19	.1991755	.2331736	0.85	0.393	-.2578363	

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
						.6561873
Iyear_20	.1383651	.2235214	0.62	0.536	-.2997288	.576459
Iyear_21	.1336213	.2358854	0.57	0.571	-.3287056	.5959482
Iyear_22	.0707774	.2431877	0.29	0.771	-.4058617	.5474165
Iyear_23	-.021597	.2354106	-0.09	0.927	-.4829933	.4397992
Iyear_24	-.1031693	.2390672	-0.43	0.666	-.5717323	.3653938
Iyear_25	-.0204023	.2334456	-0.09	0.930	-.4779472	.4371427
Iyear_26	.0328895	.3589615	0.09	0.927	-.6706621	.7364411

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
long_run_el	-.6475386	.0738227	-8.77	0.000	-.7922285	-.5028487

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
short_run_el	-.1231323	.0179602	-6.86	0.000	-.1583336	-.087931

Bias correction up to order O(1/NT)

LSDVC dynamic regression
(bootstrapped SE)

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
short_run						
LnNE						
L1.	.8126495	.0158263	51.35	0.000	.7816306	.8436685
Lnw	-37.12216	17.6889	-2.10	0.036	-71.79177	-2.452542
Lng2	.0078467	.0058816	1.33	0.182	-.003681	.0193743
Lng2w	.0156998	.0053081	2.96	0.003	.0052962	.0261034
LnGDP90	.1372427	.0163844	8.38	0.000	.1051299	.1693554
Lnyearw	4.875314	2.330749	2.09	0.036	.3071288	9.443498
Iyear_2	.0421273	.0474917	0.89	0.375	-.0509548	.1352094
Iyear_3	.0183074	.0495482	0.37	0.712	-.0788053	

```
.1154201
     Iyear_4 |   .0551259   .0456548     1.21   0.227    -.0343559
.1446078
     Iyear_5 |   .0686369   .0482708     1.42   0.155    -.0259721
.1632459
     Iyear_6 |   .0470595   .0475698     0.99   0.323    -.0461756
.1402945
     Iyear_7 |   .0564256   .0460083     1.23   0.220    -.0337489
.1466001
     Iyear_8 |   .0701574   .0440749     1.59   0.111    -.0162278
.1565426
     Iyear_9 |   .0438874   .0461523     0.95   0.342    -.0465694
.1343442
    Iyear_10 |   .0529692    .045086     1.17   0.240    -.0353977
.1413361
    Iyear_11 |   .0511603   .0449343     1.14   0.255    -.0369094
.13923
    Iyear_12 |   .0193066   .0460887     0.42   0.675    -.0710257
.1096389
    Iyear_13 |   .0304254   .0473971     0.64   0.521    -.0624711
.1233219
    Iyear_14 |   .0163609    .046725     0.35   0.726    -.0752184
.1079401
    Iyear_15 |   .0086886    .045108     0.19   0.847    -.0797214
.0970987
    Iyear_16 |   .0217807   .0468291     0.47   0.642    -.0700027
.1135641
    Iyear_17 |   .0428982   .0448219     0.96   0.339    -.0449511
.1307475
    Iyear_18 |   .0269744   .0474661     0.57   0.570    -.0660573
.1200062
    Iyear_19 |   .0377275   .0467736     0.81   0.420    -.0539471
.129402
    Iyear_20 |   .0259785   .0447128     0.58   0.561    -.0616571
.113614
    Iyear_21 |   .0249275   .0472197     0.53   0.598    -.0676214
.1174764
    Iyear_22 |   .0126378   .0488202     0.26   0.796    -.0830481
.1083236
    Iyear_23 |  -.0051507   .0468418    -0.11   0.912     -.096959
.0866575
    Iyear_24 |  -.0207319    .047625    -0.44   0.663    -.1140752
.0726114
    Iyear_25 |  -.0043476   .0464441    -0.09   0.925    -.0953763
.0866812
    Iyear_26 |   .0063016   .0723425     0.09   0.931     -.135487
.1480902

-------------+----------------------------------------------------------------
      long_run     |
         Lnw |  -196.6925   95.87501    -2.05   0.040    -384.6041
-8.780961
        Lng2 |   .0415805   .0306718     1.36   0.175    -.0185352
.1016962
       Lng2w |   .0820619   .0270903     3.03   0.002     .0289659
.1351579
     LnGDP90 |   .7290957   .0679697    10.73   0.000     .5958775
.8623138
     Lnyearw |   25.83159   12.63295     2.04   0.041     1.071477
50.59171
     Iyear_2 |   .2237871   .2378917     0.94   0.347    -.2424719
.6900462
     Iyear_3 |   .1001071   .2506878     0.40   0.690     -.391232
.5914462
     Iyear_4 |     .29191    .229205     1.27   0.203    -.1573235
.7411436
     Iyear_5 |   .3622911   .2407994     1.50   0.132     -.109667
.8342492
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Iyear_6	.2517749	.2389256	1.05	0.292	-.2165105	.7200604
Iyear_7	.2997988	.2317515	1.29	0.196	-.1544257	.7540234
Iyear_8	.3715906	.2215138	1.68	0.093	-.0625685	.8057497
Iyear_9	.2345718	.2318601	1.01	0.312	-.2198656	.6890093
Iyear_10	.2816811	.2262658	1.24	0.213	-.1617918	.725154
Iyear_11	.2720096	.227819	1.19	0.232	-.1745074	.7185266
Iyear_12	.1061123	.2327277	0.46	0.648	-.3500255	.5622502
Iyear_13	.1640107	.2399984	0.68	0.494	-.3063775	.6343988
Iyear_14	.0904648	.2374003	0.38	0.703	-.3748312	.5557608
Iyear_15	.0496431	.229659	0.22	0.829	-.4004803	.4997665
Iyear_16	.1175107	.2378401	0.49	0.621	-.3486474	.5836688
Iyear_17	.227068	.2266572	1.00	0.316	-.2171719	.671308
Iyear_18	.1441282	.2409695	0.60	0.550	-.3281633	.6164197
Iyear_19	.1997261	.2369251	0.84	0.399	-.2646386	.6640908
Iyear_20	.1383857	.2271677	0.61	0.542	-.3068548	.5836263
Iyear_21	.1334137	.2396405	0.56	0.578	-.336273	.6031003
Iyear_22	.0698128	.2470963	0.28	0.778	-.4144871	.5541127
Iyear_23	-.0232716	.2391111	-0.10	0.922	-.4919207	.4453775
Iyear_24	-.1052897	.2428432	-0.43	0.665	-.5812537	.3706743
Iyear_25	-.0212175	.2372816	-0.09	0.929	-.4862808	.4438459
Iyear_26	.0331063	.3650342	0.09	0.928	-.6823477	.7485603

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
long_run_el	-.6489353	.0749644	-8.66	0.000	-.7958627	-.5020079

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
short_run_el	-.122185	.0179322	-6.81	0.000	-.1573316	-.0870384

Bias correction up to order O(1/NT^2)

LSDVC dynamic regression
(bootstrapped SE)

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
short_run						
LnNE						
L1.	.8208447	.0199637	41.12	0.000	.7817165	.8599729
Lnw	-35.93513	17.45443	-2.06	0.040	-70.14519	-1.72508
Lng2	.007641	.0058304	1.31	0.190	-.0037863	.0190683
Lng2w	.0156936	.0053014	2.96	0.003	.0053032	.0260841
LnGDP90	.1325339	.0173426	7.64	0.000	.0985431	.1665247
Lnyearw	4.719499	2.299754	2.05	0.040	.2120637	9.226934
Iyear_2	.0405718	.0479664	0.85	0.398	-.0534407	.1345843
Iyear_3	.0164214	.0500895	0.33	0.743	-.0817522	.1145951
Iyear_4	.0534889	.0459486	1.16	0.244	-.0365688	.1435466
Iyear_5	.0670911	.0485531	1.38	0.167	-.0280712	.1622533
Iyear_6	.0446138	.0480128	0.93	0.353	-.0494895	.1387171
Iyear_7	.0543511	.0464521	1.17	0.242	-.0366934	.1453956
Iyear_8	.0680745	.0444534	1.53	0.126	-.0190526	.1552016
Iyear_9	.0416909	.046602	0.89	0.371	-.0496473	.1330291
Iyear_10	.0509145	.0454173	1.12	0.262	-.0381016	.1399307
Iyear_11	.0491887	.0452979	1.09	0.278	-.0395936	.137971
Iyear_12	.0171006	.0465019	0.37	0.713	-.0740414	.1082426
Iyear_13	.0283039	.0477159	0.59	0.553	-.0652175	.1218253
Iyear_14	.0142545	.047046	0.30	0.762	-.0779541	.1064631
Iyear_15	.0068679	.0454651	0.15	0.880	-.082242	.0959778
Iyear_16	.0201831	.0472435	0.43	0.669	-.0724125	.1127787
Iyear_17	.04163	.0450906	0.92	0.356	-.0467459	.1300059
Iyear_18	.0255934	.0478467	0.53	0.593	-.0681844	.1193712
Iyear_19	.0365911	.0470168	0.78	0.436	-.0555601	.1287423
Iyear_20	.0248173	.0449508	0.55	0.581	-.0632847	.1129193
Iyear_21	.0235721	.0476231	0.49	0.621	-.0697674	.1169117
Iyear_22	.0110402	.0491836	0.22	0.822	-.0853579	.1074382
Iyear_23	-.0066994	.0471356	-0.14	0.887	-.0990835	.0856847

Iyear_24	-.0220543	.0479849	-0.46	0.646	-.116103	.0719944
Iyear_25	-.0050521	.0467929	-0.11	0.914	-.0967645	.0866603
Iyear_26	.0062565	.0733463	0.09	0.932	-.1374997	.1500127
long_run						
Lnw	-198.4711	104.9382	-1.89	0.059	-404.1461	7.203984
Lng2	.0421396	.0338627	1.24	0.213	-.0242299	.1085092
Lng2w	.0848319	.0305498	2.78	0.005	.0249554	.1447084
LnGDP90	.7343622	.0770309	9.53	0.000	.5833844	.88534
Lnyearw	26.0655	13.82719	1.89	0.059	-1.035288	53.16628
Iyear_2	.2249516	.2647546	0.85	0.396	-.293958	.7438611
Iyear_3	.0956902	.2796201	0.34	0.732	-.4523551	.6437356
Iyear_4	.2950565	.254514	1.16	0.246	-.2037819	.7938949
Iyear_5	.3682125	.2675497	1.38	0.169	-.1561753	.8926002
Iyear_6	.2501976	.2660843	0.94	0.347	-.271318	.7717131
Iyear_7	.301398	.2572079	1.17	0.241	-.2027203	.8055163
Iyear_8	.3755988	.2462542	1.53	0.127	-.1070506	.8582483
Iyear_9	.2334441	.2578167	0.91	0.365	-.2718674	.7387556
Iyear_10	.2827462	.2515589	1.12	0.261	-.2103001	.7757925
Iyear_11	.2730907	.2534652	1.08	0.281	-.223692	.7698734
Iyear_12	.1005729	.2591709	0.39	0.698	-.4073927	.6085385
Iyear_13	.1607934	.266906	0.60	0.547	-.3623328	.6839195
Iyear_14	.0848068	.2637195	0.32	0.748	-.4320739	.6016875
Iyear_15	.043782	.2555564	0.17	0.864	-.4570993	.5446634
Iyear_16	.1148865	.2647531	0.43	0.664	-.4040201	.633793
Iyear_17	.2295403	.2517317	0.91	0.362	-.2638448	.7229255
Iyear_18	.1433089	.2677133	0.54	0.592	-.3813997	.6680174
Iyear_19	.2018148	.2634266	0.77	0.444	-.3144918	.7181214
Iyear_20	.1382834	.2521665	0.55	0.583	-.3559539	.6325207
Iyear_21	.1323344	.2668904	0.50	0.620	-.3907612	.6554301
Iyear_22	.0655617	.2749403	0.24	0.812	-.4733113	.6044346
Iyear_23	-.0304885	.2661791	-0.11	0.909	-.55219	.4912129
Iyear_24	-.1143584	.270314	-0.42	0.672	-.644164	.4154472
Iyear_25	-.0248581	.2642243	-0.09	0.925	-.5427283	.4930121
Iyear_26	.0340442	.4092848	0.08	0.934	-.7681392	

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.8362277
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              LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
       long_run_el |  -.6544474   .0848239    -7.72   0.000    -.8206991
-.4881956
------------------------------------------------------------------------------


------------------------------------------------------------------------------
              LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
      short_run_el |  -.1181952   .0185026    -6.39   0.000    -.1544596
-.0819308
------------------------------------------------------------------------------


      Bias correction initialized by Arellano and Bond estimator
      Bias correction up to order O(1/T)

      LSDVC dynamic regression
      (bootstrapped SE)
------------------------------------------------------------------------------
              LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
      short_run    |
              LnNE |
               L1. |     .81093   .0148334    54.67   0.000     .7818571
.840003
               Lnw |  -37.48922   17.29518    -2.17   0.030    -71.38715
-3.591292
              Lng2 |   .0068047   .0057475     1.18   0.236    -.0044601
.0180695
             Lng2w |   .0161855   .0049647     3.26   0.001     .0064549
.0259161
           LnGDP90 |   .1367775   .0153978     8.88   0.000     .1065984
.1669567
           Lnyearw |    4.92383   2.278926     2.16   0.031     .4572169
9.390442
           Iyear_2 |   .0413684   .0450729     0.92   0.359    -.0469729
.1297097
           Iyear_3 |   .0177511   .0470518     0.38   0.706    -.0744688
.109971
           Iyear_4 |   .0548159   .0434931     1.26   0.208     -.030429
.1400608
           Iyear_5 |   .0684923   .0459993     1.49   0.136    -.0216646
.1586493
           Iyear_6 |   .0468161   .0452183     1.04   0.301    -.0418101
.1354423
           Iyear_7 |   .0563512   .0437722     1.29   0.198    -.0294407
.1421431
           Iyear_8 |   .0700905   .0419231     1.67   0.095    -.0120772
.1522582
           Iyear_9 |   .0438861   .0439847     1.00   0.318    -.0423224
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.1300946
   Iyear_10 |   .0531657   .0430191     1.24   0.217    -.0311501
.1374816
   Iyear_11 |   .0515253   .0429092     1.20   0.230    -.0325751
.1356258
   Iyear_12 |   .0196222   .0439225     0.45   0.655    -.0664643
.1057087
   Iyear_13 |    .030718   .0451901     0.68   0.497     -.057853
.1192889
   Iyear_14 |   .0165165   .0445986     0.37   0.711    -.0708951
.1039282
   Iyear_15 |   .0089108   .0430013     0.21   0.836    -.0753701
.0931917
   Iyear_16 |   .0220088   .0446019     0.49   0.622    -.0654093
.1094269
   Iyear_17 |   .0430127   .0427683     1.01   0.315    -.0408115
.126837
   Iyear_18 |   .0272014   .0452964     0.60   0.548    -.0615779
.1159808
   Iyear_19 |   .0379497   .0446478     0.85   0.395    -.0495583
.1254578
   Iyear_20 |   .0263113   .0426756     0.62   0.538    -.0573314
.109954
   Iyear_21 |   .0251989   .0450321     0.56   0.576    -.0630624
.1134601
   Iyear_22 |   .0128658    .046526     0.28   0.782    -.0783234
.104055
   Iyear_23 |  -.0049918   .0446552    -0.11   0.911    -.0925144
.0825308
   Iyear_24 |  -.0206484   .0453304    -0.46   0.649    -.1094943
.0681975
   Iyear_25 |  -.0042492   .0442184    -0.10   0.923    -.0909156
.0824173
   Iyear_26 |   .0065919   .0689207     0.10   0.924    -.1284901
.1416739

-------------+----------------------------------------------------------------
long_run     |
         Lnw |  -196.8692   91.99204    -2.14   0.032    -377.1703
-16.5681
        Lng2 |   .0364071   .0294983     1.23   0.217    -.0214084
.0942227
       Lng2w |   .0837377   .0248645     3.37   0.001     .0350043
.1324712
     LnGDP90 |   .7212201   .0638432    11.30   0.000     .5960898
.8463505
     Lnyearw |   25.85624   12.12139     2.13   0.033     2.098759
49.61373
     Iyear_2 |   .2184863    .222393     0.98   0.326     -.217396
.6543685
     Iyear_3 |   .0965984   .2345575     0.41   0.680    -.3631258
.5563226
     Iyear_4 |   .2882047   .2151328     1.34   0.180    -.1334479
.7098572
     Iyear_5 |   .3588637    .225967     1.59   0.112    -.0840234
.8017508
     Iyear_6 |   .2485808   .2235302     1.11   0.266    -.1895304
.686692
     Iyear_7 |   .2970887   .2171351     1.37   0.171    -.1284883
.7226657
     Iyear_8 |   .3684018   .2073267     1.78   0.076    -.0379512
.7747547
     Iyear_9 |   .2326552   .2175341     1.07   0.285    -.1937039
.6590143
    Iyear_10 |   .2803646   .2122427     1.32   0.187    -.1356236
.6963527
    Iyear_11 |    .271556   .2139177     1.27   0.204     -.147715
.6908271
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         Iyear_12 |   .1065881   .2181871     0.49   0.625    -.3210507
.5342269
         Iyear_13 |   .1639748   .2249695     0.73   0.466    -.2769572
.6049069
         Iyear_14 |   .0903182   .2229858     0.41   0.685    -.3467259
.5273623
         Iyear_15 |    .050128   .2155197     0.23   0.816    -.3722828
.4725389
         Iyear_16 |   .1175623   .2228022     0.53   0.598    -.3191219
.5542466
         Iyear_17 |    .225843   .2127811     1.06   0.289    -.1912003
.6428863
         Iyear_18 |   .1440078   .2259401     0.64   0.524    -.2988267
.5868423
         Iyear_19 |   .1992126   .2224183     0.90   0.370    -.2367193
.6351445
         Iyear_20 |   .1388228   .2131109     0.65   0.515    -.2788669
.5565125
         Iyear_21 |   .1335795    .224766     0.59   0.552    -.3069538
.5741128
         Iyear_22 |   .0702053   .2318457     0.30   0.762    -.3842039
.5246145
         Iyear_23 |  -.0225307   .2241745    -0.10   0.920    -.4619047
.4168433
         Iyear_24 |  -.1042906   .2275955    -0.46   0.647    -.5503696
.3417885
         Iyear_25 |   -.020684   .2221784    -0.09   0.926    -.4561457
.4147778
         Iyear_26 |    .034218    .342325     0.10   0.920    -.6367267
.7051626
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             LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
      long_run_el |  -.6401869   .0698998    -9.16   0.000    -.7771879
-.5031858
------------------------------------------------------------------------------

------------------------------------------------------------------------------
             LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
     short_run_el |  -.1213927   .0172075    -7.05   0.000    -.1551188
-.0876667
------------------------------------------------------------------------------

      Bias correction up to order O(1/NT)

      LSDVC dynamic regression
      (bootstrapped SE)

------------------------------------------------------------------------------
             LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
      short_run    |
             LnNE |
```

L1.	.812389	.0146827	55.33	0.000	.7836114	.8411667
Lnw	-37.24224	17.25805	-2.16	0.031	-71.06739	-3.417082
Lng2	.0067095	.0057323	1.17	0.242	-.0045257	.0179447
Lng2w	.0162096	.0049454	3.28	0.001	.0065168	.0259024
LnGDP90	.1358483	.0153404	8.86	0.000	.1057817	.1659149
Lnyearw	4.891408	2.274039	2.15	0.031	.4343732	9.348442
Iyear_2	.0410543	.0450835	0.91	0.362	-.0473076	.1294163
Iyear_3	.017382	.0470615	0.37	0.712	-.0748568	.1096209
Iyear_4	.0545049	.0434999	1.25	0.210	-.0307533	.1397632
Iyear_5	.068207	.0460086	1.48	0.138	-.0219681	.1583822
Iyear_6	.0463522	.0452178	1.03	0.305	-.042273	.1349774
Iyear_7	.0559663	.0437717	1.28	0.201	-.0298247	.1417572
Iyear_8	.0697037	.0419244	1.66	0.096	-.0124667	.1518741
Iyear_9	.0434806	.0439919	0.99	0.323	-.0427419	.1297032
Iyear_10	.0527974	.0430301	1.23	0.220	-.03154	.1371348
Iyear_11	.0511814	.0429195	1.19	0.233	-.0329392	.135302
Iyear_12	.0192303	.0439343	0.44	0.662	-.0668794	.1053401
Iyear_13	.0303404	.0452023	0.67	0.502	-.0582545	.1189352
Iyear_14	.0161339	.0446036	0.36	0.718	-.0712874	.1035553
Iyear_15	.008586	.0430089	0.20	0.842	-.0757099	.0928819
Iyear_16	.0217269	.044614	0.49	0.626	-.065715	.1091687
Iyear_17	.0427877	.0427776	1.00	0.317	-.0410549	.1266303
Iyear_18	.0269615	.0453121	0.60	0.552	-.0618485	.1157716
Iyear_19	.0377568	.0446576	0.85	0.398	-.0497704	.125284
Iyear_20	.0261202	.0426858	0.61	0.541	-.0575424	.1097828
Iyear_21	.0249699	.045049	0.55	0.579	-.0633244	.1132642
Iyear_22	.0125904	.0465383	0.27	0.787	-.078623	.1038038
Iyear_23	-.0052602	.0446637	-0.12	0.906	-.0927995	.082279
Iyear_24	-.0208785	.0453399	-0.46	0.645	-.1097432	.0679862
Iyear_25	-.004361	.0442304	-0.10	0.921	-.091051	.082329
Iyear_26	.0066037	.0689887	0.10	0.924	-.1286117	.1418191
long_run						
Lnw	-197.0197	93.16465	-2.11	0.034	-379.619	-14.42032
Lng2	.0362339	.0298391	1.21	0.225	-.0222497	

.0947176

Lng2w	.0843484	.0251162	3.36	0.001	.0351216	.1335751
LnGDP90	.721734	.0646164	11.17	0.000	.5950883	.8483798
Lnyearw	25.87607	12.2759	2.11	0.035	1.815739	49.9364
Iyear_2	.2185206	.2254847	0.97	0.332	-.2234213	.6604624
Iyear_3	.0956567	.2378408	0.40	0.688	-.3705026	.561816
Iyear_4	.288674	.2181256	1.32	0.186	-.1388444	.7161923
Iyear_5	.359871	.2291007	1.57	0.116	-.089158	.8089
Iyear_6	.2481673	.2266464	1.09	0.274	-.1960514	.6923861
Iyear_7	.2973007	.220134	1.35	0.177	-.1341541	.7287554
Iyear_8	.3690407	.2101884	1.76	0.079	-.042921	.7810024
Iyear_9	.2323872	.2205708	1.05	0.292	-.1999236	.6646979
Iyear_10	.2805424	.2151987	1.30	0.192	-.1412393	.702324
Iyear_11	.2717815	.2169291	1.25	0.210	-.1533917	.6969546
Iyear_12	.1056062	.2212496	0.48	0.633	-.3280351	.5392476
Iyear_13	.1634025	.2281331	0.72	0.474	-.2837302	.6105352
Iyear_14	.0892755	.2260931	0.39	0.693	-.3538589	.5324098
Iyear_15	.0490816	.2185314	0.22	0.822	-.3792321	.4773952
Iyear_16	.1171066	.22593	0.52	0.604	-.325708	.5599212
Iyear_17	.2262866	.2157547	1.05	0.294	-.1965848	.649158
Iyear_18	.1438897	.2291173	0.63	0.530	-.305172	.5929513
Iyear_19	.199628	.2255109	0.89	0.376	-.2423651	.6416212
Iyear_20	.1388772	.2160695	0.64	0.520	-.2846113	.5623658
Iyear_21	.1334448	.2279121	0.59	0.558	-.3132548	.5801443
Iyear_22	.0694906	.2350917	0.30	0.768	-.3912807	.530262
Iyear_23	-.0237816	.2272992	-0.10	0.917	-.4692799	.4217166
Iyear_24	-.1058803	.2307686	-0.46	0.646	-.5581784	.3464178
Iyear_25	-.0212689	.2252898	-0.09	0.925	-.4628287	.4202909
Iyear_26	.0344773	.347267	0.10	0.921	-.6461535	.715108

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
long_run_el	-.6408	.0707549	-9.06	0.000	-.779477	-.502123

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
short_run_el	-.1206034	.0171638	-7.03	0.000	-.1542438	-.086963

Bias correction up to order O(1/NT^2)

LSDVC dynamic regression
(bootstrapped SE)

LnNE	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
short_run						
LnNE						
L1.	.821928	.0150802	54.50	0.000	.7923713	.8514847
Lnw	-35.89687	17.09484	-2.10	0.036	-69.40214	-2.391606
Lng2	.0060687	.005618	1.08	0.280	-.0049424	.0170798
Lng2w	.0163822	.0048071	3.41	0.001	.0069605	.025804
LnGDP90	.1298337	.0152953	8.49	0.000	.0998554	.159812
Lnyearw	4.714928	2.252512	2.09	0.036	.3000858	9.12977
Iyear_2	.0388514	.0451777	0.86	0.390	-.0496952	.1273981
Iyear_3	.0148432	.047138	0.31	0.753	-.0775456	.107232
Iyear_4	.0523654	.0435442	1.20	0.229	-.0329797	.1377105
Iyear_5	.0662416	.0460672	1.44	0.150	-.0240484	.1565317
Iyear_6	.0432329	.0452939	0.95	0.340	-.0455416	.1320074
Iyear_7	.0533698	.0437825	1.22	0.223	-.0324423	.1391818
Iyear_8	.0670993	.041971	1.60	0.110	-.0151624	.1493609
Iyear_9	.0407591	.044085	0.92	0.355	-.0456459	.1271641
Iyear_10	.0503248	.043135	1.17	0.243	-.0342182	.1348678
Iyear_11	.048874	.0430212	1.14	0.256	-.0354459	.1331939
Iyear_12	.0166135	.0440611	0.38	0.706	-.0697448	.1029717
Iyear_13	.0278199	.0453367	0.61	0.539	-.0610383	.1166782
Iyear_14	.0135816	.0446681	0.30	0.761	-.0739662	.1011295
Iyear_15	.0064129	.0430981	0.15	0.882	-.0780578	.0908835
Iyear_16	.019833	.0447338	0.44	0.658	-.0678437	

```
.1075097
             Iyear_17 |   .0412605   .0428592     0.96   0.336    -.0427421
.125263
             Iyear_18 |   .0253359   .0454594     0.56   0.577    -.0637628
.1144347
             Iyear_19 |    .036433   .0447674     0.81   0.416    -.0513095
.1241755
             Iyear_20 |   .0248065   .0427984     0.58   0.562    -.0590769
.1086898
             Iyear_21 |   .0233927   .0452042     0.52   0.605    -.0652059
.1119914
             Iyear_22 |    .010697   .0466729     0.23   0.819    -.0807802
.1021741
             Iyear_23 |  -.0071181   .0447428    -0.16   0.874    -.0948124
.0805762
             Iyear_24 |  -.0224833   .0454281    -0.49   0.621    -.1115207
.0665541
             Iyear_25 |  -.0051933   .0443418    -0.12   0.907    -.0921016
.0817149
             Iyear_26 |   .0066554   .0695552     0.10   0.924    -.1296703
.1429812
-------------+----------------------------------------------------------------
      long_run       |
                  Lnw |   -199.259   102.3614    -1.95   0.052    -399.8836
1.365662
                 Lng2 |   .0350144   .0325961     1.07   0.283    -.0288729
.0989016
                Lng2w |   .0884102   .0272522     3.24   0.001     .0349968
.1418235
               LnGDP90 |   .7253771   .0711359    10.20   0.000     .5859534
.8648008
              Lnyearw |   26.17108   13.48781     1.94   0.052    -.2645372
52.6067
               Iyear_2 |   .2180479   .2495615     0.87   0.382    -.2710837
.7071794
               Iyear_3 |   .0889144   .2635876     0.34   0.736    -.4277079
.6055366
               Iyear_4 |    .291246   .2413749     1.21   0.228    -.1818402
.7643321
               Iyear_5 |   .3659894   .2533505     1.44   0.149    -.1305684
.8625473
               Iyear_6 |   .2450616   .2511319     0.98   0.329    -.2471479
.7372711
               Iyear_7 |   .2983147   .2433912     1.23   0.220    -.1787233
.7753527
               Iyear_8 |   .3728673   .2325893     1.60   0.109    -.0829993
.8287339
               Iyear_9 |   .2303062   .2442672     0.94   0.346    -.2484488
.7090611
             Iyear_10 |   .2814046   .2382515     1.18   0.238    -.1855598
.7483691
             Iyear_11 |   .2729816   .2404498     1.14   0.256    -.1982914
.7442546
             Iyear_12 |   .0989297    .245263     0.40   0.687    -.3817769
.5796363
             Iyear_13 |   .1594196   .2527845     0.63   0.528     -.336029
.6548682
             Iyear_14 |   .0822211   .2504123     0.33   0.743     -.408578
.5730203
             Iyear_15 |   .0420084   .2421648     0.17   0.862    -.4326258
.5166426
             Iyear_16 |    .113892   .2502591     0.46   0.649    -.3766069
.6043909
             Iyear_17 |   .2289264   .2387595     0.96   0.338    -.2390335
.6968864
             Iyear_18 |   .1428513    .253492     0.56   0.573    -.3539838
.6396865
```

```
    Iyear_19 |    .202054   .2497706     0.81   0.419    -.2874873
.6915954
    Iyear_20 |   .1389344    .239159     0.58   0.561    -.3298087
.6076775
    Iyear_21 |   .1321906   .2526269     0.52   0.601    -.3629489
.6273302
    Iyear_22 |   .0643846   .2607431     0.25   0.805    -.4466624
.5754317
    Iyear_23 |  -.0324394   .2517468    -0.13   0.897     -.525854
.4609752
    Iyear_24 |  -.1167414    .255572    -0.46   0.648    -.6176534
.3841706
    Iyear_25 |  -.0255635   .2496223    -0.10   0.918    -.5148143
.4636872
    Iyear_26 |    .036055   .3865352     0.09   0.926    -.7215402
.7936501
------------------------------------------------------------------------------

------------------------------------------------------------------------------
        LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
 long_run_el |  -.6444283   .0783074    -8.23   0.000    -.7979081
-.4909485
------------------------------------------------------------------------------

------------------------------------------------------------------------------
        LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]
-------------+----------------------------------------------------------------
short_run_el |  -.1153611   .0170235    -6.78   0.000    -.1487265
-.0819957
------------------------------------------------------------------------------

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```

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  ___  ____  ____  ____
 /__    /   ____/   /
___/   /   /___/   /
  Statistics/Data Analysis
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____tm
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```

TABLE 5: GMM ESTIMATOR WITH STRICTLY EXOGENOUS REGRESSORS

Arellano-Bond dynamic panel-data estimation, one-step difference GMM results
(strictly exogenous regressors)

```
Group variable: sector                          Number of obs      =    715
Time variable : year                            Number of groups   =     31
Number of instruments = 53                      Obs per group: min =     23
F(30, 30)     =   3797.06                                      avg =  23.06
Prob > F      =     0.000                                      max =     25
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
LnNE L1.	.6446994	.0895582	7.20	0.000	.4691685	.8202303
Lnw	-89.21581	27.10152	-3.29	0.001	-142.3338	-36.0978
Lng2	.0303023	.0148259	2.04	0.041	.001244	.0593606
LnGDP90	.2713409	.0307269	8.83	0.000	.2111173	.3315645
Lng2w	.0182068	.0108034	1.69	0.092	-.0029675	.039381
Lnyearw	11.72255	3.571945	3.28	0.001	4.721668	18.72344
Iyear_3	-.015477	.0176082	-0.88	0.379	-.0499884	.0190345
Iyear_4	.0142688	.019122	0.75	0.456	-.0232097	.0517474
Iyear_5	.0236694	.021667	1.09	0.275	-.0187972	.066136
Iyear_6	.0276112	.0201453	1.37	0.170	-.0118729	.0670953
Iyear_7	.0259883	.023049	1.13	0.260	-.019187	.0711635
Iyear_8	.0400055	.025764	1.55	0.120	-.0104909	.0905019
Iyear_9	.0159601	.0271589	0.59	0.557	-.0372704	.0691907
Iyear_10	.0192515	.0297618	0.65	0.518	-.0390806	.0775836
Iyear_11	.0127436	.0308335	0.41	0.679	-.0476889	.0731761
Iyear_12	-.0120631	.0309838	-0.39	0.697	-.0727902	.0486639

```
            Iyear_13 |  -.0022149   .0287526    -0.08   0.939    -.0585689
.0541391
            Iyear_14 |  -.0138214   .0286437    -0.48   0.629     -.069962
.0423191
            Iyear_15 |  -.0291769    .027802    -1.05   0.294    -.0836678
.025314
            Iyear_16 |  -.0218115   .0301898    -0.72   0.470    -.0809823
.0373594
            Iyear_17 |  -.0075547   .0285063    -0.27   0.791     -.063426
.0483167
            Iyear_18 |  -.0230511   .0268303    -0.86   0.390    -.0756375
.0295354
            Iyear_19 |  -.0188001   .0296374    -0.63   0.526    -.0768882
.0392881
            Iyear_20 |  -.0321314   .0336448    -0.96   0.340    -.0980739
.0338112
            Iyear_21 |  -.0293106   .0303225    -0.97   0.334    -.0887417
.0301205
            Iyear_22 |  -.0364441   .0289932    -1.26   0.209    -.0932698
.0203816
            Iyear_23 |  -.0552926   .0280318    -1.97   0.049    -.1102339
-.0003512
            Iyear_24 |  -.0745483   .0267633    -2.79   0.005    -.1270034
-.0220932
            Iyear_25 |  -.0736143   .0249463    -2.95   0.003    -.1225082
-.0247205
            Iyear_26 |  -.0990762   .0270481    -3.66   0.000    -.1520895
-.0460629
            Iyear_27 |  -.1025964   .0268747    -3.82   0.000    -.1552699
-.0499228
------------------------------------------------------------------------------
      Hansen test of overid. restrictions: chi2(22) =    0.00   Prob > chi2 =
1.000

      Arellano-Bond test for AR(1) in first differences: z =  -3.50  Pr > z =
0.000
      Arellano-Bond test for AR(2) in first differences: z =   1.06  Pr > z =
0.287

------------------------------------------------------------------------------


------------------------------------------------------------------------------
                LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]

-------------+----------------------------------------------------------------
         long_run_el |  -.6474651   .2198249    -2.95   0.003    -1.078314
-.2166161

------------------------------------------------------------------------------


------------------------------------------------------------------------------
                LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]

-------------+----------------------------------------------------------------
        short_run_el |  -.2300447   .0305524    -7.53   0.000    -.2899263
-.1701632

------------------------------------------------------------------------------


-------------------------------------------------------------------------------
```

TABLE 6: GMM ESTIMATOR WITH PREDETERMINED REGRESSORS

Arellano-Bond dynamic panel-data estimation, one-step difference GMM results
(wage and wage-interacted variables predetermined)

Group variable: sector		Number of obs	= 715
Time variable : year		Number of groups	= 31
Number of instruments = 53		Obs per group: min	= 23
F(30, 30) =	2911.96	avg	= 23.06
Prob > F =	0.000	max	= 25

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval]	
LnNE L1.	.4922812	.0702238	7.01	0.000	.354645	.6299173
Lnw	-230.116	135.0258	-1.70	0.088	-494.7618	34.52976
Lng2	.0227056	.0371184	0.61	0.541	-.0500451	.0954564
LnGDP90	.3498995	.1156731	3.02	0.002	.1231844	.5766145
Lng2w	-.0190264	.1031889	-0.18	0.854	-.221273	.1832202
Lnyearw	30.27055	17.79227	1.70	0.089	-4.601661	65.14276
Iyear_3	-.0019327	.0189148	-0.10	0.919	-.0390049	.0351396
Iyear_4	.0297437	.027648	1.08	0.282	-.0244455	.0839329
Iyear_5	.0387112	.0334291	1.16	0.247	-.0268088	.1042311
Iyear_6	.0638456	.0329229	1.94	0.052	-.0006821	.1283732
Iyear_7	.0607432	.0396668	1.53	0.126	-.0170024	.1384888
Iyear_8	.0787872	.0432919	1.82	0.069	-.0060634	.1636378
Iyear_9	.0592363	.045631	1.30	0.194	-.0301989	.1486714
Iyear_10	.062163	.0506182	1.23	0.219	-.0370468	.1613728
Iyear_11	.0584604	.0548961	1.06	0.287	-.049134	.1660547
Iyear_12	.0398936	.0561255	0.71	0.477	-.0701104	.1498976

```
           Iyear_13 |   .0507115   .0540558     0.94   0.348    -.0552359
.1566589
           Iyear_14 |   .0385142   .0551001     0.70   0.485      -.06948
.1465083
           Iyear_15 |   .0181712   .0515524     0.35   0.724    -.0828695
.119212
           Iyear_16 |   .0227222   .0555048     0.41   0.682    -.0860652
.1315096
           Iyear_17 |   .0311841   .0554235     0.56   0.574     -.077444
.1398122
           Iyear_18 |   .0188988   .0552238     0.34   0.732    -.0893379
.1271355
           Iyear_19 |   .0180001    .055821     0.32   0.747     -.091407
.1274073
           Iyear_20 |   .0050346   .0537978     0.09   0.925    -.1004071
.1104763
           Iyear_21 |   .0073377   .0495461     0.15   0.882     -.089771
.1044463
           Iyear_22 |   .0005632   .0453577     0.01   0.990    -.0883362
.0894627
           Iyear_23 |  -.0225664   .0440338    -0.51   0.608     -.108871
.0637382
           Iyear_24 |  -.0464118    .044403    -1.05   0.296      -.13344
.0406165
           Iyear_25 |  -.0563096    .044302    -1.27   0.204    -.1431399
.0305208
           Iyear_26 |  -.0917605   .0447374    -2.05   0.040    -.1794442
-.0040768
           Iyear_27 |  -.0841389   .0510193    -1.65   0.099     -.184135
.0158571
------------------------------------------------------------------------------
      Hansen test of overid. restrictions: chi2(22) =    0.05   Prob > chi2 =
1.000

      Arellano-Bond test for AR(1) in first differences: z =  -3.03  Pr > z =
0.002
      Arellano-Bond test for AR(2) in first differences: z =   0.67  Pr > z =
0.503

------------------------------------------------------------------------------


------------------------------------------------------------------------------
               LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]

-------------+----------------------------------------------------------------
        long_run_el |  -.5193668   .3522883    -1.47   0.140    -1.209839
.1711056

------------------------------------------------------------------------------


------------------------------------------------------------------------------
               LnNE |      Coef.   Std. Err.      z    P>|z|     [95% Conf.
Interval]

-------------+----------------------------------------------------------------
       short_run_el |  -.2636923   .1711172    -1.54   0.123    -.5990758
.0716912

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```

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  ___  ____  ____  ____  ____tm
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/   Statistics/Data Analysis
```

TABLE 7: UNCORRECTED LSDV ESTIMATOR

```
Fixed-effects (within) regression               Number of obs      =       746
Group variable (i): sector                      Number of groups   =        31

R-sq:  within  = 0.9167                         Obs per group: min =        24
       between = 0.9964                                        avg =      24.1
       overall = 0.9948                                        max =        26

                                                F(31,684)          =    589.35
corr(u_i, Xb)  = 0.7801                         Prob > F           =    0.0000
```

LnNE	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
LnNE L1.	.7853773	.0338631	23.19	0.000	.7188892	.8518655
Lnw	-41.08362	17.04076	-2.41	0.016	-74.5421	-7.625142
Lng2	.0085294	.0078149	1.09	0.275	-.0068147	.0238735
LnGDP90	.1529185	.0189588	8.07	0.000	.115694	.1901429
Lng2w	.0157304	.0064449	2.44	0.015	.0030762	.0283845
Lnyearw	5.395321	2.245382	2.40	0.017	.9866522	9.803989
Iyear_2	.0472819	.0215419	2.19	0.029	.0049857	.0895781
Iyear_3	.0245648	.0122448	2.01	0.045	.0005229	.0486067
Iyear_4	.0605583	.0113674	5.33	0.000	.0382391	.0828774
Iyear_5	.0737663	.0106316	6.94	0.000	.0528918	.0946408
Iyear_6	.0551844	.0112973	4.88	0.000	.0330028	.0773661
Iyear_7	.0633166	.010129	6.25	0.000	.043429	.0832042
Iyear_8	.0770761	.0106835	7.21	0.000	.0560998	.0980524
Iyear_9	.0511848	.0101576	5.04	0.000	.031241	.0711286
Iyear_10	.0597961	.0104721	5.71	0.000	.0392348	.0803575

Iyear_11	.0577111	.0093223	6.19	0.000	.0394072	.0760149
Iyear_12	.0266378	.0098778	2.70	0.007	.0072433	.0460323
Iyear_13	.0374757	.0108269	3.46	0.001	.0162177	.0587336
Iyear_14	.023361	.0161069	1.45	0.147	-.0082638	.0549859
Iyear_15	.014739	.0108497	1.36	0.175	-.0065637	.0360418
Iyear_16	.0270888	.0106069	2.55	0.011	.0062627	.0479149
Iyear_17	.0471098	.0103967	4.53	0.000	.0266965	.0675231
Iyear_18	.0315613	.0099891	3.16	0.002	.0119483	.0511744
Iyear_19	.0415002	.0087121	4.76	0.000	.0243944	.0586059
Iyear_20	.0298338	.0130546	2.29	0.023	.0042019	.0554657
Iyear_21	.0294288	.009504	3.10	0.002	.0107683	.0480893
Iyear_22	.0179452	.0096018	1.87	0.062	-.0009075	.0367978
Iyear_23	-6.42e-06	.0095901	-0.00	0.999	-.0188361	.0188232
Iyear_24	-.0163404	.008897	-1.84	0.067	-.0338092	.0011284
Iyear_25	-.0020122	.0121639	-0.17	0.869	-.0258953	.0218709
Iyear_26	.0064546	.0030329	2.13	0.034	.0004998	.0124095
_cons	-2.048579	.3967534	-5.16	0.000	-2.82758	-1.269578
sigma_u	.10399104					
sigma_e	.04312569					
rho	.85325624	(fraction of variance due to u_i)				

LnNE	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
long_run_el	-.6312042	.0651798	-9.68	0.000	-.7591807	-.5032277

LnNE	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
short_run_el	-.1354707	.024172	-5.60	0.000	-.182931	-.0880104