The impact of environmental policy stringency on industrial productivity growth: A semi-parametric study of OECD countries *

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1 Introduction

No longer a distant concern, climate change and environmental problems have become an urgent challenge facing the human societies on the planet. According to the United Nations climate change report in 2019 (UNFCCC, 2019), global aggregate greenhouse gas emissions increased by 46.7% between 1990 and 2016, and the global mean temperature in 2018 is about 1°C above the pre-industrial baseline. Countries around the world have observed climate related hazards including extreme weather such as hurricanes, storms, heatwaves, and wildfires, as well as slow onset impacts such as sea level rise, soil degradation, and coral bleaching. A range of vulnerable sectors, particularly water, agriculture, ecosystems, health and forestry, are all endangered (UNFCCC, 2019). It is now well accepted by most that no action is not an option, and governments around the world have responded via co-operations such as the Kyoto Protocol in force in 2005 and the Paris Agreement adopted in 2015. Some OECD countries have already implemented a wide spectrum of environmental policies, including market instruments such as price and tax mechanisms and non-market instruments via enforcement of environmental standards and regulations.

However, the main argument against more stringent environmental policies has been the concern that their added costs may be a burden on the economy. For example, as the world's largest economy and its second biggest polluter, United States withdrew from the Paris Agreement in 2017, with its president Trump tweeting that "The Paris accord will undermine (the U.S.) economy," and "puts (the US) at a permanent disadvantage." While Obama's environmental agenda prioritised the reduction of carbon emissions through the use of clean renewable energy, the Trump administration has sought to increase fossil fuel use and to abolish environmental regulations, which President Trump referred to as an impediment to the US. In 2018, the Trump administration revealed its own Affordable Clean Energy proposal to replace Obama's Clean Power Plan. All these recent environmental policy moves are made with the notion that more stringent environmental policies harm productivity growth.

The relationship between environmental protection policies and productivity growth has been a contentious issue and the subject of debates. Economists consider environmental damage as a production input or a negative output, which results in negative externality if it is not priced. The conventional view suggests that a full internalization of the negative externalities of production would shift the marginal cost function upward. Thus environmental regulations would reduce productivity growth because measured inputs such as capital, labor, and intermediate inputs such as energy are diverted to the production of an additional output – environmental quality – that is not included in conventional measures of output and hence would reduce measured productivity (Repetto, 1990; Solow, 1993). In contrast, the more recent evolutionary view, originating from Porter (1991) and Porter and Van Der Linde (1995), suggests that more stringent environmental policies may have a positive effect on productivity growth by intensifying international competitiveness and stimulating innovation, the so-called Porter Hypothesis. More recently, Karydas and Zhang (2019) have showed that environmental tax reforms can generate an innovation growth dividend by economizing on the use of environment-related factors in a dynamic general equilibrium model. The typical argument is that a cleaner environment in the long run will increase the quality of various production inputs, such as better health of the workforce, and better quality of water and air. Environmental regulations may also act as a possible stimulus for the production of compliance capital goods. Additionally, imposing more stringent environmental regulations may also prompt industries to actively seek for and purge possible inefficiencies from their production processes. All of these in the long run would result in an increase in productivity.

Empirical evidence on the impact of more stringent environmental policies is mixed and country- and context-specific. One major difficulty in this literature is the appropriate measure of environmental stringency to allow for appropriate international comparisons. Recently, using a standard neoclassical cost function approach, van Soest et al. (2006) proposed an indirect measure through the difference between a polluting input's shadow price and its purchase price; however, this paper had no intention of examining how economic activity is influenced by compliance costs. Modelling and estimating the impact of environmental policy stringency (EPS) on production is a challenging task as different environmental policy instruments may affect production in complex ways via production processes, resource reallocation, capital investment, labor intensity and innovation incentives (Albrizio et al., 2017). A more recent study, due to Albrizio et al. (2017), makes use of a new composite index of EPS developed by the OECD (Botta and Kozluk, 2014), to study the impact of environmental policy on multi-factor productivity (MFP) growth. This EPS index is designed as a country-specific and internationally comparable measure based on quantitative and qualitative information contained in a country's normative environmental instruments such as laws and regulations, primarily in the energy sector. Albrizio et al. (2017) further augmented the linear parametric neo-Schumpeterian productivity model of Bourles et al. (2013) by adding interactions between environmental policy and the technological gap to allow for some degree of heterogeneity in the effects on multi-factor productivity growth to be captured. They found that a tightening of environmental policy is associated with a short-term increase in industry-level productivity growth in most technologically-advanced countries.

Our study uses a novel approach to contribute to the limited empirical literature to study the impacts of EPS on the total industry production technology of OECD countries. In the spirit of van Soest et al. (2006), we estimate a system model of a cost function and input demand functions using panel data from 22 OECD countries over two decades. Our paper also employs this new cross-country proxy index of EPS as in Albrizio et al. (2017). However, what distinguishes our paper from the existing studies is that we allow the EPS index to impact on every aspect of the production technology by allowing it to affect all model coefficients in the most flexible manner. Specifically we build upon a varying coefficient model with the heterogeneity of the EPS effects captured through a semi-parametric setting and thus allow for a much larger degree of heterogeneity. As a consequence of this approach, all key technological measures of total industry production can be expressed as semi-parametric functions of the EPS index, including various elasticities and productivity growth measures.

The remainder of this paper proceeds as follows. Section 2 presents the methodology. Section 3 introduces the EPS index and details about the data used for the analysis, followed by Section 4 where main results are presented and discussed. The final section concludes.

2 Methodology

2.1 A Semi-parametric Varying Coefficient Translog Cost Function with EPS Indices

Following the spirit of Hastie and Tibshirani (1993), we specify a three-factor (capital (K), labor (L), and intermediate inputs (E) which consist of energy, materials and services) translog cost function where each coefficient is assumed to be a nonparametric function of EPS. Considering that it takes time for firms to adjust to changes in environmental policies, we let each coefficient of the translog cost function be a function of the first, the second and the third lag of EPS [1]. Compared with the standard translog cost function where the EPS indices would be incorporated in the cost function in the same manner as if it were another input price or output quantity, the semi-parametric varying coefficient translog cost function has the advantage of allowing productivity and technical change also to be a semi-parametric function of EPS indices and thus vary with the latter. In addition, as shown in Feng et al. (2017), the varying coefficient translog cost function nests the standard translog cost function as a special case, making the use of the former cost function more appealing.

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[1] Theoretically speaking, we could include any number of lags of EPS in the coefficient functions. However, in practice, the curse of dimensionality would occur if more than three covariates (which in our case are lags of EPS) were included in the nonparametric coefficient functions. See, for example, Gao (2007) and Yatchew (2003). In the literature, Albrizio et al. (2014) and Albrizio et al. (2017) find that a three-lag structure is the optimal structure in capturing the anticipation effect of environmental policy stringency changes on productivity growth in OECD countries and use the average of three lags as a single regressor in their specification. In contrast, our specification achieves a considerable generalization by using each of the three lags as individual regressors in our nonparametric coefficient functions.

In particular, we consider the following semi-parametric varying coefficient translog cost function:

$$
\begin{aligned}
&\ln C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) = \\
&\quad \alpha_0(\boldsymbol{eps}_{it}) + \sum_{v=L,E} \alpha_v(\boldsymbol{eps}_{it}) \ln w_{it,v} + \gamma(\boldsymbol{eps}_{it}) \ln y_{it} + \tau(\boldsymbol{eps}_{it}) t + \eta(\boldsymbol{eps}_{it}) \ln z_{it} \\
&\quad + \frac{1}{2} \sum_{v=L,E} \sum_{h=L,E} \beta_{vh}(\boldsymbol{eps}_{it}) \ln w_{it,v} \ln w_{it,h} + \frac{1}{2} \gamma^*(\boldsymbol{eps}_{it}) (\ln y_{it})^2 \\
&\quad + \frac{1}{2} \delta(\boldsymbol{eps}_{it}) t^2 + \frac{1}{2} \zeta(\boldsymbol{eps}_{it}) (\ln z_{it})^2 + \sum_{v=L,E} \psi_v(\boldsymbol{eps}_{it}) \ln w_{it,v} \ln y_{it} \\
&\quad + \sum_{v=L,E} \phi_v(\boldsymbol{eps}_{it}) t \ln w_{it,v} + \sum_{v=L,E} \rho_v(\boldsymbol{eps}_{it}) \ln z_{it} \ln w_{it,v} + \varphi(\boldsymbol{eps}_{it}) t \ln y_{it} \\
&\quad + \sigma(\boldsymbol{eps}_{it}) \ln z_{it} \ln y_{it} + \kappa(\boldsymbol{eps}_{it}) t \ln z_{it} + \alpha_i, \\
&\quad i = 1, \cdots, N; t = 1, \cdots, T, \qquad (1)
\end{aligned}
$$

where N is the total number of countries; T is the total number of years; w_v, $v = L, E$, is the price of the two variable inputs; z is the quantity of the quasi-fixed capital input; y is the quantity of output; t is a time trend; α_i is the country-specific effect; $\boldsymbol{eps}$ is a vector of the three lags of EPS, i.e. $\boldsymbol{eps}_{it} = (eps_{i,t-1}, eps_{i,t-2}, eps_{i,t-3})'$. Symmetry restrictions require $\beta_{LE}(\boldsymbol{eps}_{it}) = \beta_{EL}(\boldsymbol{eps}_{it})$. Moreover, homogeneity of degree one in input prices implies the following constraints:

$$
\begin{aligned}
&\sum_{v=L,E} \alpha_v(\boldsymbol{eps}_{it}) = 1, \\
&\sum_{v=L,E} \beta_{vL}(\boldsymbol{eps}_{it}) = \sum_{v=L,E} \beta_{vE}(\boldsymbol{eps}_{it}) = 0, \\
&\sum_{v=L,E} \psi_v(\boldsymbol{eps}_{it}) = \sum_{v=L,E} \phi_v(\boldsymbol{eps}_{it}) = \sum_{v=L,E} \rho_v(\boldsymbol{eps}_{it}) = 0. \qquad (2)
\end{aligned}
$$

Applying Shephard's lemma to the cost function (1) yields the following cost share equations:

$$\begin{aligned} s_v(\boldsymbol{eps}_{it}) &= \frac{w_{it,v}x_{it,v}}{C_{it}} \\ &= \alpha_v(\boldsymbol{eps}_{it}) + \sum_{h=L,E} \beta_{vh}(\boldsymbol{eps}_{it}) \ln w_{it,h} + \psi_v(\boldsymbol{eps}_{it}) \ln y_{it} + \phi_v(\boldsymbol{eps}_{it})t \\ &\quad + \rho_v(\boldsymbol{eps}_{it}) \ln z_{it}, \quad v = L, E, \end{aligned} \tag{3}$$

where $x_{it,v}$ is the input v's quantity for country i at time t.

The linear homogeneity constraints (2) are imposed by normalizing the cost and input prices in (1) and (3) by one of the input prices (w_E):

$$\begin{aligned} &\ln \frac{C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{w_{it,E}} = \\ &\alpha_0(\boldsymbol{eps}_{it}) + \alpha_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} + \gamma(\boldsymbol{eps}_{it}) \ln y_{it} + \tau(\boldsymbol{eps}_{it})t + \eta(\boldsymbol{eps}_{it}) \ln z_{it} \\ &+ \frac{1}{2}\beta_{LL}(\boldsymbol{eps}_{it})(\ln \frac{w_{it,L}}{w_{it,E}})^2 + \frac{1}{2}\gamma^*(\boldsymbol{eps}_{it})(\ln y_{it})^2 \\ &+ \frac{1}{2}\delta(\boldsymbol{eps}_{it})t^2 + \frac{1}{2}\zeta(\boldsymbol{eps}_{it})(\ln z_{it})^2 + \psi_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} \ln y_{it} \\ &+ \phi_L(\boldsymbol{eps}_{it})t \ln \frac{w_{it,L}}{w_{it,E}} + \rho_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} \ln z_{it} + \varphi(\boldsymbol{eps}_{it})t \ln y_{it} \\ &+ \sigma(\boldsymbol{eps}_{it}) \ln z_{it} \ln y_{it} + \kappa(\boldsymbol{eps}_{it})t \ln z_{it} + \alpha_i, \end{aligned} \tag{4}$$

and

$$\begin{aligned} s_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) &= \alpha_L\left(\boldsymbol{eps}_{it}\right) + \beta_{LL}\left(\boldsymbol{eps}_{it}\right) \ln \frac{w_{it,L}}{w_{it,E}} + \psi_L\left(\boldsymbol{eps}_{it}\right) \ln y_{it} \\ &\quad + \phi_L\left(\boldsymbol{eps}_{it}\right) t + \rho_L\left(\boldsymbol{eps}_{it}\right) \ln z_{it}. \end{aligned} \tag{5}$$

Equations (4) and (5) can then be combined to form a system of two equations. Such a system is therefore a complete system (McLaren and Zhao, 2009). Upon appending idiosyncratic error terms, in the spirit of Bai (2009), we use an iteration scheme for estimation. Each iteration involves two steps: 1) given initial values of the eps-invariant country-specific effects (i.e. α_i's), we estimate the eps-varying coefficients for the non-dummy variables (i.e. $\alpha_0(\boldsymbol{eps}_{it})$, $\alpha_L(\boldsymbol{eps}_{it})$, $\gamma(\boldsymbol{eps}_{it})$, $\tau(\boldsymbol{eps}_{it})$, $\eta(\boldsymbol{eps}_{it})$, $\beta_{LL}(\boldsymbol{eps}_{it})$, $\gamma^*(\boldsymbol{eps}_{it})$, $\delta(\boldsymbol{eps}_{it})$, $\zeta(\boldsymbol{eps}_{it})$, $\psi_L(\boldsymbol{eps}_{it})$, $\phi_L(\boldsymbol{eps}_{it})$, $\rho_L(\boldsymbol{eps}_{it})$, $\varphi(\boldsymbol{eps}_{it})$, $\sigma(\boldsymbol{eps}_{it})$, and $\kappa(\boldsymbol{eps}_{it})$) using varying coefficient kernel regression bandwidth selection and estimation techniques (Li and Racine, 2003, 2010; Li et al., 2013); and 2) given the estimated eps-varying coefficients, estimate the eps-invariant country-specific effects. As pointed by Bai (2009), this iteration scheme is very robust and has an excellent convergence property.

The two-equation system in the first step is subject to a number of cross-equation constraints implied by the economic theory. In particular, in (4) and (5), the coefficients $\alpha_L(\boldsymbol{eps}_{it})$, $\beta_{LL}(\boldsymbol{eps}_i)$, $\psi_L(\boldsymbol{eps}_{it})$, $\phi_L(\boldsymbol{eps}_{it})$ and $\rho_L(\boldsymbol{eps}_{it})$ are common across the cost and share equations. To allow for such equality constraints, we follow Wooldridge (2010, p.188) and Cameron and Trivedi (2005, p.210) and re-define the regressors and coefficients given in (4) and (5) in a way such that the two-equation system in the first step can be estimated by least squares. A detailed description of the estimation procedure can be found in Appendix A.

2.2 Total Factor Productivity Growth and Decomposition

Following Baltagi and Griffin (1988) and Fuss (1994), the Total Factor Productivity Growth (TFPG) can be decomposed as:

$$TFPG_{it} = TC_{it} + SE_{it}, \tag{6}$$

where productivity growth $TFPG_{it}$ can be decomposed into technical change TC_{it} and scale effects SE_{it}.

Given the estimated parameters from equations (4) and (5), the technical change and scale effects can respectively be estimated as follows:

$$\begin{aligned} TC_{it} =& -\frac{\partial \ln C(y_{it}, w_{it,L}, w_{it,E}, t, \boldsymbol{eps_{it}})}{\partial t} \\ =& -\left(\tau(\boldsymbol{eps_{it}}) + \delta(\boldsymbol{eps_{it}})t + \sum_{v=L,E} \phi_v(\boldsymbol{eps_{it}}) \ln w_{v,it} + \varphi(\boldsymbol{eps_{it}}) \ln y_{it} + \kappa(\boldsymbol{eps_{it}}) \ln z_{it}\right) \end{aligned} \tag{7}$$

and

$$SE_{it} = (1 - \epsilon_{cy_{it}})\, \dot{y}_{it}, \tag{8}$$

where

$$\dot{y_{it}} = \partial \ln y_{it} / \partial t$$

and

$$\begin{aligned} \epsilon_{cy_{it}} =& \frac{\partial \ln C(y_{it}, w_{it,L}, w_{it,E}, t, eps_{it})}{\partial \ln y_{it}} \\ =& \gamma(\boldsymbol{eps}_{it}) + \gamma^*(\boldsymbol{eps}_{it}) \ln y_{it} + \sum_{v=L,E} \psi_v(\boldsymbol{eps}_{it}) \ln w_v + \varphi(\boldsymbol{eps}_{it})t + \sigma(\boldsymbol{eps}_{it}) \ln z. \end{aligned}$$

2.3 Specification Test

To justify the semi-parametric varying coefficient specification, two specification tests are conducted in this section. We first test a parametric specification of a translog cost function involving interactions between a three-year moving average of EPS and input variables versus a standard translog cost function specification which does not accommodate the impact of EPS in any form.

Specifically, the null hypothesis H_0 is specified as:

$$\begin{aligned}
\ln C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}\right) = {} & \alpha_0 + \sum_{v=L,E} \alpha_v \ln w_{it,v} + \gamma \ln y_{it} + \tau t + \eta \ln z_{it} \\
& + \frac{1}{2} \sum_{v=L,E} \sum_{h=L,E} \beta_{vh} \ln w_{it,v} \ln w_{it,h} + \frac{1}{2}\gamma^*(\ln y_{it})^2 + \frac{1}{2}\delta t^2 + \frac{1}{2}\zeta(\ln z_{it})^2 \\
& + \sum_{v=L,E} \psi_v \ln w_{it,v} \ln y_{it} + \sum_{v=L,E} \phi_v t \ln w_{it,v} + \sum_{v=L,E} \rho_v \ln z_{it} \ln w_{it,v} + \varphi t \ln y_{it} \\
& + \sigma \ln z_{it} \ln y_{it} + \kappa t \ln z_{it} + \alpha_i, \quad i = 1, \cdots, N; t = 1, \cdots, T, \qquad (9)
\end{aligned}$$

versus the alternative hypothesis H_1 specified as:

$$\begin{aligned}
\ln C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) = {} & \alpha_0 + \sum_{v=L,E} \alpha_v \ln w_{it,v} + \gamma \ln y_{it} + \tau t + \eta \ln z_{it} \\
& + \frac{1}{2} \sum_{v=L,E} \sum_{h=L,E} \beta_{vh} \ln w_{it,v} \ln w_{it,h} + \frac{1}{2}\gamma^*(\ln y_{it})^2 + \frac{1}{2}\delta t^2 + \frac{1}{2}\zeta(\ln z_{it})^2 + \sum_{v=L,E} \psi_v \ln w_{it,v} \ln y_{it} \\
& + \sum_{v=L,E} \phi_v t \ln w_{it,v} + \sum_{v=L,E} \rho_v \ln z_{it} \ln w_{it,v} + \varphi t \ln y_{it} + \sigma \ln z_{it} \ln y_{it} + \kappa t \ln z_{it} \\
& + \alpha_{01} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} + \sum_{v=L,E} \alpha_{v1} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln w_{it,v} + \gamma_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln y_{it} \\
& + \tau_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} t + \eta_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln z_{it} + \frac{1}{2} \sum_{v=L,E} \sum_{h=L,E} \beta_{vh1} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln w_{it,v} \ln w_{it,h} \\
& + \frac{1}{2}\gamma_1^* \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} (\ln y_{it})^2 + \frac{1}{2}\delta_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} t^2 + \frac{1}{2}\zeta_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} (\ln z_{it})^2 \\
& + \sum_{v=L,E} \psi_{v1} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln w_{it,v} \ln y_{it} + \sum_{v=L,E} \phi_{v1} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} t \ln w_{it,v} \\
& + \sum_{v=L,E} \rho_{v1} \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln z_{it} \ln w_{it,v} + \varphi_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} t \ln y_{it} \\
& + \sigma_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} \ln z_{it} \ln y_{it} + \kappa_1 \frac{1}{3} \sum_{j=1}^{3} esp_{i,t-j} t \ln z_{it} + \alpha_i, \quad i = 1, \cdots, N; t = 1, \cdots, T. \qquad (10)
\end{aligned}$$

Note that equation (10) is similar in spirit to Albrizio et al. (2017) by interacting a three-year moving average of EPS with cost function input variables. This specification can also be regarded as a special case of equation (1) by explicitly specifying the nonparametric coefficient functions of lags of EPS as a linear function of the three-year moving average of lags of EPS. Since (9) is nested in (10), a Likelihood Ratio test is conducted using the R language. The null hypothesis is rejected at a 1% significance level. As a result, a parametric specification accommodating the impact of EPS, similar to Albrizio et al. (2017), is preferred to a standard translog cost function specification.

In the second test, our flexible semi-parametric varying coefficient translog cost function specification is tested versus the parametric specification in (10) as the null hypothesis. The specification test proposed by Li and Racine (2010) is employed and carried out using the R language. The null hypothesis is rejected at a 1% significance level. Accordingly, our flexible semi-parametric varying coefficient specification is preferred to its parametric counterpart.

3 Description of Data

A key variable in our analysis is the Environmental Policy Stringency (EPS) index. It is a country-specific and internationally-comparable measure of the stringency of environmental policy. Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. This composite index, recently developed by the OECD, renders cross-country comparison over a meaningful time-dimension possible. The latest EPS composite index covers 28 OECD and 6 BRIICS countries, i.e. Brazil, Russia, India, Indonesia, China and South Africa, for the period 1990-2015 (OECD, 2016).

The construction of the index, which builds upon the taxonomy developed by De Serres et al. (2010), involves two steps: selection and scoring of single instruments, and then aggregation of the information. In the first step, the instruments considered have been selected in order to cover, as broadly as possible, both market and non-market approaches to environmental policies. The market-based component comprises instruments which assign an explicit price to the externalities (such as taxes: CO_2, SO_X, NO_X, and diesel fuel; trading schemes: CO_2, renewable energy certificates, energy efficiency certificates, feed-in-tariffs, and deposit-refund-schemes), whereas the non-market component encompasses command-and-control instruments, such as standards (emission limit values for NO_X, SO_X, and PM, limits on sulfur content in diesel) and technology-support policies (such as government R&D subsidies). The scoring procedure is based on a comparison of the stringency of each instrument against the distribution of values for the same type of instrument across countries and time. It reflects the relative stringency that is the country's position on each instrument relative to the other countries (and years).

The information aggregation procedure follows a two-step approach. The instrument specific indicators (e.g. taxes on CO_2, SO_X and NO_X) are first aggregated into mid-level indicators as to their type (e.g. environmental taxes). Then, the resulting mid-level indicators are grouped into the two broad categories of market and non-market based instruments. At each level of aggregation, equal weights are applied, due to the lack of priors in this regard. The resulting composite index ranges in value from 0 to 6, with higher numbers being associated with more stringent environmental policies. Refer to Botta and Kozluk, 2014 for a more detailed and comprehensive description.

Apart from the OECD EPS index, we also collected information on total values and prices of a country's total industry output and labor, intermediate (comprising energy, materials and services) and capital inputs from the EU KLEMS database for the period 1970-2007 (November 2009 release, see O'Mahony and Timmer (2009) for a summary overview of the methodology and construction of the EU KLEMS database). Among the 28 OECD countries covered in the EPS index, after excluding countries that are not covered in the EU KLEMS database for all the years with overlap between EPS index and the EU KLEMS database and excluding observations with missing values for variables specified in equations (4) and (5), there are in total 375 observations for 22 OECD countries in the unbalanced estimation panel. The following is a list of these 22 countries with observation years in brackets: Australia (1990-2007), Austria (1990-2007), Belgium (1990-2006), Czech Republic (1995-2007), Denmark (1990-2007), Finland (1990-2007), France (1990-2007), Germany (1990-2007), Greece (1990-2007), Hungary (1992-2007), Ireland (1990-2007), Italy (1990-2007), Japan (1990-2006), Korea (1990-2007), Netherlands (1990-2007), Poland (1995-2006), Portugal(1990-2006), Slovak Republic (1995-2007), Spain (1990-2007), Sweden (1990-2007), United Kingdom (1990-2007) and United States (1990-2007).

The measure of output examined is a country's total-industry gross output. On the input side, two variable inputs are specified: the total-industry aggregate of labor input and intermediate inputs (comprising energy, materials and services). Capital is treated as a quasi-fixed input, the value of which is equal to the capital compensation collected from EU KLEMS. Table 1 outlines definitions of the variables in equations (4) and (5). Monetary values measured in different national currencies have been converted to US dollars of the year 2000.

[Insert Table 1 near here]

Table 2 presents the descriptive statistics for EPS by country. Figure 1 displays plots of EPS for the 22 countries from the year 1990 through 2007. Although EPS progresses in a general upward trend for all the countries in question, a substantial increase is not seen for many countries until the year of 2000. Also of interest is the sharp decrease towards the last year of the sample for most countries, which might reflect substantial changes in governments' environmental policy landscape in the light of the onset of the Global Financial Crisis.

[Insert Table 2 near here]

[Insert Figure 1 near here]

4 Results

Following the model and estimation method described in Section 2, our approach is operationalised using the R language. Given the panel structure of our data, all 95% confidence intervals are obtained through a wild cluster bootstrap procedure (Cameron et al., 2008; Hansen, 2000) with 1000 replications. Specifically, treating each country as a cluster of observations, it was whole clusters as re-sampling units that were re-sampled with replacement. Given that all model coefficients are estimated as nonparametric functions of EPS, we do not present all of these detailed functions. Instead, we present the estimated coefficients at the mean of EPS in Table 3. Additionally, all technological measures of interest are also estimated as semi-parametric functions of EPS and can thus be computed by individual countries and by years. We focus on presenting only key results in tables and graphs.

[**Insert Table 3 near here**]

4.1 Total Factor Productivity Growth

Figure 2 presents plots of the estimated Total Factor Productivity Growth (TFPG) from 1990 to 2007 by individual countries. The estimated values of TFPG by countries and years can also be found in Table 4. Specifically, having controlled for intermediate inputs on top of the conventional labor and capital inputs, Figure 2 indicates that by and large, the TFPGs of most countries considered follow a general increasing trend. In particular, we observe that the TFPGs of Austria, Belgium, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Poland, Slovak Republic, Spain, Sweden, United Kingdom and United States in the last year observed in the sample have increased compared to their first-year TFPGs. Many countries' TFPGs plummet from 2006 to 2007 which might reflect the onset of the Global Financial Crisis.

[Insert Figure 2 near here]

[Insert Table 4 near here]

Table 5 presents the estimated average Technical Change, Scale Effect, and TFPG by individual countries. According to Figure 1, many countries saw a remarkable increase in EPS from 2003 to 2004. The country which saw the highest average TFPG, 1.0%, in Table 5 is Slovak Republic; however, it should be noted that observations for Slovak Republic are only available from 1996 onwards and therefore, the average TFPG of Slovak Republic might be overestimated compared to countries for which observations are available over the entire 18 years from 1990 to 2007. Among countries for which all 18 observations are available, Germany boasts the highest growth of TFP, 0.8%. A further decomposition of Germany's TFPG indicates that Technical Change contributes 37.5% and Scale Effect contributes 62.5% to its productivity growth.

[Insert Table 5 near here]

Given that we are primarily interested in how tougher EPS policy would affect a country's industry-level TFPG, we first examine the results for productivity growth. With the semi-parametric setting of our approach, one sensible illustration of the impact of EPS would be a plot of predicted TFPGs calculated respectively at deciles of each of the three lags of EPS, while keeping all the other two lags and inputs constant. Particularly, taking eps_{-1} as an example, while keeping all the other two lags, i.e. eps_{-2} and eps_{-3}, and other variable inputs constant, e.g. prices, time, output etc., fixed at their sample means, the predicted TFPGs are calculated and plotted versus deciles of eps_{-1}. Figure 3 presents all the plots of the predicted TFPGs against the EPS indices lagged one, two and three periods, with shaded 95% confidence bands.

According to Figure 3, what the model suggests is that while keeping all other factors constant, a tightening in environmental policy stringency of the previous years generally seems to boost a country's TFPG. Particularly, while a tightening of environmental policy stringency one year ago does not statistically and significantly increase the current year's TFPG with all the predicted TFPGs being insignificantly different from zero, the predicted TFPGs follow a clear and significant increasing trend once the EPS index lagged two periods is over the level of 1.5, despite the fact that the predicted TFPGs are all below zero and initially follow a statistically insignificant decreasing trend. As the environmental policy three years ago is getting more and more demanding, predicted TFPGs of the current year are significantly increasing over all the range of the EPS index lagged three periods. The predicted TFPGs start to become statistically and significantly positive as the EPS index lagged three periods is roughly over the level of 1.6. Hence, our results seem to suggest that for countries which have already adopted relatively more stringent environmental policies (e.g. EPS > 1.6), the long-term effect on productivity growth is positive.

[**Insert Figure 3 near here**]

4.2 Elasticities

We also evaluate how the demand elasticities of labor and intermediate inputs with respect to input prices and the elasticity of cost with respect to EPS would change as EPS becomes more stringent while keeping all other arguments constant. Let $\boldsymbol{eps}_{it}$ denote the vector of $(eps_{i,t-1}, eps_{i,t-2}, eps_{i,t-3})'$. These elasticities of interest can be respectively expressed as follows:

1) The demand elasticity of labor (L) w.r.t own price:

$$\eta_{LL}(.) = \frac{\partial \ln X_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{\partial \ln w_{it,L}} = \frac{\beta_{LL}\left(\boldsymbol{eps}_{it}\right)}{s_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)} + s_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) - 1; \tag{11}$$

2) The demand elasticity of intermediate inputs (E) w.r.t own price:

$$\eta_{EE}(.) = \frac{\partial \ln X_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{\partial \ln w_{it,E}} = \frac{\beta_{LL}\left(\boldsymbol{eps}_{it}\right)}{s_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)} + s_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) - 1; \tag{12}$$

3) The demand elasticity of labor (L) w.r.t intermediate inputs (E) price:

$$\eta_{LE}(.) = \frac{\partial \ln X_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{\partial \ln w_{it,E}} = -\frac{\beta_{LL}\left(\boldsymbol{eps}_{it}\right)}{s_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)} + s_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right); \tag{13}$$

4) The demand elasticity of intermediate inputs (E) w.r.t labor (L) price:

$$\eta_{EL}(.) = \frac{\partial \ln X_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{\partial \ln w_{it,L}} = -\frac{\beta_{LL}\left(\boldsymbol{eps}_{it}\right)}{s_E\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)} + s_L\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right); \tag{14}$$

5) The elasticity of cost (C) w.r.t lags of EPS

$$\eta_{CE}(.) = \frac{\partial \ln C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{\partial eps_{i,l}}, l \in \{t-1, t-2, t-3\}. \tag{15}$$

According to Figures 4 and 6, labor demand seems to generally become less own-price elastic, as the three EPS lags increase respectively while keeping all other arguments constant. In contrast, although intermediate input demand seems to become statistically insignificantly more own-price elastic as the first two lags of EPS increase respectively, by and large, it becomes less own-price elastic as the third lag of EPS increases, particularly when the level of EPS is roughly greater than 1.25. As for cross-price elasticities, Figure 5 suggests that as all the three lags of EPS increase respectively, while keeping all other arguments constant, labor demand is generally getting less elastic to change in intermediate input price. Additionally in Figure 7, while the intermediate input demand labor-price elasticity seems to follow a statistically insignificant increasing trend as the first two lags of EPS increase respectively, a very demanding environmental policy three years ago appears to clearly render the current year's intermediate input demand less elastic to change in labor price, in particular when eps_{t-3} is roughly over the level of 1.2. These observations seem to suggest that more demanding environmental policies in the long run would lead to smaller substitutability between labor and intermediate inputs which consist of, among others, energy and pollution-intensive materials and services.

[**Insert Figure 4 near here**]
[**Insert Figure 5 near here**]
[**Insert Figure 6 near here**]
[**Insert Figure 7 near here**]

As per Figure 8, our model seems to indicate that for lags of either one or two years, adopting more stringent environmental policies has either statistically insignificant or marginal, albeit statistically significant, effect on total cost in the first or two years, whereas it starts to have some appreciable effect in the third year with elasticities with respect to change in EPS being statistically and significantly positive at two ranges of EPS respectively around the level of 1.0 and 1.6 and statistically significantly negative at one other range around the level of 1.3.

[**Insert Figure 8 near here**]

Another economic measure of significance that is commonly reported is the elasticity of input substitution. It is well-defined for two inputs. This paper concentrates on the widely used Allen-Uzawa Elasticity of Substitution (AES), derived from the cost function (1) according to the formula:

$$\begin{aligned} & AES_{EL}\left(.\right) \\ & \quad = \frac{C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) C_{w_{it,L} w_{it,E}}\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{C_{w_{it,L}}\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right) C_{w_{it,E}}\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)} \\ & \quad = 1 + \frac{\beta_{EL}}{s_E s_L}, \end{aligned} \tag{16}$$

where $C_{w_{it,L}}\left(.\right)$ and $C_{w_{it,E}}\left(.\right)$ are respectively the first-order partial derivatives of the cost function $C\left(.\right)$ w.r.t the prices of labor and intermediate inputs, $C_{w_{it,L} w_{it,E}}\left(.\right)$ is the mixed second-order partial derivative of $C\left(.\right)$ w.r.t the prices of labor and intermediate inputs, and the notation indicates that the AES is not a parameter, but varies across the sample with exogenous variables including EPS. Figure 9 presents the predicted AES between the two variable labor and intermediate inputs against the EPS index lagged one, two and three years with the 95% confidence bands. It shows similar patterns to the labor demand elasticity w.r.t. intermediate inputs in Figure 5, suggesting more demanding environmental policies reduce the substitutability between labor and intermediate inputs, and the reduction seems more appreciable as time goes on.

[**Insert Figure 9 near here**]

4.3 Comparison to a Similar Previous Study

Our study is closely comparable to Albrizio et al. (2017) which also uses the same recently developed EPS index to investigate how EPS impacts on the productivity of a number of OECD countries. Nevertheless, there exist a number of salient differences between our methodology and that of Albrizio et al. (2017), which allows us to generate several distinctive insights and contributions to the literature. Firstly, as opposed to Albrizio et al. (2017) which assumes the underlying technology to be a predetermined two-factor Cobb-Douglas function“with the capital share set to 1/3” *a priori*, taking a dual approach (Diewert, 1974, 1982; Hastie and Tibshirani, 1993), we specify and estimate a three-factor translog cost function. Apart from issues around justification of using a predetermined production function to represent the underlying technology, it is well known in the literature that despite its simple and desirable globally regular structure (McLaren and Yang, 2016), a Cobb-Douglas system is inflexible in the sense that it *a priori* restricts, for instance, the elasticity of substitution between any two input factors to be unity.

Secondly, as opposed to specifying a standard Cobb-Douglas production function or specifying a standard translog cost function, our flexible semi-parametric varying coefficient specification is more comprehensive by allowing EPS to impact on any aspect of the technology in the most flexible way, so that we can estimate not only its impact on TFP/MFP, but also the impact of EPS on interesting economic elasticities, such as the demand, cost and substitution elasticities estimated in this study. As detailed in Section 2.3, the specification tests conducted in this study also lend support to this semi-parametric varying coefficient specification.

Last but not least, as opposed to specifying TFP/MFP as a function of the three-year moving average of EPS and thus implicitly assuming an equal marginal effect on TFP for all the three lags of EPS, our specification instead allows each lag to have its own individual impact on TFP and this impact varies by the magnitude of each lag. As a result, the interesting insight of how the impact of EPS varies by time and magnitude of each lag can be generated as illustrated in Figures 3-9.

5 Conclusion

Over the recent two decades, OECD governments have implemented a wide spectrum of environmental policies committed to improving environmental conditions. Not only do these policies inevitably impact on environmental outcomes, but also the ongoing and increasing environmental stringency affects all aspects of production and economic performance. The strong version of the Porter Hypothesis suggests that although full internalization of the environmental negative externalities in association with production activities shifts the marginal cost upward in the short term, more stringent environmental policies may eventually stimulate innovation, encourage international competitiveness, and increase productivity growth in the long term.

This paper has employed a new cross-country proxy measure for environmental policy stringency and estimated a semi-parametric varying coefficient system model with a translog cost function, which allows for the effects of EPS to be captured in the most flexible manner. Our approach allows key measures of production technology, including the various elasticities, to vary semi-parametrically with EPS. It is well known in the economic growth literature that productivity growth is the most important determinant of living standards, and it is an essential attribute contributing to competitiveness (Oral et al., 1999).

Our results show that changes in environmental stringency seem to take at least two years to significantly impact on a country's technology. It appears that while stricter environmental policies would mostly shift a country's cost in production upward, for countries which have already adopted relatively more stringent environmental policies, further increasing their policy stringency seems to enhance their productivity in the long run. We also find that higher EPS levels are associated with intermediate inputs being more inelastic to changes in own price. Arguably, more stringent environmental policies would exert tighter control over the use of a number of intermediate inputs such as energy, raw materials, pollution-intensive services etc., leading to the use of these inputs being less sensitive to changes in their market prices than otherwise. Likewise, tighter control over the use of these intermediate inputs arising from more demanding environmental policies would render the intermediate inputs less of a substitute for labor input, which is consistent with our predictions.

The impact of environmental policies on production technology and productivity is an important question for economists of our time, but empirical examination of this effect is difficult due to the non-existence of a fully-fledged pollution trading market, or detailed firm or sectoral data on production and pollution over a substantial time period, or comprehensive information on environmental policies in individual countries. This paper tries to offer some empirical evidence to this literature using available data and a more flexible econometric methodology. Our results offer some positive evidence on the effect of environmental policies.

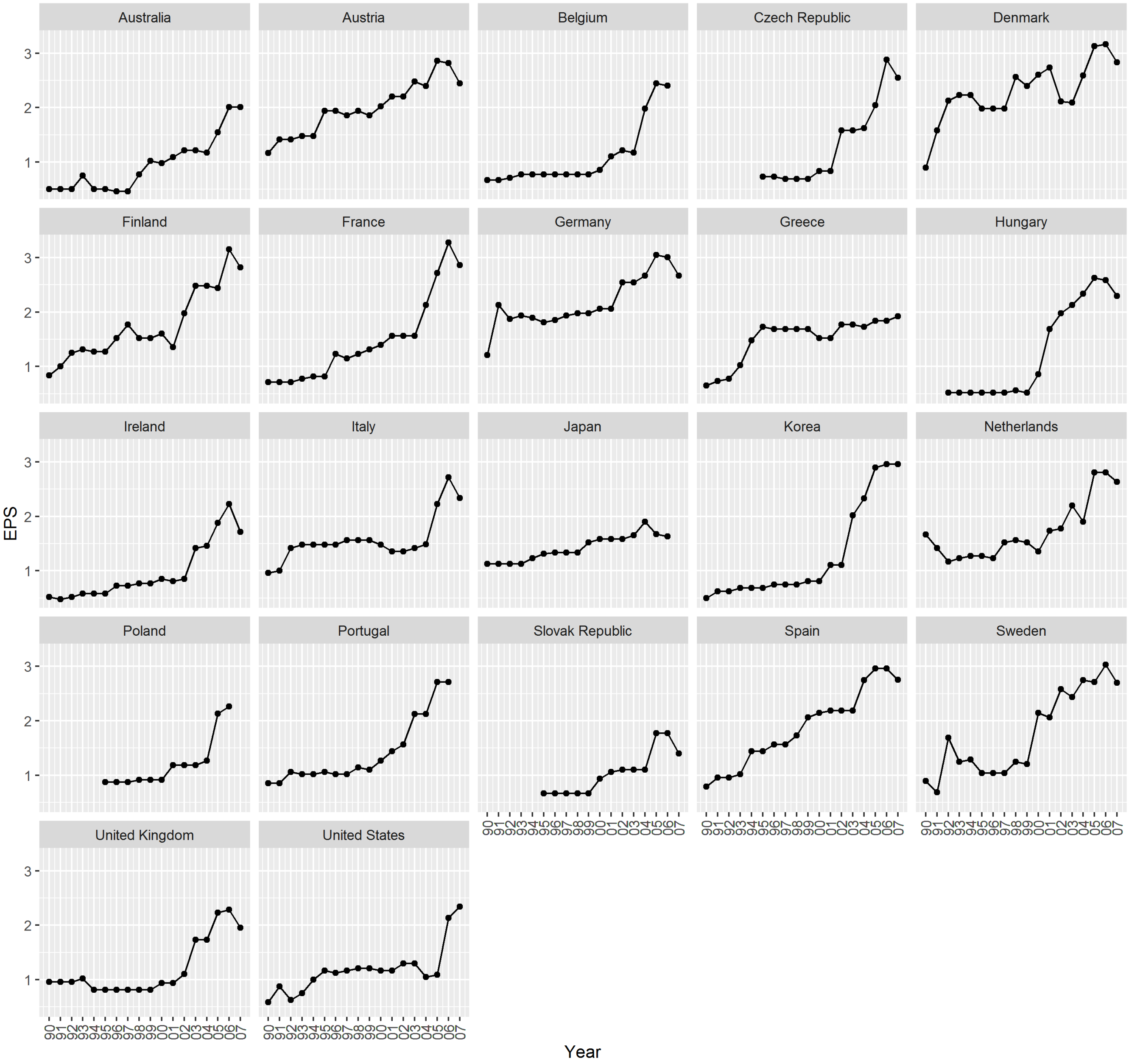

Figure 1: Plots of EPS from the year 1990 to 2007 by country

Table 1: Definition of Variable

Variable	Definition
Price of labor input (w_L)	= Labor compensation / Number of employees
Price of Intermediate inputs (w_E)	= Intermediate inputs price indices (2000 = 100)
Total value of quasi-fixed capital input (z)	= Capital compensation
Quantity of output (y)	= Gross output / Gross output price indices (1995 = 100)
Total cost of Labor input	= Labor compensation
Total cost of Intermediate inputs	= Total value of Intermediate inputs at purchasers' prices
Total cost (C)	= Total cost of Labor input + Total cost of Intermediate inputs
s_L	= Total cost of Labor input / Total cost
s_E	= Total cost of Intermediate inputs / Total cost;
t	= Year
eps	= Environmental policy stringency index;

Data sources: EU KLEMS (November 2009 release) and OECD (2016).

Table 2: Descriptive Statistics of EPS by Countries

Country	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Australia	0.458	0.500	0.875	0.955	1.202	2.008
Austria	1.167	1.573	1.938	1.994	2.348	2.858
Belgium	0.667	0.771	0.771	1.095	1.171	2.446
Czech Republic	0.688	0.729	0.833	1.342	1.625	2.879
Denmark	0.896	2.007	2.229	2.290	2.601	3.163
Finland	0.833	1.281	1.521	1.754	2.326	3.150
France	0.708	0.813	1.271	1.472	1.563	3.279
Germany	1.208	1.906	2.021	2.178	2.542	3.046
Greece	0.646	1.490	1.688	1.502	1.760	1.921
Hungary	0.521	0.521	0.708	1.294	2.168	2.629
Ireland	0.479	0.583	0.771	0.972	1.276	2.229
Italy	0.958	1.418	1.479	1.576	1.563	2.721
Japan	1.125	1.229	1.333	1.421	1.583	1.900
Korea	0.500	0.688	0.781	1.281	1.792	2.958
Netherlands	1.167	1.292	1.542	1.726	1.873	2.084
Poland	0.875	0.906	1.052	1.217	1.208	2.263
Portugal	0.854	1.021	1.104	1.418	1.563	2.713
Slovak Republic	0.667	0.667	1.063	1.046	1.104	1.775
Spain	0.792	1.438	1.896	1.870	2.188	2.963
Sweden	0.688	1.083	1.490	1.767	2.546	3.029
United Kingdom	0.813	0.813	0.958	1.205	1.576	2.288
United States	0.583	1.013	1.167	1.181	1.208	2.342

Table 3: The Estimated Coefficients at the mean of EPS

Coefficient	Estimate	S.E.	Lower95	Upper95
$\alpha_0(\overline{\boldsymbol{eps}})$	1.520**	(0.593)	0.358	2.682
$\alpha_L(\overline{\boldsymbol{eps}})$	-0.073	(0.053)	-0.177	0.031
$\gamma(\overline{\boldsymbol{eps}})$	1.404***	(0.232)	0.951	1.858
$\beta_{LL}(\overline{\boldsymbol{eps}})$	-0.037***	(0.006)	-0.048	-0.026
$\gamma^*(\overline{\boldsymbol{eps}})$	0.170***	(0.061)	0.050	0.290
$\psi_L(\overline{\boldsymbol{eps}})$	0.004	(0.020)	-0.035	0.042
$\tau(\overline{\boldsymbol{eps}})$	0.041***	(0.007)	0.027	0.054
$\delta(\overline{\boldsymbol{eps}})$	0.000	(0.000)	0.000	0.000
$\phi_L(\overline{\boldsymbol{eps}})$	-0.005***	(0.001)	-0.007	-0.003
$\varphi(\overline{\boldsymbol{eps}})$	0.013***	(0.002)	0.008	0.018
$\eta(\overline{\boldsymbol{eps}})$	-0.506**	(0.254)	-1.003	-0.008
$\zeta(\overline{\boldsymbol{eps}})$	0.183***	(0.067)	0.051	0.315
$\kappa(\overline{\boldsymbol{eps}})$	-0.013***	(0.002)	-0.018	-0.008
$\sigma(\overline{\boldsymbol{eps}})$	-0.178***	(0.063)	-0.303	-0.054
$\rho_L(\overline{\boldsymbol{eps}})$	0.010	(0.019)	-0.026	0.047
$d_{Austria}$	-0.123***	(0.010)	-0.143	-0.103
$d_{Belgium}$	-0.046***	(0.009)	-0.063	-0.029
$d_{CzechRepublic}$	-0.048***	(0.010)	-0.067	-0.029
$d_{Denmark}$	-0.133***	(0.011)	-0.155	-0.110
$d_{Finland}$	-0.163***	(0.012)	-0.187	-0.139
d_{France}	0.147***	(0.011)	0.127	0.168
$d_{Germany}$	0.185***	(0.016)	0.153	0.216
d_{Greece}	-0.268***	(0.016)	-0.300	-0.236
$d_{Hungary}$	-0.109***	(0.009)	-0.126	-0.091
$d_{Ireland}$	-0.186***	(0.016)	-0.217	-0.155
d_{Italy}	0.143***	(0.010)	0.124	0.162
d_{Japan}	0.210***	(0.028)	0.154	0.266
d_{Korea}	0.122***	(0.015)	0.093	0.150
$d_{Netherlands}$	0.000	(0.005)	-0.009	0.009
d_{Poland}	0.034***	(0.009)	0.015	0.052
$d_{Portugal}$	-0.100***	(0.008)	-0.115	-0.084
$d_{SlovakRepublic}$	0.056	(0.038)	-0.019	0.131
d_{Spain}	0.066***	(0.006)	0.054	0.078
d_{Sweden}	-0.078***	(0.007)	-0.092	-0.064
$d_{UnitedKingdom}$	0.178***	(0.012)	0.154	0.202
$d_{UnitedStates}$	0.380***	(0.046)	0.289	0.470

Table 4: The Estimated Growth of TFP from the year 1990 to 2007 by Countries

	AUS	AUT	BEL	CZE	DNK	FIN	FRA	DEU	GRC	HUN	IRL	ITA
1993	-0.009	-0.010	-0.009		-0.008	-0.008	-0.014	-0.002	-0.028	-0.009	-0.004	-0.007
1994	0.009	-0.006	-0.002		-0.003	-0.005	-0.004	-0.007	-0.017	-0.005	-0.003	-0.003
1995	-0.012	-0.004	-0.001		-0.005	-0.005	-0.002	-0.004	-0.018	-0.015	-0.004	-0.006
1996	-0.007	-0.006	-0.004	-0.020	-0.008	-0.004	-0.006	-0.003	-0.006	-0.017	-0.003	-0.010
1997	-0.005	-0.005	-0.002	-0.019	-0.007	-0.004	0.001	-0.003	-0.011	-0.018	-0.001	-0.001
1998	-0.004	0.002	-0.002	-0.021	-0.004	-0.005	0.003	-0.002	-0.010	-0.015	-0.001	0.002
1999	-0.002	0.001	-0.003	-0.012	-0.009	0.001	0.003	0.000	-0.009	-0.014	-0.002	0.001
2000	-0.008	0.003	-0.003	-0.010	-0.003	0.002	0.004	0.002	-0.003	-0.012	-0.002	0.004
2001	-0.005	-0.003	-0.004	-0.010	-0.010	-0.008	0.000	0.001	-0.005	-0.012	-0.002	0.000
2002	-0.001	0.000	-0.004	-0.010	-0.010	-0.001	-0.002	0.000	-0.003	-0.016	-0.002	-0.001
2003	0.000	0.000	-0.003	-0.011	-0.008	-0.004	-0.004	0.019	-0.005	-0.016	0.000	-0.002
2004	0.001	0.011	-0.001	-0.012	-0.009	-0.002	0.004	0.027	-0.004	-0.013	0.001	-0.002
2005	0.002	0.004	-0.004	0.002	-0.012	-0.012	0.000	0.023	-0.003	-0.008	-0.005	-0.002
2006	-0.006	0.036	-0.001	0.003	-0.021	-0.016	0.007	0.041	0.000	-0.010	-0.002	0.000
2007	-0.009	0.010		-0.024	-0.012	0.004	0.016	0.025	-0.002	-0.019	0.002	0.003
Mean	-0.004	0.002	-0.003	-0.012	-0.009	-0.004	0.000	0.008	-0.008	-0.013	-0.002	-0.001

	JPN	KOR	NLD	POL	PRT	SVK	ESP	SWE	GRB	USA
1993	-0.004	-0.015	-0.006		-0.017		-0.016	-0.007	-0.011	-0.015
1994	0.005	-0.015	-0.005		-0.015		-0.012	-0.004	-0.004	0.001
1995	0.013	-0.014	-0.005		-0.010		-0.010	-0.008	-0.017	-0.003
1996	0.013	-0.014	-0.004	-0.022	-0.008	0.013	-0.006	-0.003	-0.006	0.000
1997	0.002	-0.012	-0.003	-0.019	-0.006	0.010	-0.002	-0.002	-0.004	0.003
1998	-0.003	-0.020	-0.004	-0.016	-0.006	0.010	0.000	-0.002	-0.008	0.003
1999	0.004	-0.001	-0.005	-0.012	-0.005	-0.011	-0.001	0.000	-0.006	0.003
2000	0.007	-0.004	0.003	-0.013	-0.004	-0.010	-0.003	0.000	-0.002	0.000
2001	0.004	-0.011	-0.005	-0.009	-0.007	0.009	-0.002	-0.008	-0.006	-0.004
2002	0.002	-0.009	-0.006	-0.007	-0.009	0.014	0.005	-0.008	-0.006	-0.001
2003	0.004	-0.009	-0.009	-0.005	-0.010	0.004	-0.005	-0.007	-0.004	0.001
2004	0.006	-0.003	-0.001	-0.001	-0.010	0.006	0.004	-0.005	-0.006	0.004
2005	0.000	-0.003	0.000	-0.003	-0.006	0.013	0.023	-0.005	-0.011	0.003
2006	0.010	-0.043	0.017	-0.006	-0.017	0.030	0.048	0.007	-0.001	0.003
2007		-0.064	0.010			0.028	0.021	0.000	-0.003	0.000
Mean	0.005	-0.016	-0.002	-0.010	-0.009	0.010	0.003	-0.003	-0.006	0.000

Note: AUS: Australia; AUT: Austria; BEL: Belgium; CZE: Czech Republic; DNK: Denmark; FIN: Finland; FRA: France; DEU: Germany; GRC: Greece; HUN: Hungary; IRL: Ireland; ITA: Italy; JPN: Japan; KOR: Korea; NLD: Netherlands; POL: Poland; PRT: Portugal; SVK: Slovak Republic; ESP: Spain; SWE: Sweden; GRB: United Kingdom; USA: United States.

Table 5: The Estimated Average Technical Change, Scale Effects and TFPG by Countries

	AUS	AUT	BEL	CZE	DNK	FIN	FRA	DEU	GRC	HUN	IRL
TC	-0.005***	-0.001	-0.004***	-0.011***	-0.009***	-0.006***	-0.002**	0.003**	-0.003**	-0.009***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SE	0.001***	0.003***	0.001**	-0.002***	0.000	0.002**	0.002***	0.005***	-0.006***	-0.004	0.001
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.004)	(0.001)
TFPG	-0.004***	0.002*	-0.003***	-0.012***	-0.009***	-0.004***	0.000	0.008***	-0.008***	-0.013***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)

	ITA	JPN	KOR	NLD	POL	PRT	SVK	ESP	SWE	GRB	USA
TC	0.000	0.001	-0.014***	-0.003***	-0.008***	-0.008***	0.014***	0.001	-0.005***	-0.007***	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
SE	-0.001***	0.004***	-0.002***	0.002***	-0.002*	-0.001***	-0.005***	0.002***	0.002***	0.001***	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
TFPG	-0.001*	0.005***	-0.016***	-0.002*	-0.010***	-0.009***	0.010***	0.003**	-0.003***	-0.006***	0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)

Note: TC: Technical Change; SE: Scale Effects; TFPG: Total Factor Productivity Growth; AUS: Australia; AUT: Austria; BEL: Belgium; CZE: Czech Republic; DNK: Denmark; FIN: Finland; FRA: France; DEU: Germany; GRC: Greece; HUN: Hungary; IRL: Ireland; ITA: Italy; JPN: Japan; KOR: Korea; NLD: Netherlands; POL: Poland; PRT: Portugal; SVK: Slovak Republic; ESP: Spain; SWE: Sweden; GRB: United Kingdom; USA: United States

Figure 2: Plots of Estimated TFPG from the year 1990 to 2007 by Countries with 95% Confidence Band

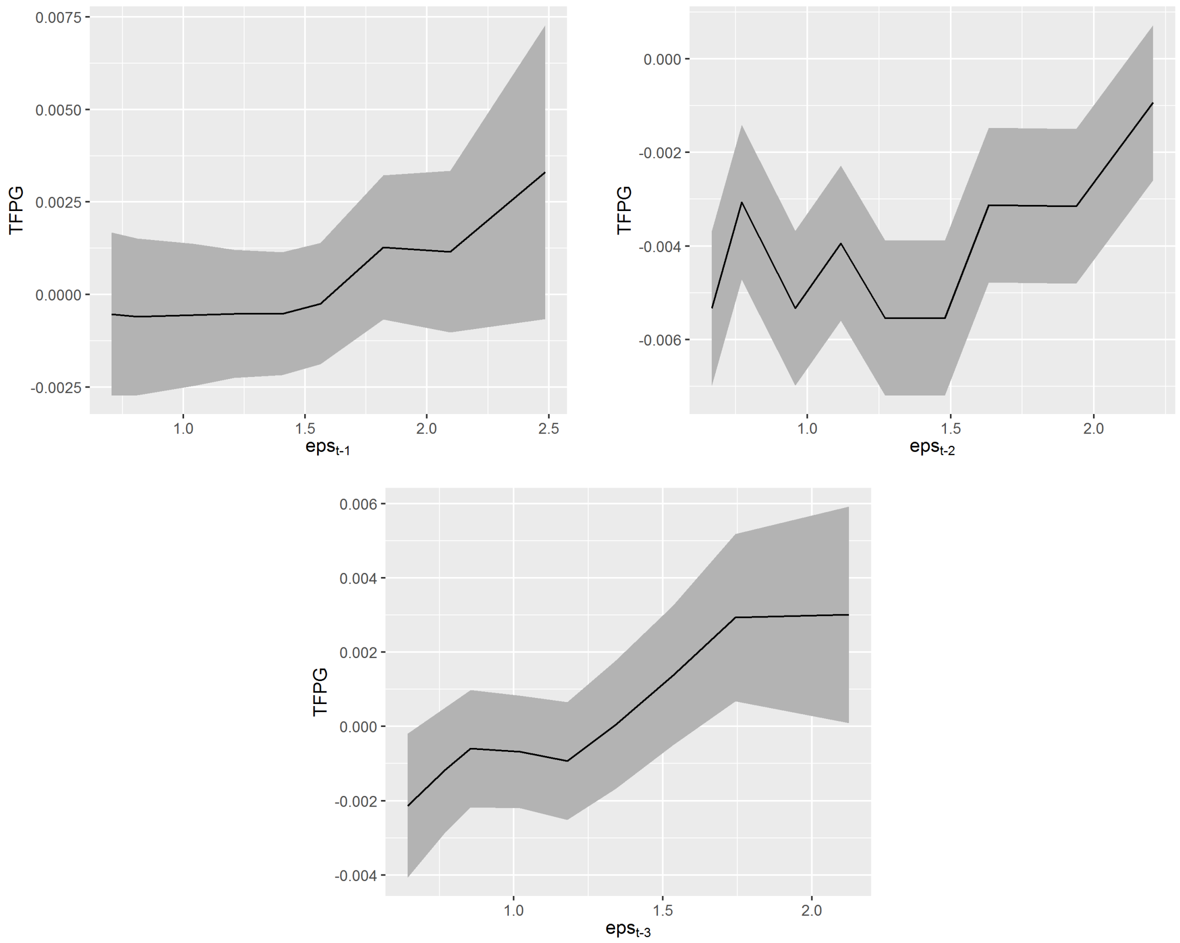

Figure 3: Predicted TFPG against EPS index lagged one, two and three years with 95% Confidence Band

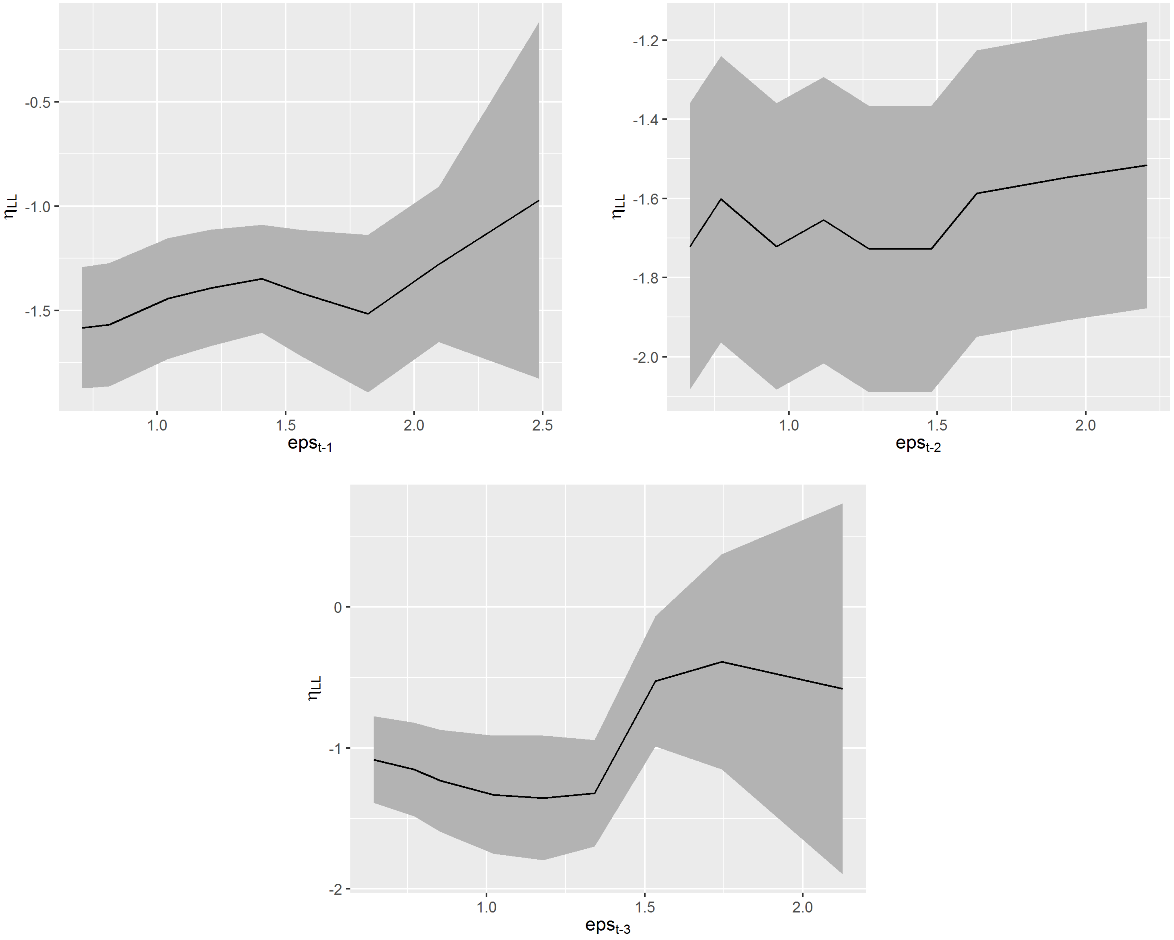

Figure 4: Predicted Labor Demand Own-Price Elasticities, η_{LL}, against EPS index lagged one, two and three years with 95% Confidence Band

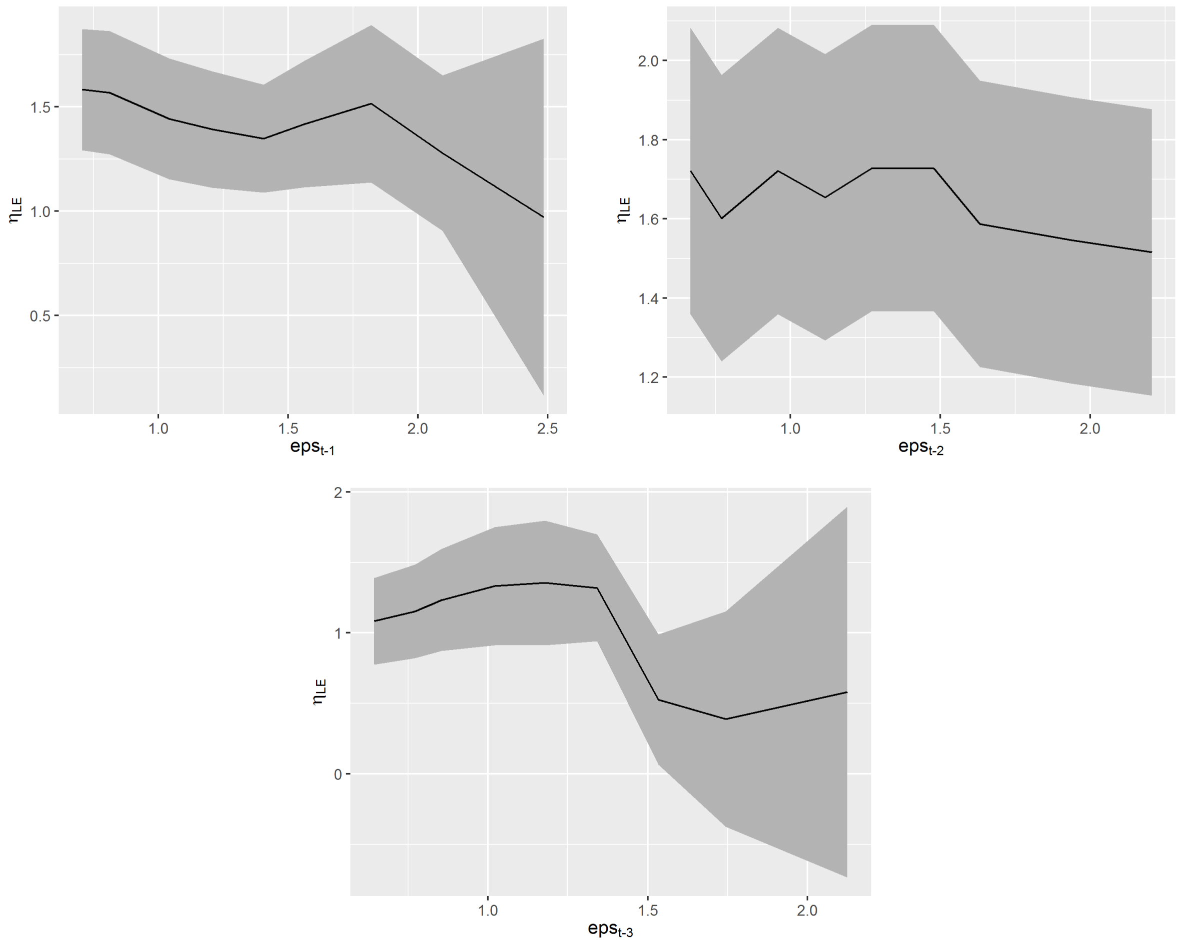

Figure 5: Predicted Labor Demand Intermediate-Input-Price Elasticities, η_{LE}, against EPS index lagged one, two and three years with 95% Confidence Band

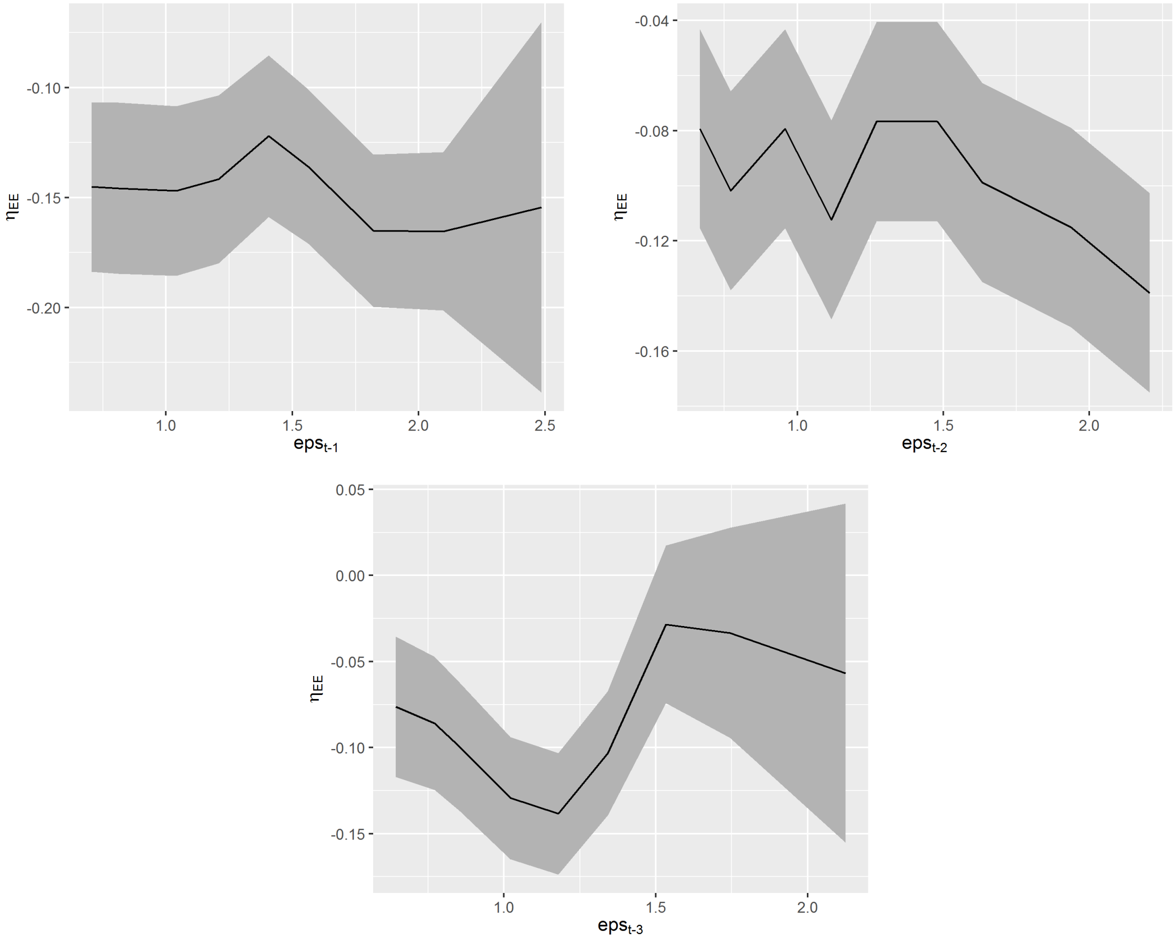

Figure 6: Predicted Intermediate Input Demand Own-Price Elasticities, η_{EE}, against EPS index lagged one, two and three years with 95% Confidence Band

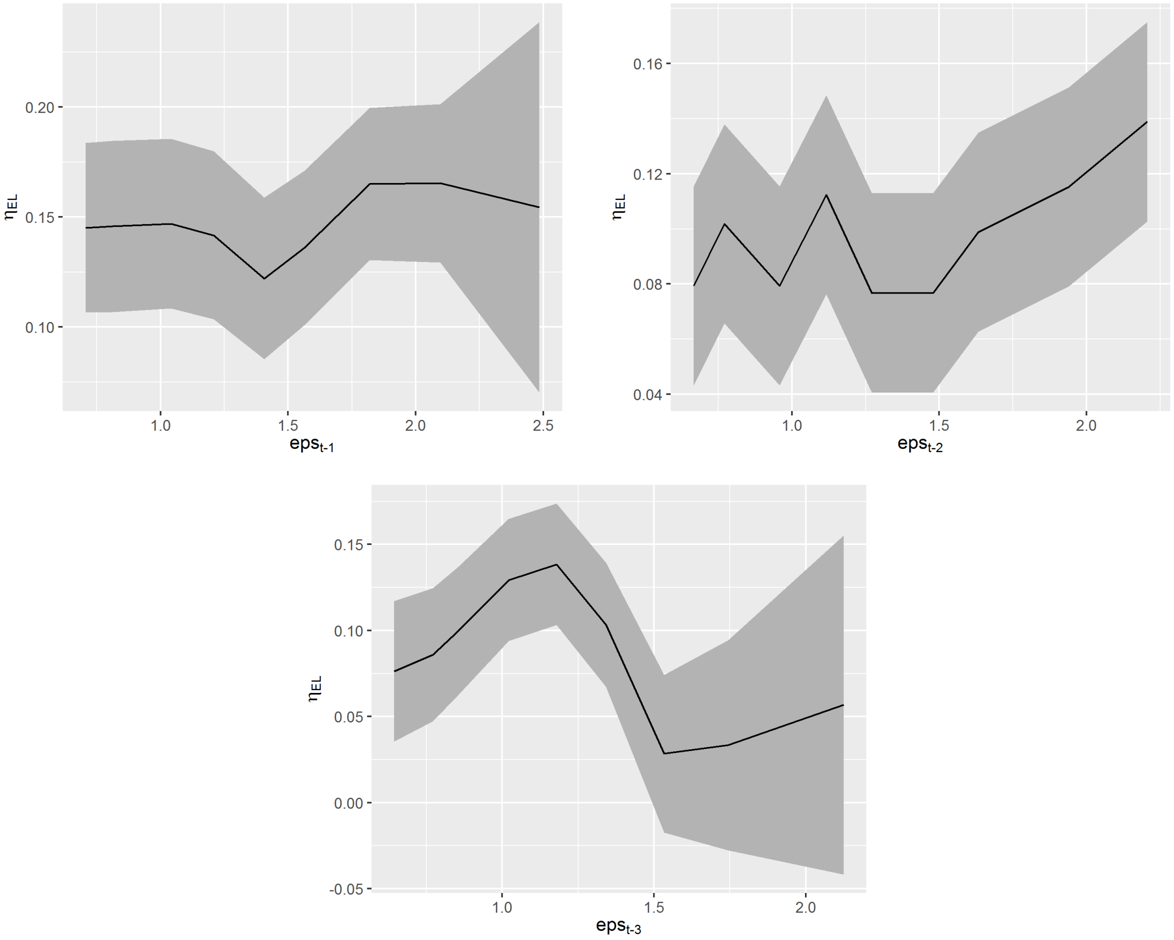

Figure 7: Predicted Intermediate Input Demand Labor-Price Elasticities, η_{EL}, against EPS index lagged one, two and three years with 95% Confidence Band

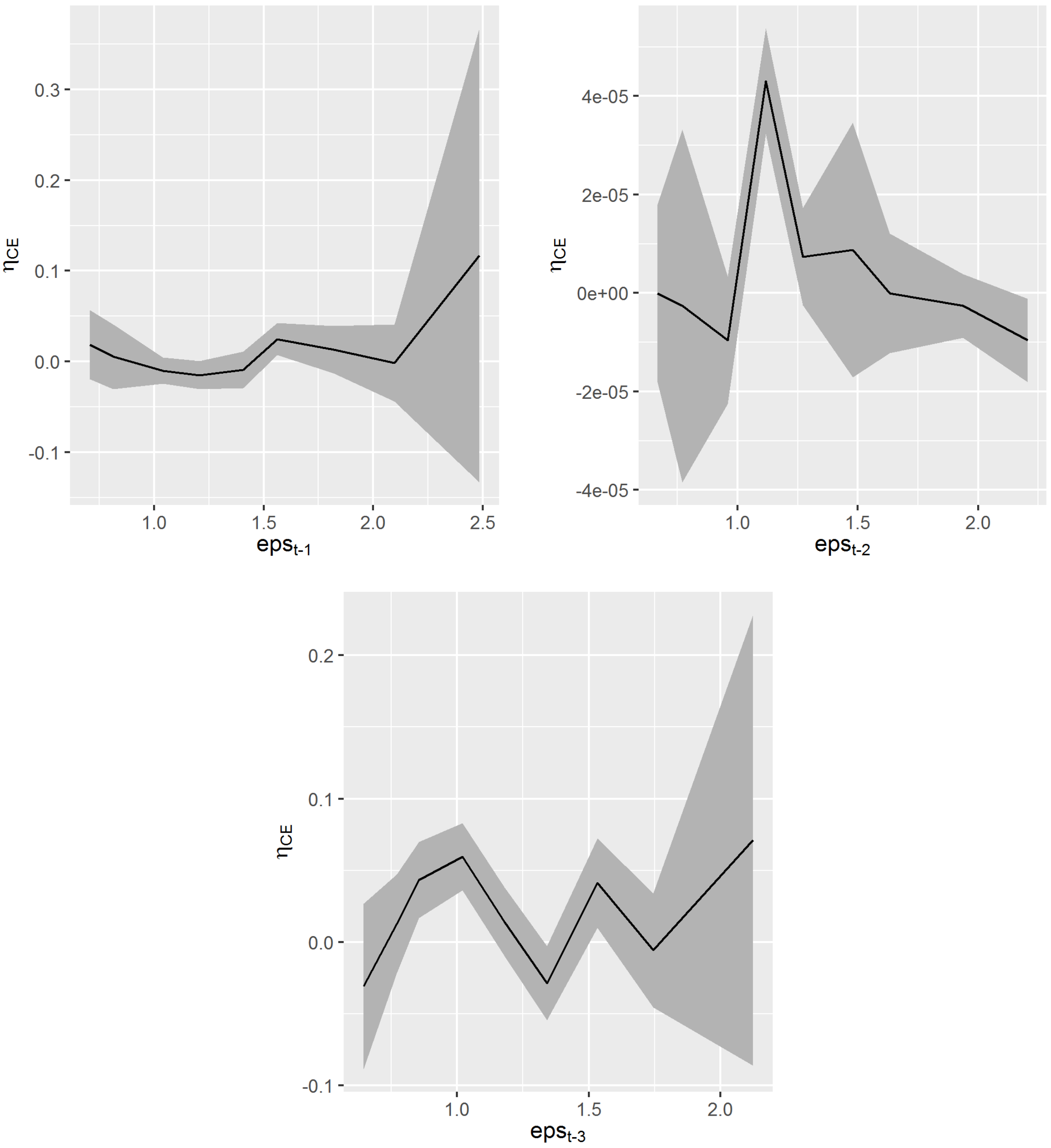

Figure 8: Predicted Cost EPS-lag Elasticities, η_{CE}, against EPS index lagged one, two and three years with 95% Confidence Band

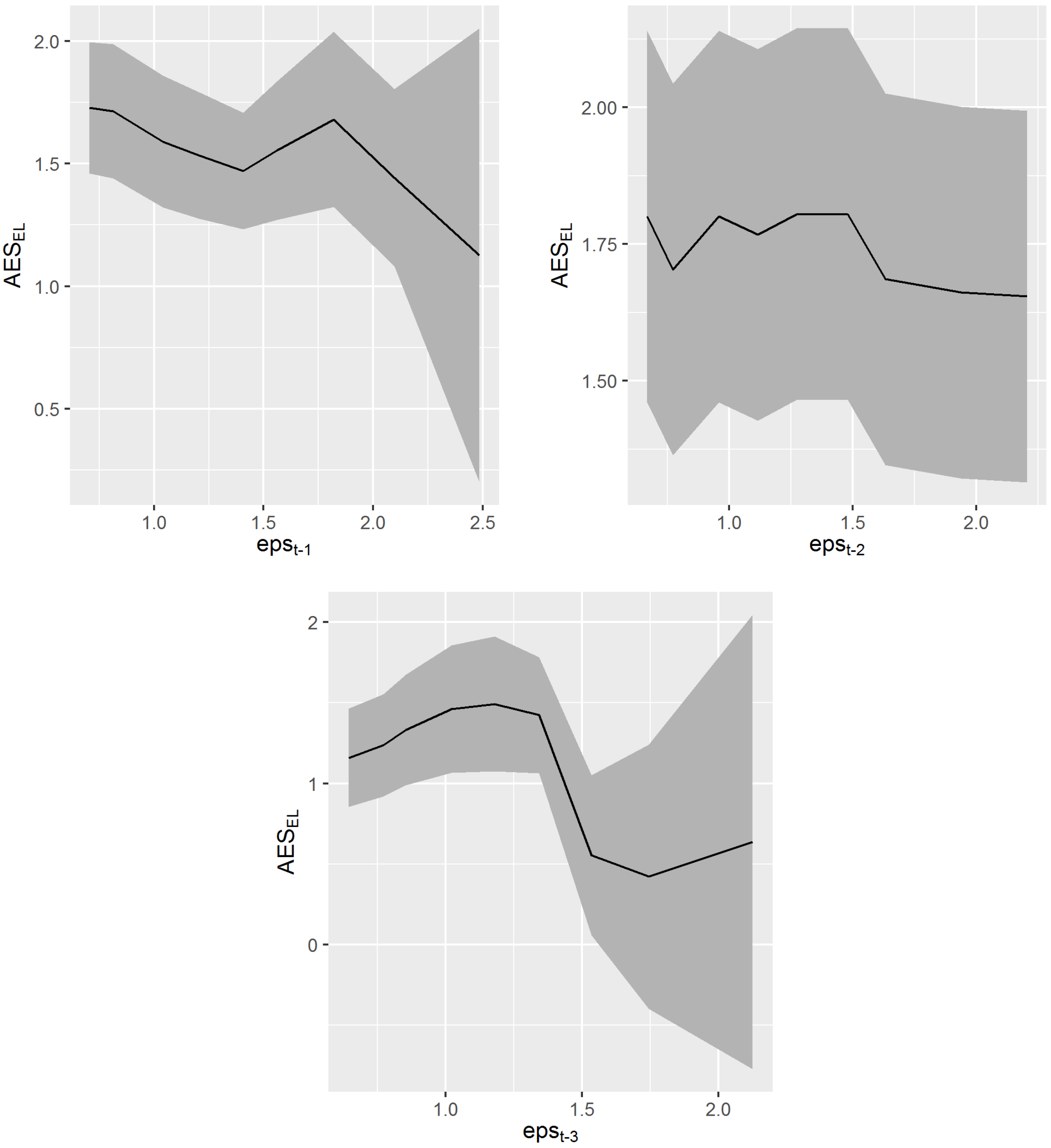

Figure 9: Predicted Allen-Uzawa Elasticity of Substitution, AES_{CE}, against EPS index lagged one, two and three years with 95% Confidence Band

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Appendix A

In the spirit of Bai (2009), an iteration scheme is employed to estimate the system of equations (4) and (5), which takes the common seemingly unrelated regression (SUR) form upon appending idiosyncratic error terms. Each iteration involves two steps as follows.

Step 1: given initial values of eps-invariant country-specific effects (i.e. α_i's), we estimate the eps-varying coefficients for the non-dummy variables (i.e. $\alpha_0(\boldsymbol{eps}_{it})$, $\alpha_L(\boldsymbol{eps}_{it})$, $\gamma(\boldsymbol{eps}_{it})$, $\tau(\boldsymbol{eps}_{it})$, $\eta(\boldsymbol{eps}_{it})$, $\beta_{LL}(\boldsymbol{eps}_{it})$, $\gamma^*(\boldsymbol{eps}_{it})$, $\delta(\boldsymbol{eps}_{it})$, $\zeta(\boldsymbol{eps}_{it})$, $\psi_L(\boldsymbol{eps}_{it})$, $\phi_L(\boldsymbol{eps}_{it})$, $\rho_L(\boldsymbol{eps}_{it})$, $\varphi(\boldsymbol{eps}_{it})$, $\sigma(\boldsymbol{eps}_{it})$, and $\kappa(\boldsymbol{eps}_{it})$) using varying coefficient kernel regression bandwidth selection and estimation techniques (Li and Racine, 2003, 2010; Li et al., 2013).

Specifically, we first define the dependent variable vector and the disturbance vector. Let q_{it} be a 2×1 vector representing the dependent variables associated with the $(i \times t)$th observation with the first element being $\left(\ln \frac{C(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it})}{w_{it,E}} - \sum_{i=2}^{N} \hat{\alpha}_i D_i\right)$, where $D_i (i = 1, \cdots, N)$ are the country-specific dummies, and the second element being the share of labor, i.e. $s_{it,L}$. Let $\boldsymbol{u_{it}} = (u_{it,C}, u_{it,L})'$ be an 2×1 disturbance vector, whose variance-covariance matrix is $\Sigma_{it} = E(\boldsymbol{u_{it}}\boldsymbol{u_{it}}'|X_{it})$. We then define regressors and coefficients equation by equation. For the normalised cost equation, let $X_{it,C}$ be a 1×15 vector representing all the non-dummy regressors in the normalised cost function (4) and $B(\boldsymbol{eps}_{it})$ be the corresponding coefficients, i.e., all coefficients except country-specific effects in (4). The first equation of the two-equation system can be written as:

$$q_{it,C} = X_{it,C} B(\boldsymbol{eps}_{it}) + u_{it,C}.$$

For the normalised labor share equation, we still use $B(\boldsymbol{eps}_{it})$ as our redefined coefficient vector. The regressor vector, $X_{it,L}$, is however redefined in such a way that $X_{it,L} B(\boldsymbol{eps}_{it})$ is equal to the right hand side of the normalised labor share equation. Formally, $X_{it,L} = (0, 1, 0, \ln \frac{w_{it,L}}{w_{it,E}}, 0, \ln y_{it}, \mathbf{0}_2, t, \mathbf{0}_5, \ln z_{it})$, where $\mathbf{0}_p$ is a $1 \times p$ vector of zeros. Hence, the second equation of the two-equation system can be written as:

$$q_{it,L} = X_{it,L} B(\boldsymbol{eps}_{it}) + u_{it,L}.$$

Stacking the two equations associated with the ith country at the tth year gives rise to:

$$\boldsymbol{q}_{it} = \boldsymbol{X}_{it} \boldsymbol{B}(\boldsymbol{eps}_{it}) + \boldsymbol{u}_{it}. \tag{A.1}$$

The full system of equations consists of $NT - 3N$ equations (where $NT = \sum_{i=1}^{N} T_i$, with T_i being the number of observations for the ith country. In particular, for balanced panel data, $T_i = T$ for any i). It can then be expressed as:

$$\begin{bmatrix} \boldsymbol{q_{14}} \\ \vdots \\ \boldsymbol{q_{1T_1}} \\ \vdots \\ \boldsymbol{q_{N4}} \\ \vdots \\ \boldsymbol{q_{NT_N}} \end{bmatrix} = \begin{bmatrix} \boldsymbol{X_{14}} \\ \vdots \\ \boldsymbol{X_{1T_1}} \\ \vdots \\ \boldsymbol{X_{N4}} \\ \vdots \\ \boldsymbol{X_{NT_N}} \end{bmatrix} \left[\boldsymbol{B}(\boldsymbol{eps}_{14}), ..., \boldsymbol{B}(\boldsymbol{eps}_{1T_1}), ..., \boldsymbol{B}(\boldsymbol{eps}_{N4}), ..., \boldsymbol{B}(\boldsymbol{eps}_{NT_N})\right] + \begin{bmatrix} \boldsymbol{u_{14}} \\ \vdots \\ \boldsymbol{u_{1T_1}} \\ \vdots \\ \boldsymbol{u_{N4}} \\ \vdots \\ \boldsymbol{u_{NT_N)}} \end{bmatrix}, \tag{A.2}$$

which can be written in a more compact form as:

$$\boldsymbol{q} = \boldsymbol{X}\boldsymbol{B}(\boldsymbol{eps}) + \boldsymbol{u}, \tag{A.3}$$

where $\boldsymbol{q}$ and $\boldsymbol{u}$ are $2(NT - 3N) \times 1$ vectors and $\boldsymbol{X}$ is a $2(NT - 3N) \times 15$ matrix. The $2(NT - 3N) \times 1$ disturbance vector $\boldsymbol{u}$ has the following variance-covariance matrix: $\boldsymbol{\Omega} = E(\boldsymbol{u}\boldsymbol{u}') = \boldsymbol{I}_{NT-3N} \otimes \boldsymbol{\Sigma}$, where $\boldsymbol{I}_{NT-3N}$ is an identity matrix of dimension $NT - 3N$.

The least-squares estimator of $\boldsymbol{B}(\boldsymbol{eps})$ in (A.3) is the solution to

$$0 = \boldsymbol{X}'\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\boldsymbol{\Omega}^{-1}\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\left[\boldsymbol{q} - \boldsymbol{X}\boldsymbol{B}(\boldsymbol{eps})\right], \tag{A.4}$$

where $\boldsymbol{K}(\boldsymbol{eps})$ is a $2(NT-3N) \times 2(NT-3N)$ diagonal matrix with the diagonal element corresponding to the ith country at the tth time period for the kth equation ($k = 1$ for cost equation or $k = 2$ for labor cost share equation) being $K_{itk}(\boldsymbol{eps}_{it}, \boldsymbol{eps}) = W_h(\frac{\boldsymbol{eps}_{it}-\boldsymbol{eps}}{h})$, where $W_h(\frac{\boldsymbol{eps}_{it},\boldsymbol{eps}}{h}) = \prod_{s=1}^{3}\frac{1}{h_s}w(\frac{eps_{i,t-s}-eps_s}{h_s})$ and $w(\cdot)$ is a symmetric univariate density function and where $0 < h_s < \infty$ is the smoothing parameter.

Solving for $\boldsymbol{B}(\boldsymbol{eps})$ in (A.4) leads to the estimator

$$\hat{\boldsymbol{B}}(\boldsymbol{eps}) = \left[\boldsymbol{X}'\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\boldsymbol{\Omega}^{-1}\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\boldsymbol{X}\right]^{-1}\boldsymbol{X}'\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\boldsymbol{\Omega}^{-1}\boldsymbol{K}(\boldsymbol{eps})^{\frac{1}{2}}\boldsymbol{q}, \tag{A.5}$$

where the error covariance matrix $\boldsymbol{\Omega}$ as in the case of the standard feasible generalised least squares (FGLS) method for SUR models (Wooldridge, 2010, p.176), can be estimated by using a consistent system estimator which ignores the information in the variance-covariance matrix (i.e., by setting $\boldsymbol{\Omega} = I_{2(NT-3N)}$). In this case, (A.5) reduces to

$$\tilde{\boldsymbol{B}}(\boldsymbol{eps}_t) = \left[\boldsymbol{X}'\boldsymbol{K}(\boldsymbol{eps})\boldsymbol{X}\right]^{-1}\boldsymbol{X}'\boldsymbol{K}(\boldsymbol{eps})\boldsymbol{q}. \tag{A.6}$$

Using (A.6), we can obtain the 2×1 vector of residuals associated with the equation for the ith country at the tth time period as $\tilde{\boldsymbol{u}}_{it} = \boldsymbol{q}_{it} - \boldsymbol{X}_{it}\tilde{\boldsymbol{B}}(\boldsymbol{eps}) = [\tilde{\boldsymbol{u}}_{it,C}, \tilde{\boldsymbol{u}}_{it,L}]'$. The estimate of the variance-covariance matrix is given by $\hat{\Sigma} = \frac{1}{NT-3N}\sum \tilde{\boldsymbol{u}}_{it}\tilde{\boldsymbol{u}}'_{it}$, and hence we can construct our estimator of $\boldsymbol{\Sigma}$.

Following Li and Racine (2010), we choose $\boldsymbol{h} = (h_1, h_2, h_3)$ to minimise the following cross-validation function

$$CV(\boldsymbol{h}) = \frac{1}{2(NT-3N)}\sum_{l=1}^{2(NT-3N)}\left[g_l - z_l\hat{\boldsymbol{B}}_{-l}(\boldsymbol{eps_l})\right]^2, \tag{A.7}$$

where g_l is the lth row of $\boldsymbol{q}$, z_l is the lth row of $\boldsymbol{X}$, $\boldsymbol{eps_l}$ is the observed $\boldsymbol{eps}$ corresponding to the lth observation in $\boldsymbol{X}$. The leave-one-out kernel estimator of the eps-varying coefficients can be given as:

$$\hat{\boldsymbol{B}}_{-l}(\boldsymbol{eps}_l) = \left[\boldsymbol{X'}_{-l}\boldsymbol{K}_{-l}(\boldsymbol{eps}_l)^{1/2}\boldsymbol{\Omega}_{-l}^{-1}\boldsymbol{K}_{-l}(\boldsymbol{eps}_l)^{1/2}\boldsymbol{X}_{-l}\right]^{-1} \cdot \\ \boldsymbol{X'}_{-l}\boldsymbol{K}_{-l}(\boldsymbol{eps}_l)^{1/2}\boldsymbol{\Omega}_{-l}^{-1}\boldsymbol{K}_{-l}(\boldsymbol{eps}_l)^{1/2}\boldsymbol{q_{-l}}, \quad \text{(A.8)}$$

with the notation $-l$ implying that the l^{th} row is removed from $\boldsymbol{\Omega}$, $\boldsymbol{K}(\boldsymbol{eps}_l)$, $\boldsymbol{X}$ and $\boldsymbol{q}$.

Step 2: given the estimated eps-varying coefficients, we define a new dependent variable, denoted by R, as:

$$\begin{aligned} R = \ln & \frac{C\left(y_{it}, w_{it,L}, w_{it,E}, t, z_{it}, \boldsymbol{eps}_{it}\right)}{w_{it,E}} - \\ & \{\hat{\alpha}_0(\boldsymbol{eps}_{it}) + \hat{\alpha}_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} + \hat{\gamma}(\boldsymbol{eps}_{it}) \ln y_{it} + \hat{\tau}(\boldsymbol{eps}_{it})t + \hat{\eta}(\boldsymbol{eps}_{it}) \ln z_{it} \\ & + \frac{1}{2}\hat{\beta}_{LL}(\boldsymbol{eps}_{it})(\ln \frac{w_{it,L}}{w_{it,E}})^2 + \frac{1}{2}\hat{\gamma}^*(\boldsymbol{eps}_{it})(\ln y_{it})^2 \\ & + \frac{1}{2}\hat{\delta}(\boldsymbol{eps}_{it})t^2 + \frac{1}{2}\hat{\zeta}(\boldsymbol{eps}_{it})(\ln z_{it})^2 + \hat{\psi}_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} \ln y_{it} \\ & + \hat{\phi}_L(\boldsymbol{eps}_{it})t \ln \frac{w_{it,L}}{w_{it,E}} + \hat{\rho}_L(\boldsymbol{eps}_{it}) \ln \frac{w_{it,L}}{w_{it,E}} \ln z_{it} + \hat{\varphi}(\boldsymbol{eps}_{it})t \ln y_{it} \\ & + \hat{\sigma}(\boldsymbol{eps}_{it}) \ln z_{it} \ln y_{it} + \hat{\kappa}(\boldsymbol{eps}_{it})t \ln z_{it}\}. \end{aligned} \quad \text{(A.9)}$$

We regress R on $\sum_{i=2}^{N} \hat{\alpha}_i D_i$ by OLS to get estimates $\hat{\alpha}_i$'s, where $D_i (i = 1, \cdots, N)$ are the country-specific dummies. $\hat{\alpha}_i$'s will then be substituted in Step 1 for the initial values of α_i's, and continue the iteration until $\hat{\alpha}_i$'s converge, which we define as the Euclidean distance of $\hat{\alpha}_i$'s from any two consecutive iterations is no larger than 10^{-7}.