Fiscal Policy and TFP in the OECD: a non-stationary panel approach

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Abstract

We analyse the influence of government size, government deficits and the composition of taxes and expenditures on TFP in a panel of OECD countries since 1975. Our contribution is double. First, we identify both direct and indirect effects of fiscal policy on TFP. The latter stem from the influence of taxes and government expenditures on countries’ access to worldwide available technology. A second contribution is methodological. The role of the worldwide level of technology introduces a common factor in individual countries’ TFP. This common factor is unobserved and most likely non-stationary. To deal with the econometric complications that arise from this, and to allow for time-varying factor loadings, we suggest and adopt a continuously-updated CCEP (CCEPcu) estimator. Our main findings are as follows. Through the direct channel, an overall increase in government size reduces TFP and per capita output. Expenditure shifts towards more productive purposes have strong positive effects on TFP whereas shifts in favour of social transfers reduce TFP. Deficit reduction policies raise TFP and hence per capita output. Through the indirect channel, a rise in the corporate tax rate negatively affects a country’s access to worldwide available technology.

JEL Classification: C31, C33, E62, O38.

Keywords: Fiscal policy, Total Factor Productivity, Worldwide Available Technology, Unobserved Common Factors, Panel Data

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1 Introduction

Rising pressure on the welfare state due to ageing, and the need to bring down government debts and deficits after the recent recession, force all countries to develop effective productivity and growth policies. The importance of higher productivity (per capita output) to face the pension challenge has long been demonstrated in various studies (e.g. Docquier and Michel, 1999; Fougère and Mérette, 1999). So has the importance of high growth for successful fiscal consolidation (e.g. Alesina and Perotti, 1995; Heylen and Everaert, 2000). There is a general agreement in the literature that total factor productivity (TFP) is a very important driver of long-run economic growth. De La Fuente and Domènech (2001) find that TFP differences account for about half of the differences in per capita income across OECD countries. Klenow and Rodríguez-Clare (1997) report an even higher contribution of TFP. Knowing that both the ageing of the labour force and the recent economic crisis may have a negative impact on TFP (Werding, 2008), insight in the way governments can counter this negative impact is very important.

This paper analyses the influence of fiscal policy on TFP and per capita output in a panel of 17 OECD countries in 1975-2007. We focus on the effects of government size, government deficits and the composition of taxes and expenditures. A large body of empirical studies have already examined the effects of fiscal policy on economic growth and the long-run output level. However, existing empirical results are far from robust. For example, the sign of the effects of government size and of social security expenditures is ambiguous in the literature. Compared to existing studies our contribution is double. First, we are able to identify both direct and indirect effects of
fiscal policy on TFP. The latter stem from the influence of taxes and expenditures on countries’ access to and efficient use of the world stock of technology and knowledge (see also Parente and Prescott, 2002). In this sense, our paper is complementary to recent work which has mainly emphasized the role of institutions for a country’s access to world technology (e.g. Alfaro et al., 2008; Coe et al., 2009; Faria and Mauro, 2009). A second contribution is methodological. The role of the worldwide level of technology introduces a common factor (and therefore cross-sectional dependence) in individual countries’ TFP. This common factor is unobserved and most likely non-stationary. The existing empirical literature on fiscal policy and growth largely neglects the econometric complications that may arise from cross-sectionally correlated error terms due to unobserved (and potentially non-stationary) common factors. This leads to inconsistent estimates if the unobserved factors are correlated with the explanatory variables and to a spurious regression problem if they are non-stationary. We basically deal with these econometric issues by using the methodology and idea behind the Common Correlated Effects Pooled (CCEP) estimator of Pesaran (2006) and Kapetanios et al. (2011). However, to allow for time-varying access of countries to the common factor, i.e. time-varying factor loadings, we extend the CCEP methodology. We suggest and adopt a continuously-updated CCEP (CCEPcu) estimator.

Our main findings are quite robust. Through the direct channel, an overall increase in government size reduces TFP and per capita output, except when the increase results from higher productive expenditures (e.g. education, R&D). Expenditure shifts in favour of productive purposes have strong and robust positive effects on TFP. Shifts in favour of social transfers reduce TFP. Deficit reduction policies raise TFP and hence per capita output. Through the indirect channel, a rise in the corporate tax rate negatively affects a country’s access to and efficient use of the worldwide level of technology. Our analysis also yields indicative evidence on the role of institutions for countries’ access to worldwide technological progress. More open economies and economies with high quality of tertiary education benefit more.

The paper is organized as follows. In section 2 we model the direct and indirect effects of fiscal policy on TFP. In section 3 we describe our econometric model and methodology. Section 4 contains our empirical analysis, which is split up in a description of the data followed by a discussion of the results. Section 5 concludes.
2 Modelling direct and indirect effects of fiscal policy on TFP

In this section we model the potential effects of fiscal policy and its composition on long-run per capita output through TFP. We identify both direct and indirect effects on TFP starting from a production function framework.

The production function for country $i$ at time $t$ is

$$Q_{it} = A_{it}K_{it}^{\alpha_1}G_{it}^{\alpha_2}[h_{it}L_{it}]^{1-\alpha_1-\alpha_2}, \quad (1)$$

with $0 < \alpha_1, \alpha_2 < 1$ and $\alpha_1 + \alpha_2 < 1$. Production of real output $Q$ exhibits constant returns to scale in aggregate private capital $K$, public capital $G$ and labour $hL$, where $L$ is total employment in persons, and $h$ average hours worked per employed. $A$ represents the level of TFP. It captures the contribution to output of the overall level of efficiency, technology and knowledge. Given our specification of the production function, TFP also incorporates advances in human capital.

In logs and in per capita terms this gives

$$\ln q_{it} = \ln A_{it} + \ln \left[ \frac{h_{it}L_{it}}{N_{it}} \right] + \alpha_1 \ln \left[ \frac{K_{it}}{h_{it}L_{it}} \right] + \alpha_2 \ln \left[ \frac{G_{it}}{h_{it}L_{it}} \right], \quad (2)$$

where $N$ is population and $q$ real output per capita ($Q/N$). Per capita output rises in TFP, hours worked per capita, physical capital per hour worked and public capital per hour worked.

The key variable in our model is the level of TFP. Fiscal policy can affect it both directly and indirectly. We call 'direct' the within-country effects of fiscal policy, i.e. the effects on TFP that one would have in a closed economy. 'Indirect' effects run via a country’s access to and efficient use of the world stock of technology and knowledge.

In analyzing the direct effects of fiscal policy on TFP, we look at the impact of both government size and the composition of expenditures and taxes.

A large literature has discussed the effects of government size on economic growth (e.g. Agell et al., 1997, 1999; Fölster and Henrekson, 1999, 2001; Wyatt, 2005). The overall evidence is ambiguous, which is not surprising. More important than their size may be the composition of
total expenditures and/or taxes. Moreover, the effects of changes in government size may differ depending on the historical level (Barro, 1990).

On the expenditure side, we distinguish productive and unproductive expenditures. The former include mainly government financed R&D, education expenditures and infrastructure investment (see also Kneller et al., 1999; Dhont and Heylen, 2009). There is a clear consensus in the literature that a rise in, or a shift towards, more productive expenditures enhances TFP directly, i.e. productive expenditures raise per capita output and/or growth for given hours worked and input of physical capital. A clear majority of empirical studies find positive effects of public R&D support on overall R&D spending and innovation output (see e.g. González and Pazó, 2008; and a recent survey by Cox and Gagliardi, 2009). A wealth of studies show positive effects of education expenditures on productivity and growth, both theoretically (e.g. Glomm and Ravikumar, 1997; Docquier and Michel, 1999; Dhont and Heylen, 2009) and empirically (e.g. Nijkamp and Poot, 2004; Blankenau et al., 2007). Some authors emphasize the importance of tertiary education and tertiary education expenditures for innovation and new technology adoption (Krueger and Kumar, 2004; Aghion and Howitt, 2006). In the unproductive expenditure category we find mainly social security expenditures and government consumption net of education. The literature is divided on the impact of social security expenditures. Some studies find a negative effect on TFP, e.g. Hansson and Henrekson (1994) and Arjona et al. (2003). One of the explanations is that high social spending reduces inequality. Since low inequality implies a low return to high-productivity qualifications and effort, social spending may inhibit the efficient use of factors of production (see also Lindbeck, 2006). Other studies find positive effects, e.g. Herce et al. (2001) and Zhang and Zhang (2004). Lower inequality may also lead to a more cohesive society. Such societies may be better able to make difficult political or economic decisions that promote structural adjustment and efficiency. Furthermore, it has been shown that unfunded social security programs may raise productivity by promoting investment in human capital (Zhang, 1995). Overall effects of government consumption on productivity are generally very small. More important is the way in which they are financed (Turnovsky, 2000; Dhont and Heylen, 2009).

On the revenue side of fiscal policy, we look at the impact of corporate, personal and ‘other’ taxes. The literature shows overall consensus that the impact of corporate and personal taxes on TFP is negative, whereas the effects of other taxes is less clear. High corporate taxes may for example reduce the incentive for firms to invest in innovative activities by reducing their after-tax return (Arnold et al., 2011). In line with the arguments raised by Arjona et al. (2003) on the effects
of (in)equality, high personal taxes may reduce TFP by discouraging work effort. Personal taxes also lower the expected return to investing in schooling, thus resulting in less accumulation of human capital (Ferreira and Pesa, 2007). The latter effect is obvious when it involves taxes on middle aged and older workers. Taxes on labor income of young individuals, however, reduce the opportunity cost of education. They may promote schooling (Heylen and Van de Kerckhove, 2010).

Finally, we analyse the direct effects of government debt and deficits on TFP. We expect a negative relationship. Debt accumulation can be associated with more future taxes, lower future productive expenditures and maybe more uncertainty and instability. Elaborating on the above mentioned arguments, this will hinder improvements in technology and efficiency (Fischer, 1993; Blankenau et al., 2007).

In a closed economy, fiscal policy only has ‘direct’ effects on TFP. In an open economy, however, additional indirect effects occur. These effects run via a country’s access to and efficient use of the worldwide available stock of technology and knowledge. We follow Parente and Prescott (2002) that world technology is commonly available, but that access may differ across countries and over time. Channels of knowledge and technology transfers are multiple: incoming FDI, internet, international publications, import of high technology goods and services etc. Different policies and institutions can either facilitate or put constraints on the availability and efficient use of these channels. Here, we look at the effect of fiscal policy variables on the use of these channels. Our attention goes to the effects of corporate taxes, and education expenditures and human capital formation. These are also most prominent in the literature. High corporate tax rates reduce the after-tax return to investing in a country and may discourage the inflow of FDI, as shown e.g. by De Mooij and Ederveen (2003) and Hajkova et al. (2006). Public education expenditures promote the accumulation of human capital. Various studies demonstrate the importance of human capital for the access to and efficient use of the channels of knowledge and technology transfers (e.g. Nelson and Phelps, 1966; Coe et al., 2009; Faria and Mauro, 2009). A country needs to have a certain level of skills in order to be able to successfully adopt foreign technology, brought by foreign firms for example, or incorporated in imported high technology goods or international publications.

These direct and indirect effects of fiscal policy lead to the following common-factor specifica-
tion of TFP

\[ A_{it} = e^{\gamma_i + \lambda_{it} F_t + \delta GOVD_{it}}, \tag{3} \]

In this equation, \( \gamma_i \) denotes an idiosyncratic country technology term (Costantini and Destefanis, 2009). \( GOVD_{it} \) assembles fiscal policy variables of country \( i \) in period \( t \) which influence TFP directly. The worldwide available stock of technology and knowledge is captured by the single common factor \( F_t \). Country \( i \)’s access to and efficient use of this world technology, \( \lambda_{it} \), consists of a time-invariant part, \( \lambda_{i0} \) (which may reflect institutions), and a part that depends on policy variables, \( \lambda_{GOVIN_{it}} \),

\[ \lambda_{it} = \lambda_{i0} + \lambda_{GOVIN_{it}}, \tag{4} \]

where \( GOVIN_{it} \) also assembles variables related to fiscal policy. In this paper, we limit our attention to the effects of a change in the corporate tax rate and the effects of public education expenditures and investment in human capital. We expect an increase in a country’s corporate tax rate to lower its access to world technology (De Mooij and Ederveen, 2003; Hajkova et al., 2006). A rise in public education expenditures and hence an increase in the educational attainment of the population is expected to have a positive impact on \( \lambda_{it} \).

Our final model follows from substituting equations (3) and (4) into (2)

\[
\ln q_{it} = \gamma_i + \lambda_{i0} F_t + \lambda_{GOVIN_{it}} F_t + \delta GOVD_{it} + \ln \left( \frac{h_{it} L_{it}}{N_{it}} \right) + \alpha_1 \ln \left( \frac{K_{it}}{h_{it} L_{it}} \right) + \alpha_2 \ln \left( \frac{G_{it}}{h_{it} L_{it}} \right). \tag{5}
\]
3 Econometric methodology

3.1 Model and assumptions

Starting from (5) we will estimate the following model:

\[ y_{it} = \gamma_i + \lambda_{it} F_t + x_{it} \beta + \varepsilon_{it}, \]  

(6)

\[ \lambda_{it} = \lambda_{i0} + z_{it} \lambda, \]  

(7)

where \( y_{it} = \left( \ln q_{it} - \ln h_{it} L_{it} N_{it} \right) \), \( x_{it} = \left( \ln K_{it} h_{it} L_{it}, \ln G_{it} h_{it} L_{it}, GOVD_{it} \right) \), \( z_{it} = \left( GOVIN_{it} \right) \), \( \beta = (\alpha_1, \alpha_2, \delta)' \), \( \varepsilon_{it} \) is an idiosyncratic error and \( F_t \) is a single unobserved common factor with factor loading \( \lambda_{it} \). The data \( x_{it}, z_{it} \) and \( F_t \) are assumed to be I(1) processes generated as

\[ x_{it} = \rho_i + x_{i,t-1} + \psi_{it}, \]  

(8)

\[ z_{it} = \delta_i + z_{i,t-1} + \mu_{it}, \]  

(9)

\[ F_t = c + F_{t-1} + \eta_t. \]  

(10)

Our analysis is based on a set of assumptions similar to those in Bai (2009):

**Assumption A1.** The individual-specific factor loadings \( \lambda_{i0} \) satisfy (i) \( \text{plim}_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \lambda_{i0}^2 = m_\lambda^2 \) being finite and (ii) \( E|\lambda_{i0}|^4 < M \) with \( M < \infty \) a generic positive number, not depending on \( T \) and \( N \).

**Assumption A2.** Let \( w_{it} = (\varepsilon_{it}, \psi_{it}, \mu_{it}, \eta_t)' \). For each \( i \), \( w_{it} = \pi_i(L) \nu_{it} = \sum_{j=0}^{\infty} \pi_{ij} \nu_{i,t-j} \), with \( \sum_{j=0}^{\infty} \| \pi_{ij} \| \leq M \) and where \( \nu_{it} \) are zero-mean errors which are mutually independent and i.i.d. over \( i \) and \( t \). \( \nu_{it} \) are independent of \( \lambda_{j0} \) for all \( i, j, t \).

Partition \( \pi_i(L) \) and \( \nu_{it} \) conformable with \( w_{it} \),

\[
\pi_i(L) = \begin{bmatrix}
\pi_{i\varepsilon}(L) & \pi_{i\psi}(L) & \pi_{i\mu}(L) & \pi_{i\eta}(L) \\
\pi_{i\varepsilon}'(L) & \pi_{i\psi}'(L) & \pi_{i\mu}'(L) & \pi_{i\eta}'(L) \\
\pi_{i\mu}(L) & \pi_{i\psi}(L) & \pi_{i\mu}(L) & \pi_{i\eta}(L) \\
\pi_{i\eta}(L) & \pi_{i\psi}(L) & \pi_{i\mu}(L) & \pi_{i\eta}(L) \\
\end{bmatrix}, \quad \nu_{it} = \begin{bmatrix}
\nu_{i\varepsilon} \\
\nu_{i\psi} \\
\nu_{i\mu} \\
\nu_{i\eta} \\
\end{bmatrix}.
\]

As \( \eta_t \) does not depend on \( i \), we restrict \( \pi_{i\varepsilon}(L) = \pi_{i\psi}(L) = \pi_{i\mu}(L) = 0 \) and \( \pi_{i\eta}(L) = \pi_{i\eta}(L) \). Moreover, to prevent the regression errors \( \varepsilon_{it} \) to exhibit strong cross-sectional correlation, we restrict \( \pi_{i\eta}(L) = 0 \).
Assumption A3. The individual effects $\gamma_i$, $\rho_i$ and $\delta_i$ are i.i.d. across $i$, and independent of the individual specific errors, $\varepsilon_{jt}$, $\psi_{jt}$, $\mu_{jt}$, and shocks to the common factors, $\eta_t$, for all $i$, $j$ and $t$.

Assumption A4. \{x_{it}, F_t\} are not cointegrated.

Assumption A1 on the factor loadings is to ensure that the factor structure is identifiable. Assumption A2 restricts the error terms ($\varepsilon_{it}, \psi'_{it}, \mu'_{it}, \eta_t$) to be $I(0)$ processes, but allows them to exhibit rich dynamics. Moreover, $x_{it}$ and $z_{it}$ can be endogenous and correlated with the common factor $F_t$.

For notational convenience in the presentation of the estimation methodology below, (6) is first rewritten as

$$y_{it} = \gamma_i + \lambda_0 F_t + x^+_i \phi + \varepsilon_{it},$$

with $x^+_i = (x_{it}, F_t z_{it})$ and $\phi = (\beta, \lambda)'$. Next, stacking over time for each $i$

$$y_i = \gamma_i + \lambda_0 F + x^+_i \phi + \varepsilon_i,$$

where $y_i = (y_{i1}, \ldots, y_{iT})'$, $F = (F_1, \ldots, F_T)'$, $x^+_i = (x^+_i1, \ldots, x^+_iT)'$ and $\varepsilon_i = (\varepsilon_{i1}, \ldots, \varepsilon_{iT})'$.

### 3.2 Identifying the unobserved common factor $F_t$

In line with Pesaran (2006) and Kapetanios et al. (2011), we identify the unobserved common factor $F_t$ from the cross-sectional dimension of the data. Taking cross-sectional averages of the model in (6)-(7) gives

$$\bar{y}_t = \gamma + (\bar{\lambda}_0 + \bar{\pi}_t \lambda) F_t + \bar{\pi}_t \beta + \bar{\varepsilon}_t,$$

where $\bar{y}_t = \frac{1}{N} \sum_{i=1}^{N} y_{it}$ and similarly for $\gamma$, $\bar{\lambda}_0$, $\bar{\pi}_t$, $\bar{\pi}_{it}$ and $\bar{\varepsilon}_t$. Equation (13) can then be solved for $F_t$ as

$$F_t = \frac{1}{\bar{\lambda}_0 + \bar{\pi}_t \lambda} (\bar{y}_t - \gamma - \bar{\pi}_t \beta - \bar{\varepsilon}_t),$$

such that from using A2, which implies that $\lim_{N \to \infty} \bar{\varepsilon}_t = 0$ for each $t$, we have for $N \to \infty$

$$\hat{F}_t = \frac{1}{\bar{\lambda}_0 + \bar{\pi}_t \lambda} (\bar{y}_t - \gamma - \bar{\pi}_t \beta) \overset{P}{\to} F_t.$$
This is the main result in Pesaran (2006) that the cross-sectional averages of the observed data $(\bar{y}_t, \bar{x}_t, \bar{z}_t)$ can be used as observable proxies of $F_t$. Although the construction of $\hat{F}_t$ as a consistent estimator of $F_t$ requires knowledge of the unknown underlying parameters, Pesaran (2006) shows that these parameters can be consistently estimated from an augmented model which is obtained by replacing the unobserved $F_t$ in the model by the cross-sectional averages of the observed data and estimating this augmented model - ignoring any parameter restrictions - with a least squares (LS) estimator. This estimator is known as the common correlated effects pooled (CCEP) estimator.

In our case, inserting (14) in (6) yields

$$ y_{it} = \gamma_i + \lambda_{it} \frac{1}{\lambda_0 + \bar{z}_t \lambda} (\bar{y}_t - \bar{y} - \bar{x}_t \beta - \bar{z}_t) + x_{it} \beta + \varepsilon_{it}. \quad (16) $$

The main difference with the augmented model suggested by Pesaran (2006) is the time-varying parameter loading $\lambda_{it}$. This implies that the augmented form in (16) is non-linear in the parameters $(\beta, \lambda)$ and (16) cannot be estimated using LS. Moreover, the model is not identified as $\lambda_{it}$ and $\hat{F}_t$ are not identified separately, only their product is. For instance, multiplying $\lambda_{i0}$ and $\lambda$ by a constant $a$ leaves the model in (16) unchanged as $\frac{a \lambda_{it}}{a \lambda_0 + a \bar{z}_t \lambda} = \frac{\lambda_{it}}{\lambda_0 + \bar{z}_t \lambda}$. To solve the identification problem, we impose $\lambda_0 = 1$ in (15), i.e. we normalize the average over all countries of the country-specific time-invariant access to worldwide technology to 1. In the next section, we suggest a continuously-updated CCEP (CCEPcu) estimator to deal with the non-linearity of the model.

### 3.3 CCEPcu estimator

Given the time-varying factor loadings $\lambda_{it}$, the standard CCEP estimator is inappropriate. As an alternative, we estimate $\phi$ in (12) along with $F$ in (14) by minimizing the least squares objective function

$$ S_{NT} (\phi, F) = \frac{1}{NT} \sum_{t=1}^{NT} \left( y_i - x_{it}^+ \phi \right)' \hat{M}_F \left( y_i - x_{it}^+ \phi \right), \quad (17) $$

where $M_F = I_T - \hat{F}' \hat{F}'^{-1} \hat{F}', \hat{F} = (\Upsilon, F)$ and $\Upsilon$ a $(T \times 1)$ vector of ones. The matrix $M_F$ is an orthogonal projection matrix that concentrates out the individual-specific parameters $\gamma_i$ and $\lambda_{i0}$. Although $F$ is not observed when estimating $\phi$ and similarly $\phi$ is not observed when estimating $F$, we can replace the unobserved quantities by initial estimates and iterate until convergence. The
continuously-updated estimator for \((\phi, F)\) is defined as
\[
\left(\hat{\phi}, \hat{F}\right) = \arg\min_{\phi,F} S_{NT}(\phi,F).
\] (18)

More specifically, \((\hat{\phi}, \hat{F})\) is the solution to the following two equations
\[
\hat{\phi} = \left(\sum_{i=1}^{N} \hat{x}_{i}^{+} M_{\hat{F}} \hat{x}_{i}^{+}\right)^{-1} \sum_{i=1}^{N} \hat{x}_{i}^{+} M_{\hat{F}} y_{i},
\]
\[
\hat{F} = \frac{1}{1 + \pi t \lambda} \left(\bar{y}_{t} - \bar{x} - \bar{x} \hat{\beta}\right),
\]
where \(M_{\hat{F}} = I_{T} - \hat{F} \left(\hat{F}^{' \hat{F}}\right)^{-1} \hat{F}^{'}\) with \(\hat{F} = \left(\hat{f}_{1}, \hat{f}_{2}, \cdots, \hat{f}_{m}\right)\) and \(\hat{F} = \left(\hat{x}_{1}, \hat{x}_{2}, \cdots, \hat{x}_{N}\right)\) with \(\hat{x}_{N} = \left(x_{it}, \hat{F}_{i}, \hat{z}_{it}\right)\).

Note that, as argued in Section 3.2, (20) is obtained by normalizing \(\lambda_{0}^{*} = 1\) in (15) to identify the model. Estimates for \(\hat{\gamma}_{i}\) and \(\hat{\lambda}_{i0}\) are obtained as
\[
\left(\hat{\gamma}_{i}, \hat{\lambda}_{i0}\right) = \left(\hat{F}^{' \hat{F}}\right)^{-1} \hat{F}^{'} \left(y_{i} - \hat{x}_{i}^{+} \hat{\phi}\right), \quad i = 1, \ldots, N.
\]

The CCEPcu estimator \(\hat{\phi}\) defined in (18) is consistent for \(\phi\) as \((N,T) \rightarrow \infty\). We prove this result in Appendix A. In this appendix we also include a Monte Carlo experiment to assess the finite sample properties of the CCEPcu estimator. The simulation results show that the CCEPcu estimator has very satisfactory small sample properties in an empirical setup like ours.

Note that the CCEPcu estimator bears some similarities with the continuously updated (Cup) estimator presented in Bai et al. (2009). The difference being that the Cup estimator identifies the unobserved components using a principal component approach, whereas the CCEPcu estimator uses the cross-sectional averages of both dependent and independent variables. The latter approach is chosen as it can more easily be adjusted to allow for a time-varying factor loading \(\lambda_{it}\).

3.4 Cointegration analysis

A crucial assumption for consistency of the CCEPcu estimator is that \(\varepsilon_{it}\) is stationary, i.e. there is cointegration between \(y_{it}, x_{it}^{+}\) and \(F_{i}\). The most obvious approach to test whether our variables are cointegrated would be to first estimate the model in (6)-(7) and then test the null hypothesis of no cointegration using e.g. a Maddala and Wu (1999) (MW) panel unit root test on the estimated idiosyncratic error terms \(\hat{\varepsilon}_{it}\). As Everaert (2012) points out, however, this is problematic because the country-by-country cointegration tests are not independent and therefore the MW panel unit
root test does not have the standard $\chi^2$ distribution. As a natural alternative approach, instead of $\hat{\varepsilon}_{it}$, Everaert (2012) suggests to use

$$\hat{c}_{it} = y_{it} - \phi^* \hat{\phi} = \hat{\gamma}_i + \hat{\lambda}_0 F_t + \hat{\varepsilon}_{it},$$

and apply a PANIC analysis as in Bai and Ng (2004) to split $\hat{c}_{it}$ in a set of common factors and an idiosyncratic error term and then test whether the idiosyncratic error is stationary or not. The advantage of this approach is that, as shown by Bai and Ng (2004), the test whether the idiosyncratic errors are stationary or not does not depend on the presence or absence of common stochastic trends and/or their integration properties. Standard panel unit root tests can then be used. It only requires specifying the number of common factors, which is 1 in our setting. Everaert (2012) also conducts a small-scaled Monte Carlo experiment to assess the size and power of the cointegration test mentioned above. He finds that a PANIC test on the composite error term $\hat{c}_{it}$ is an appropriate approach to test for common factor-augmented panel cointegration.

4 Empirical Analysis

We estimate the empirical model (6) and (7) for a panel of 17 OECD countries over the period 1975-2007. Before we discuss our results, we look at the data.

4.1 Data

We have three categories of variables: standard variables like physical capital and labor input, fiscal policy variables which influence TFP directly, and policy variables which influence TFP indirectly through their impact on a country’s access to and efficient use of the world stock of technology and knowledge. Appendix B contains a more detailed description of the data and their sources.

The standard variables consist of real GDP ($Q_{it}$), real private non-residential net capital stock ($K_{it}$), real government net capital stock ($G_{it}$), and total hours worked ($h_{it}L_{it}$).

Among the fiscal policy variables that influence TFP directly ($GOVD_{it}$), we include both government expenditure variables and tax variables. In some regressions we also include the government budget surplus. All variables are expressed in percent of GDP. As government expenditure vari-

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1These countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, United Kingdom and United States. The selection of countries has been driven by data availability.
ables we distinguish total expenditures, productive expenditures, social security expenditures, and government consumption (net of education). As tax variables we consider the total tax burden, personal income taxes, corporate income taxes and 'other' taxes received by the government. The latter contain mainly consumption taxes and property taxes. In each equation that we estimate we will include all but one components of the government budget constraint. This approach allows us to control the implicit financing element behind each fiscal policy change that we investigate. It also allows a correct interpretation of the estimated coefficients on each fiscal variable as the effect of a one percent change in the relevant variable offset by a change in the omitted category (Kneller et al., 1999).

The need to account for the government budget constraint also comes at a cost however, especially when the effects of tax changes are involved. The tax variables that we include are so-called macro backward-looking indicators. They are computed as the ratio of taxes received by the government to a measure of the tax base. Due to difficulty to find reliable data on the relevant tax base, GDP is often used as a proxy. The issue here is that these indicators may not be the best proxies of actual tax rates that firms and individuals may expect when they take decisions. Thinking about corporate taxes, backward-looking indicators reflect past investment decisions, past tax systems and past profits. Moreover, the amount of corporate tax receipts in the numerator is the product of the tax rate on the one hand and taxable profit on the other. This is a serious drawback, as Devereux (2007) and Backus et al. (2008) point out. Corporate tax receipts in percent of GDP may rise even when tax rates are reduced. Devereux (2007) concludes that there is no straightforward relationship between the two. It should then come as no surprise that correlation between corporate income tax receipts in percent of GDP and tax rates themselves is very low. In Appendix C we report coefficients of correlation with the statutory corporate tax rate (STR) and two so-called micro forward-looking tax variables provided by Devereux and Griffith (2003). These authors rely on the theoretical features of the tax system to compute effective marginal and average tax rates that firms can actually expect for several types of hypothetical investment (see their EMTR and EATR). Correlation over all countries and years in our dataset between the three tax rates (STR, EMTR, EATR) is above 0.6. Correlation with corporate tax receipts in percent of GDP, however, always remains below 0.09. It goes without saying that these findings are a reason for caution.

---

2 Productive expenditures include government financed R&D, education spending and fixed investment.

3 He gives a clarifying example. When a government chooses to lower corporate taxes by means of a lower statutory tax rate or a smaller tax base, this stimulates investment and raises profits. A lower statutory rate may also encourage business to take incorporated form, which implies liability to corporation taxes rather than personal income taxes. As a consequence, corporate income tax revenues could rise, and a lower effective corporate tax rate may even result in a higher macro-backward looking rate.
when we interpret our results on the direct effects of corporate tax changes on TFP in the next section.

Finally we consider policy variables that influence TFP indirectly through their impact on $\lambda_{it}$. Our attention in this paper goes to the effects of changes in governments’ corporate tax and education policies. As we have mentioned in section 2, these are also most prominent in the literature when it comes to a country’s attractiveness to foreign investors or its ability to adopt foreign technologies. For corporate tax policy, we again face the problem of choosing the right corporate tax rate indicator. Since here we do not have to control for the government budget constraint, we may optimally use the micro-forward looking effective tax rates from Devereux and Griffith (2003). However, for these indicators data availability is limited, they are not available for the 1970s. We therefore use the statutory corporate tax rate (STR). As we have shown before, the latter is highly positively correlated with the EMTR and EATR, meaning that these three indicators pick up the same things. We estimate our equations with a country’s relative STR in the regression. The relative STR of a particular country is the STR of that country in percent of the average of the STR’s of all other countries. When it comes to attracting foreign investors by means of tax signals, relative tax rates may be the most telling (Bénassy-Quéré et al., 2005). To study the effects of education policy and human capital formation, we include as a proxy the percentage of the population (aged 15 and over) with a tertiary degree. When a government raises its educational expenditures this will promote the accumulation of human capital and hence the educational attainment of the population. By including this variable, we try to capture the educational attainment of the working age population. The idea is that a rise in educational expenditures leads to a higher skilled workforce. In our empirical analysis, all the policy variables are expressed in logarithms.

4.2 Results

We begin by testing all series for the presence of a unit root. Since we are dealing with cross-sectional dependence in our variables, we use the PANIC approach of Bai and Ng (2004). From the test results we can only reject the null hypothesis of a unit root for the government budget surplus in percentage of GDP. For all other variables, we cannot reject non-stationarity at the 5% significance level. The unit root test results can be found in Appendix D. In order to avoid a spurious regression problem, we test all our regression specifications for the existence of a cointe-
grating relationship. For specifications 1 and 2 in Table 1 we can reject the null of no cointegration at the 5% significance level whereas for specification 3 and 4 we can reject the null hypothesis at the 10% level. This implies that dynamics and endogeneity issues can be ignored asymptotically and that our results impart meaningful information about the long-run relationship in (6)-(7).

In the empirical setting we consider four different specifications. Specification 1 reveals the effects on TFP of a shift in government expenditures and of a rise in government expenditures financed by increasing taxes. Specification 2 analyses the impact of a rise in a certain government expenditure category financed by accumulating more debt. Specification 3 considers the consequences for TFP of a shift in the tax structure and of an increase in total taxes to reduce the government debt level. Finally, specification 4 investigates the effects on TFP of a rise in a certain tax category used to increase government expenditures. When turning to the results, we first look at the coefficients on the standard variables. Depending on the different specifications in columns 1 to 4, the private capital income share varies between 0.3310 and 0.3862, the public capital income share between 0.1793 and 0.1991. Both these results are in line with existing literature. Next, we consider the fiscal policy variables that directly influence TFP. We observe that a rise in total government expenditures has a negative effect on TFP when it is financed by borrowing (column 3). When considering the direct effects of a change in the structure of government expenditures, we find in column 1 that a shift in government expenditures from government consumption or rest expenditures (implicit financing elements) towards more productive expenditures, is positive for TFP and hence for long-run per capita output. Concerning social security expenditures, there is no consensus in the literature. Our results are more robust. We find in column 1 that a shift in government expenditures towards more social security expenditures is associated with a lower level of TFP. This result is also confirmed in column 2 where the implicit financing element is new debt. So from this point of view, higher productive expenditures are good and higher social expenditures are bad for the long-run output level of an economy (through TFP). From column 2 we also see that a rise in government consumption, paid by borrowing, has a negative effect on TFP. We proceed by analyzing the direct effect of taxes on TFP in columns 3 and 4. From column 3 we can see that a shift in taxes from e.g. consumption taxes and/or property taxes towards more personal tax revenues is associated with a lower level of TFP. However, this effect is not significant at the 10% level. A shift in tax revenues in favour of corporate taxes has a significant positive impact on TFP and hence on the long-run output level. This finding is counterintuitive and not

\footnote{Column 3 investigates the effect of a change in total government expenditure while controlling for the total taxburden. The latter variable is also included in the regression, and therefore kept constant when one interprets the partial effect of a change in expenditures.}
### Table 1
Regression results

Dependent variable: $y_{it} = \ln q_{it} - \ln \left[ \frac{h_{it}L_{it}}{K_{it}} \right]$

Sample period: 1975-2007, 17 OECD countries

<table>
<thead>
<tr>
<th>Coefficient estimates</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tr>
<td><strong>Standard Variables</strong></td>
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<td></td>
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</tr>
<tr>
<td>$\ln \left[ \frac{K_{it}}{h_{it}L_{it}} \right]$</td>
<td>0.3733***</td>
<td>0.3862***</td>
<td>0.3789***</td>
<td>0.3310***</td>
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<tr>
<td></td>
<td>(0.0256)</td>
<td>(0.0252)</td>
<td>(0.0247)</td>
<td>(0.0250)</td>
</tr>
<tr>
<td>$\ln \left[ \frac{G_{it}}{h_{it}L_{it}} \right]$</td>
<td>0.1991***</td>
<td>0.1881***</td>
<td>0.1793***</td>
<td>0.1832***</td>
</tr>
<tr>
<td></td>
<td>(0.0196)</td>
<td>(0.0196)</td>
<td>(0.0202)</td>
<td>(0.0200)</td>
</tr>
<tr>
<td><strong>Variables that influence TFP directly:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Total Government Expenditures}$</td>
<td>−0.0528</td>
<td>−0.1657***</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>(0.0429)</td>
<td>(0.0227)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Total Taxburden}$</td>
<td>0.1517**</td>
<td></td>
<td>0.3496***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0621)</td>
<td></td>
<td>(0.0447)</td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Personal Taxes}$</td>
<td>0.0472*</td>
<td>0.0761*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0282)</td>
<td>(0.0428)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Corporate Taxes}$</td>
<td>0.0666***</td>
<td>0.0162***</td>
<td>0.0132**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0051)</td>
<td>(0.0061)</td>
<td>(0.0052)</td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Rest Taxes}$</td>
<td>−0.0121**</td>
<td></td>
<td></td>
<td>−0.0650***</td>
</tr>
<tr>
<td></td>
<td>(0.0051)</td>
<td></td>
<td></td>
<td>(0.0190)</td>
</tr>
<tr>
<td><strong>Variables that influence TFP indirectly:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\ln \text{Relative STR}$</td>
<td>−0.5814***</td>
<td>−0.6435***</td>
<td>−0.7450***</td>
<td>−0.7681***</td>
</tr>
<tr>
<td></td>
<td>(0.1147)</td>
<td>(0.1389)</td>
<td>(0.1557)</td>
<td>(0.1582)</td>
</tr>
<tr>
<td>$\ln \text{Rate of population with tertiary degree}$</td>
<td>−0.0465</td>
<td>0.0058</td>
<td>−0.0359</td>
<td>0.0148</td>
</tr>
<tr>
<td></td>
<td>(0.0472)</td>
<td>(0.0619)</td>
<td>(0.0558)</td>
<td>(0.0646)</td>
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<tr>
<td><strong>Cointegration test</strong></td>
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<td></td>
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<tr>
<td>p-value(a)</td>
<td>0.0305</td>
<td>0.0061</td>
<td>0.0685</td>
<td>0.0789</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. For a detailed description of data and data sources, we refer to Appendix B. All $GOV\bar{D}$ variables are variables in percent of GDP (of which we have taken logs). All $GOVIN$ variables are percentages (of which we have taken logs). Because the unobserved common factor $F_t$ is only identified upon a rotating factor, we need a normalisation to be able to interpret the indirect effects of fiscal policy on TFP. As a normalisation we choose to put the average over all countries of the country-specific, time-invariant part of access to worldwide available technology on 1 ($\lambda_0 = 1$). (a): the null hypothesis is the existence of a unit root in the idiosyncratic component of $\hat{e}_{it}$.

Supported by theory. A possible explanation lies in the construction of our tax rates, as we have already discussed in our data section. The incentives of firms may not be captured adequately by
the ratio of corporate income tax receipts to GDP. Column 4 shows the effects on TFP of a rise in a tax category, used to finance more government consumption and social security expenditures. For personal taxes and rest taxes (e.g. property taxes and consumption taxes), we find a significant negative effect. Again corporate taxes have the wrong sign. Finally, from columns 1 and 4 we can also derive the effect of government deficit reduction on TFP. In column 1, this deficit reduction is financed by increasing the taxburden whereas in column 4 the implicit financing element is a cut in government consumption and social security expenditures. We see that a reduction of the government deficit financed by a cut in unproductive expenditures is very positive for TFP and the long-run output level. When financed by higher taxes however the effect of deficit reduction becomes much smaller. These results confirm earlier findings in the fiscal consolidation literature (e.g. Alesina and Perotti, 1995; Heylen and Everaert, 2000).

We end this section by looking at the policy variables that influence TFP indirectly. The reported coefficients of the GOVIN variables in Table 1 correspond to \( \lambda \) and thus measure the impact of these variables on a country’s access \( (=\lambda_{it}) \) to world technology \( (=F_t) \). As \( F_t \) or the worldwide available level of technology and knowledge is positive and rises over time, variables that increase \( \lambda_{it} \) will have a positive impact on TFP. In all different specifications, the relative STR has a significant negative coefficient. This means that decreasing the STR in a country, relative to all other countries, increases \( \lambda_{it} \) and hence increases a country’s access to worldwide available technology. This will increase TFP and the long-run output level. Corporate tax policy is therefore effective in this sense. Looking at the rate of population with a tertiary degree, we see that this variable has no significant effect on \( \lambda_{it} \). In specifications 2 and 3, the effect is insignificant positive but in specifications 1 and 3 the effect becomes insignificant negative. So, empirically we do not find an effect from variation in the educational attainment of the population on a country’s access to worldwide available technology. As we show immediately, however, this result does not exclude that educational variables may affect a country’s \( \lambda_{i0} \) (see equation (4)).

Our empirical analysis also provides estimates for the time-invariant part of countries’ access to world technology, \( \lambda_{i0} \). In Figure 1 we report these on the vertical axis and relate them to the degree of openness of the economy. We observe the highest estimates for \( \lambda_{i0} \) in countries like Finland, Ireland and Norway, and low estimates for Spain, Canada and Greece. \(^5\) Existing literature would point at the role of institutions (e.g. Alfaro et al., 2008; Coe et al., 2009). An

\(^{5}\) The data that we show have been obtained from specification 1 in Table 1. The other specifications yield highly similar numbers.
Explorative regression analysis using the institutional data reported by Coe et al. (2009) yields two significant explanatory variables: openness and the quality of tertiary education. Regressing our $\lambda_{i0}$ on a constant, log(imports/GDP) and a dummy for high quality of tertiary education, we obtain positive and statistically significant coefficients on both variables and an adjusted $R^2$ equal to 0.36. We obtain no significant results in our set of countries for "ease of doing business" and "patent protection". Extending the analysis by also including data on the perception of corruption (Transparency International) yields no significant results either. These results can be found in Appendix E. The significant role of the quality of tertiary education is in line with the literature that we have referred to earlier in this paper (e.g. Krueger and Kumar, 2006; Aghion and Howitt, 2006).

Before concluding, it is useful to emphasize a number of limitations of our empirical analysis. First, we need to acknowledge that the important advantage of our methodology, which is the introduction of time-varying factor loadings to estimate the indirect channel of fiscal policy effects,
also comes at a cost. In contrast to Pesaran (2006) and Kapetanios et al. (2011), we have to restrict the analysis to a single common factor, the world stock of technology. Empirically, there could of course be additional common shocks due to other factors such as international business cycles. We leave the extension of our methodology to multiple factors for future research.

Second, as we recognize at the end of Section 3.2, the introduction of a time-varying factor loading generates an identification problem. To solve this problem, we have imposed $\lambda_0 = 1$. Since countries cannot have negative access to worldwide technology, it is obvious to have a positive number here. Thinking about the relationship between world technology and TFP in individual countries, $\lambda_0 = 1$ would also seem a most natural choice. However, since this restriction will affect the estimated $\lambda$, we ran a number of robustness checks, starting from different values for $\lambda_0$. The negative sign and the statistical significance (p-values) of the estimated indirect corporate tax rate effect that we report in Table 1 were never affected. Neither were the estimated $\alpha$ and $\delta$ parameters and their statistical significance. Only the estimated level of $\lambda$ changed. More detailed results are available upon request.

Third, although most of our findings can be justified from theory as causal relationships, it should be acknowledged that such an interpretation is not always obvious empirically. Finding cointegration is reassuring since cointegrating relationships can be consistently estimated irrespective of endogeneity issues, but they are not immune to problems of reverse causality. The counterintuitive sign on the estimated direct effects of corporate taxes may provide an example. Rather than higher corporate taxes leading to higher productivity, causality in this case is more likely to run the other way. A positive TFP shock may also induce a shift in tax revenues in favour of corporate taxes. This example is at least a reason for caution when interpreting our results.

5 Conclusion

This paper analyses the influence of fiscal policy on TFP and per capita output in a panel of 17 OECD countries in 1975-2007. We focus on the effects of government size, government deficits and the composition of taxes and expenditures. New is that we are able to identify not only direct but also indirect effects of fiscal policy on TFP. The latter stem from the influence of taxes and expenditures on countries’ access to and use of the world stock of technology. This worldwide available level of technology and knowledge introduces a common factor (and therefore cross-sectional dependence) in individual countries’ TFP, and is unobserved. Neglecting it can lead to inconsistent estimates if it is correlated with the explanatory variables. Moreover, this factor is
most likely non-stationary which can cause a spurious regression problem. Therefore we explicitly model TFP through a common-factor specification and empirically we exploit the cross-section correlation to identify the unobserved common factor. In order to deal with the time-varying factor loadings in our empirical framework, we suggest and adopt a continuously-updated CCEP (CCEPcu) estimator. Our main findings are as follows. Through the direct channel, an overall increase in government size reduces TFP and per capita output. Expenditure shifts in favour of productive purposes have strong and robust positive effects on TFP. Shifts in favour of social transfers reduce TFP. Deficit reduction policies raise TFP and hence per capita output. Through the indirect channel, a rise in the corporate tax rate negatively affects a country’s access to the worldwide level of technology. Our analysis also yields indicative evidence on the role of some institutions for countries’ access to worldwide technological progress. More open economies and economies with high quality of tertiary education benefit more.
References


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Kapetanios, G., M.H. Pesaran and T. Yamagata (2011), "Panels with Nonstationary Multifac-


Appendices

Appendix A  Consistency CCEPcu estimator

A.1 Proof of consistency

We use \((\phi^0, F^0)\) to denote the true parameter vector \(\phi\) and the true factor \(F\) respectively, and still use \(\lambda_{0i}\) without the superscript 0 as it is not directly estimated. As in the Supplementary Appendix to Bai et al. (2009) and in Bai (2009b), we next let for notational convenience \(\phi^0 = 0\).

After centering, the objective function in (17) is given by

\[
S_{NT} (\phi, F) = \frac{1}{NT^2} \sum_{i=1}^{N} (y_i - x_i^+ \phi)' M_F (y_i - x_i^+ \phi) - \frac{1}{NT^2} \sum_{i=1}^{N} \varepsilon_i' M_{\varepsilon_0} \varepsilon_i.
\]

Note that the last term does not depend on \((\phi, F)\) and is for the purpose of centering the objective function around zero. Substituting \(y_i\) from (12) yields

\[
S_{NT} (\phi, F) = \frac{1}{NT^2} \sum_{i=1}^{N} (\lambda_{0i} F^0 + \varepsilon_i - x_i^+ \phi)' M_F (\lambda_{0i} F^0 + \varepsilon_i - x_i^+ \phi) - \frac{1}{NT^2} \sum_{i=1}^{N} \varepsilon_i' M_{\varepsilon_0} \varepsilon_i,
\]

where use is made of the fact that by construction \(\gamma_i M_F = 0\). Next, we work this out as

\[
S_{NT} (\phi, F) = \tilde{S}_{NT} (\phi, F) - 2\phi' \frac{1}{NT^2} \sum_{i=1}^{N} x_i^+ M_F \varepsilon_i + 2 \frac{1}{NT^2} \sum_{i=1}^{N} \lambda_{0i} F^0' M_F \varepsilon_i
\]

\[+ \frac{1}{NT^2} \sum_{i=1}^{N} \varepsilon_i' (M_F - M_{F^0}) \varepsilon_i, \tag{A-1}\]

with

\[
\tilde{S}_{NT} (\phi, F) = \phi' \left( \frac{1}{NT^2} \sum_{i=1}^{N} x_i^+ M_F x_i^+ \right) \phi + \frac{1}{NT^2} \sum_{i=1}^{N} \lambda_{0i}^2 F^0' M_F F^0 - 2\phi' \frac{1}{NT^2} \sum_{i=1}^{N} x_i^+ M_F F^0 \lambda_{0i}.
\]

For \((N, T) \to \infty\), we have under Assumptions A2-A3

\[
\frac{1}{NT^2} \sum_{i=1}^{N} x_i^+ M_F \varepsilon_i = \frac{1}{NT^2} \sum_{i=1}^{N} x_i^+ \left( I_T - F (F' F)^{-1} F' \right) \varepsilon_i,
\]

\[
= \frac{1}{T} \left( \frac{1}{N} \sum_{i=1}^{N} x_i^+ \varepsilon_i - \frac{1}{N} \sum_{i=1}^{N} x_i^+ F (F' F)^{-1} F' \varepsilon_i \right),
\]

\[
= \frac{1}{T} O_p (1) = o_p (1), \tag{A-2}
\]

27
and similarly
\[
\frac{1}{NT^2} \sum_{i=1}^{N} \lambda \epsilon_i' F_0' M_{\xi} \epsilon_i = \frac{1}{T} \left( \frac{1}{N} \sum_{i=1}^{N} \lambda \epsilon_i' F_0' - \frac{1}{N} \sum_{i=1}^{N} \lambda \epsilon_i' F_0' \left( \frac{F_0' F_0'}{T} \right)^{-1} \right),
\]
\[= o_p(1), \quad (A-3)\]

\[
\frac{1}{NT^2} \sum_{i=1}^{N} \epsilon_i' (M_{\xi} - M_{\xi^0}) \epsilon_i = \frac{1}{T} \left( \frac{1}{N} \sum_{i=1}^{N} \epsilon_i' F_0' \left( \frac{F_0' F_0'}{T} \right)^{-1} \right) - \frac{1}{N} \sum_{i=1}^{N} \epsilon_i' F_0' \left( \frac{F_0' F_0'}{T} \right)^{-1} \epsilon_i,
\]
\[= o_p(1), \quad (A-4)\]

Using (A-2), (A-3) and (A-4) in (A-1), we have
\[
S_{NT} (\phi, F) = \tilde{S}_{NT} (\phi, F) + o_p(1), \quad (A-5)\]
uniformly in \((\phi, F)\).

First note that \(\tilde{S}_{NT} (\phi^0, aF^0) = 0\) for any constant \(a\) as \(M_{aF^0} = M_{F^0}\) and \(M_{F^0} F^0 = 0\). Second, we show that for any \((\phi, F) \neq (\phi^0, aF^0)\), \(\tilde{S}_{NT} (\phi, F) > 0;\) thus \(\tilde{S}_{NT} (\phi, F)\) attains its unique minimum value at \((\phi^0, aF^0)\). Define
\[
A = \frac{1}{NT^2} \sum_{i=1}^{N} x_i' M_{\xi} x_i; \quad B = \frac{1}{NT^2} \sum_{i=1}^{N} \lambda \epsilon_i x_i; \quad C = \frac{1}{NT^2} \sum_{i=1}^{N} \lambda \epsilon_i M_{\xi} x_i; \quad \eta = M_{\xi} F^0.
\]
Then
\[
\tilde{S}_{NT} (\phi, F) = \phi' A \phi + \eta' B \eta + 2 \phi' C' \eta,
\]
\[= \phi' \left( A - C' B^{-1} C \right) \phi + (\eta' - \phi' C' B^{-1}) B (\eta - B^{-1} C \phi),
\]
\[= \phi' D (F) \phi + \theta' B \theta, \quad (A-6)\]
where \(\theta = \eta - B^{-1} C \phi\). Since \(D (F) = A - C' B^{-1} C\) is a positive definite matrix by Assumption () and \(B > 0\), we have that \(\tilde{S}_{NT} (\phi, F) > 0\) if either \(\phi \neq \phi^0\) or \(F \neq aF^0\). This implies that \(\hat{\phi}\) is consistent for \(\phi\) as \((N, T) \to \infty\).
A.2 Monte Carlo experiment

We conduct a small-scaled Monte Carlo experiment to assess the finite sample properties of the CCEPcu estimator. To make sure that the results are relevant for putting our empirical results presented in Section 4 in perspective, we use exactly the same sample size \((T = 33, N = 17)\) that is available to us while the data generating process (DGP) and population parameters are chosen such that the properties of the simulated data match with those of the real data. More specifically, we generate artificial data for \(y_{it}\) from the DGP in (6)-(7) using the observed data for \(x_{it}\) and \(z_{it}\) and drawing \(\varepsilon_{it}\) randomly from \(i.i.d.N(0, \sigma^2)\) in each replication. We conduct a separate experiment for each of the four specifications that we estimate in Section 4. These specifications differ only over the variables included in \(GOVD_{it}\). Parameter values for \(\gamma_i, \lambda_{i0}, \lambda, \beta\) and \(\sigma^2\) and data for the unobserved factor \(F_t\) are obtained by using the coefficients estimates and estimated factor \(\tilde{F}_t\) from the empirical analysis in Section 4 (See Table 1). Each experiment is based on 5000 iterations.

The simulation results can be found in Table 2. We report the (i) mean bias (bias), (ii) standard deviation (stdv) and (iii) mean of the estimated standard errors (stde) of the coefficient estimates. We also report the (iv) median bias (med bias) and (v) median absolute deviation (mad) as these measures are less vulnerable to outliers in the distribution.

<table>
<thead>
<tr>
<th>Specification 1</th>
<th>Specification 3</th>
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<tbody>
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<td>(\alpha_1)</td>
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<table>
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<th>Specification 4</th>
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<td>0.018</td>
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<td>0.012</td>
</tr>
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<td>0.016</td>
<td>0.016</td>
<td>0.001</td>
<td>0.011</td>
</tr>
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</table>

Table 2

Monte Carlo Results
The most important conclusion is that despite the limited sample size \( (T = 33, N = 17) \) the bias in estimating \( \beta \) and \( \lambda \) is negligibly small and the mean of the estimated standard errors is fairly close to the actual standard deviation of the estimates in each of the specifications.
Appendix B  Construction of data and data sources

Standard Variables

Real GDP (\(=Q_{it}\))
Source: OECD Statistical Compendium, Economic Outlook (series GDPVD).

Private non-residential net capital stock (\(=K_{it}\))
Source: Data from Kamps (2006).
Data adjustments: We extend this data for the period 2003-2007.

Real government net capital stock (\(=G_{it}\))
Source: Data from Kamps (2006).
Data adjustments: We extend this data for the period 2003-2007.

Working age population (\(=N_{it}\))
Description: Population of the age 15-64.

Total annual hours worked (\(=h_{it}L_{it}\))
Description: Total annual hours worked in the economy.

Policy variables that influence TFP directly (\(=GOVD_{it}\))

Government total expenditures in percent of GDP
Source: OECD Statistical Compendium, Economic Outlook (series YPGT, GDP).

Productive government expenditures in percent of GDP
Description: Sum of nominal public expenditures on education, government fixed capital formation and government financed R&D, in percent of nominal GDP.
Sources and data adjustments: Berger and Heylen (2011). See their data appendix for further
Government social security expenditures in percent of GDP
Description: Nominal social security benefits paid by general government, in percent of nominal GDP.
Source: OECD Statistical Compendium, Economic Outlook (series SSPG and GDP) and Berger and Heylen (2011).

Government consumption in percent of GDP
Description: Government final consumption net of final consumption expenditures in education, in percent of GDP.
Sources and data adjustments: Berger and Heylen (2011). See their data appendix for further description.

Government rest expenditures in percent of GDP
Description: Government total expenditures in percent of GDP minus productive government expenditures in percent of GDP, government social security expenditures in percent of GDP and government consumption in percent of GDP.

Government Budget Surplus in percent of GDP
Description: Total taxburden minus total government expenditures in percent of GDP.
Data adjustments: Because this variable can be negative, we take the logarithm of 1 plus the government budget surplus.

Total taxburden
Description: Total nominal tax revenues of general government, in percent of nominal GDP.

Personal taxes
Description: Nominal tax revenues of general government of categories 1100 (taxes on income, profits and capital gains of individuals), 2000 (social security contributions) and 3000 (payroll
taxes) of the OECD classification of taxes in percent of nominal GDP.


**Corporate taxes**

Description: Nominal tax revenues of category 1200 (corporate taxes on income, profits and capital gains) of the OECD classification of taxes in percent of nominal GDP.


**Rest taxes**

Description: Total tax burden minus the sum of personal taxes and corporate taxes. This variable mainly includes nominal tax revenues of consumption and property taxes in percent of nominal GDP.

**Policy variables that influence TFP indirectly (GOVIN)***

**Statutory corporate income tax rate (STR)**

Source: OECD Tax Database (Table II.1, Corporate income tax rate). We use the combined corporate income tax rate, including both central and sub-central government taxes.

Data shortages and adjustments: The OECD does not present data for 1975-1980. For these years we added the data as collected by Berger and Heylen (2011). See their data appendix for further description.

**Rate of population with a higher degree**

Definition: Tertiary level completed in % of population aged 15 and over.

Source: Barro and Lee (2010), Educational attainment for population aged 15 and over.

Appendix C  Coefficients of correlation between different corporate tax rate indicators

Table 3
Correlation matrix (a)

<table>
<thead>
<tr>
<th></th>
<th>Corp.taxreceipts</th>
<th>GDP</th>
<th>STR</th>
<th>EMTR</th>
<th>EATR</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-0.17</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>STR</td>
<td>0.08</td>
<td>0.64</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EMTR</td>
<td>0.07</td>
<td>0.65</td>
<td>0.93</td>
<td>1</td>
<td></td>
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</table>

(a): Correlation over 17 countries and 33 years (1975-2007).

Appendix D  PANIC unit root tests on variables

Table 4
PANIC unit root tests (model with constant)

<table>
<thead>
<tr>
<th>Variable</th>
<th>$\hat{F}_t$</th>
<th>$\hat{e}_{it}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln Q_{it}$</td>
<td>-1.07 (0.25)</td>
<td>43.09 (0.14)</td>
</tr>
<tr>
<td>$\ln \left( \frac{K_{it}}{h_{it}L_{it}} \right)$</td>
<td>0.31 (0.77 )</td>
<td>49.38 (0.04)</td>
</tr>
<tr>
<td>$\ln \left( \frac{G_{it}}{h_{it}L_{it}} \right)$</td>
<td>-0.74 (0.39)</td>
<td>40.72 (0.2)</td>
</tr>
<tr>
<td>$\ln \text{Personal Taxes}$</td>
<td>-1.04 (0.26)</td>
<td>38.41 (0.28)</td>
</tr>
<tr>
<td>$\ln \text{Corporate Taxes}$</td>
<td>-1.61 (0.1 )</td>
<td>32.78 (0.53)</td>
</tr>
<tr>
<td>$\ln \text{Rest Taxes}$</td>
<td>-2.11 (0.04)</td>
<td>21.94 (0.95)</td>
</tr>
<tr>
<td>$\ln \text{Total Taxburden}$</td>
<td>-0.65 (0.43)</td>
<td>43.35 (0.13)</td>
</tr>
<tr>
<td>$\ln \text{Government Consumption}$</td>
<td>-1.97 (0.05)</td>
<td>31.86 (0.57)</td>
</tr>
<tr>
<td>$\ln \text{Productive Government Expenditures}$</td>
<td>-0.52 (0.49)</td>
<td>30.22 (0.65)</td>
</tr>
<tr>
<td>$\ln \text{Social Security Expenditures}$</td>
<td>-1.05 (0.26)</td>
<td>25.92 (0.84)</td>
</tr>
<tr>
<td>$\ln \text{Rest Expenditures}$</td>
<td>-1.26 (0.19)</td>
<td>27.7 (0.77)</td>
</tr>
<tr>
<td>$\ln \text{Total Government Expenditures}$</td>
<td>-1.72 (0.08)</td>
<td>33.97 (0.47)</td>
</tr>
<tr>
<td>$\ln \text{Government Budget Surplus}$</td>
<td>-2.09 (0.04)</td>
<td>63.58 (0 )</td>
</tr>
<tr>
<td>$\ln \text{Relative STR}$</td>
<td>-2.46 (0.02)</td>
<td>37.46 (0.31)</td>
</tr>
<tr>
<td>$\ln \text{rate of population with higher degree}$</td>
<td>-0.73 (0.39)</td>
<td>67.1 (0 )</td>
</tr>
</tbody>
</table>

Notes: Following our model and empirical methodology we assume for each variable one common factor. The unit root test on the common factor $\hat{F}_t$ is a ADF-GLS test for a model with constant. The corresponding $p$-values are reported in parentheses. On the estimated idiosyncratic errors $\hat{e}_{it}$ we perform a Maddala Wu panel unit root test (=MW). The corresponding $p$-values are reported in parentheses. The null hypothesis of the test is that the series is a unit root process. Variables have a unit root if the common factor has a unit root and/or the idiosyncratic component has a unit root.
Appendix E  An explorative regression analysis for $\lambda_{i0}$

Table 5  
Regression analysis for $\lambda_{i0}$

<table>
<thead>
<tr>
<th>Dependent variable: $\lambda_{i0}$</th>
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<th>(2)</th>
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<tr>
<td>Constant</td>
<td>1.3222*** (0.2163)</td>
<td>1.2941 (0.8626)</td>
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<tr>
<td>Log (imports/GDP)</td>
<td>0.4037** (0.1714)</td>
<td>0.3012 (0.2091)</td>
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</tr>
<tr>
<td>Quality of high education</td>
<td>0.5451*** (0.1785)</td>
<td>0.4853** (0.2187)</td>
<td></td>
</tr>
<tr>
<td>Ease of doing business</td>
<td>-0.12 (0.2079)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patent protection</td>
<td>-0.1510 (0.2269)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corruption</td>
<td>0.0705 (0.0683)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.3567</td>
<td>0.2628</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. *, ** and *** indicate significance at the 10 %, 5 % and 1 % level respectively. All explanatory variables, except corruption, have been taken from Coe et al. (2009). For each country we include the average of annual data for 1975-2004. Corruption is the average "corruption perceptions index" of Transparency International for 1995 and 2001. Higher numbers reflect lower perception of corruption.