

Fiscal policy and TFP in the OECD: Measuring direct and indirect effects



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by Gerdie Everaert, Freddy Heylen and Ruben Schoonackers

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Abstract

This paper analyzes the direct and indirect effects of fiscal policy on total factor productivity (TFP) in a panel of OECD countries over the period 1970-2012. Our contribution is twofold. First, when estimating the impact of fiscal policy on TFP from a production function approach, we identify the worldwide available level of technology by exploiting the observed strong cross-sectional dependence between countries instead of using ad hoc proxies for technology. Second, next to direct effects, we allow for indirect effects of fiscal policy by modelling the access of countries to worldwide available technology as a function of fiscal policy and other variables. Empirically, we propose and implement a non-linear version of the Common Correlated Effects Pooled (CCEP) estimator of Pesaran (2006). The estimation results show that through the direct channel budget deficits harm TFP. A shift towards productive expenditures has a strong positive impact on TFP, whereas a shift towards social transfers reduces TFP. Through the indirect channel, significant positive effects on a country's access to global technology come from reducing the statutory corporate tax rate and from reducing barriers to trade.

JEL classification: C31, C33, E62, O38

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Authors:

Gerdie Everaert, Sherppa, Ghent University
Freddy Heylen, Sherppa, Ghent University
corresponding author:
Ruben Schoonackers, Research Department, NBB
e-mail: ruben.schoonackers@nbb.be

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1 Introduction

Rising pressure on the welfare state due to aging and the need to bring down government debts and deficits after the recent recession force many countries to develop policies that can effectively enhance productivity and growth. The importance of higher productivity and 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), and so has the importance of high growth for successful fiscal consolidation (e.g. Alesina and Perotti, 1995; Heylen and Everaert, 2000). It is well known that total factor productivity (TFP) is a very important driver of long-run economic growth. Among others, de la Fuente and Doménech (2001) find that TFP differences account for about half of the differences in per capita income across OECD countries. Klenow and Rodriguez-Clare (1997) report an even higher contribution of TFP. Knowing that both the aging of the labor force and the recent economic crisis may have a negative impact on aggregate productivity, insights in the way governments can counter this are very important.

This paper analyzes the influence of fiscal policy on TFP and per capita output in a panel of 15 OECD countries over the period 1970-2012 using an aggregate production function framework. More precisely, following de la Fuente (1997) and Romero-Avila (2006), among others, we estimate a production function augmented with fiscal policy variables. Compared to previous research on fiscal policy and economic growth our contribution is twofold. First, an important issue in the growth literature is the fact that TFP is unobserved. Omitting TFP leads to inconsistent estimates if it is correlated with the observed explanatory variables and even to a spurious regression problem if it is non-stationary. Existing empirical work on fiscal policy and economic activity typically employs ad hoc proxies for technology. The standard approach is to include a common time trend (or time fixed effects) and country fixed effects, as done in e.g. Kneller et al. (1999), Romero-Avila (2006) and Arnold et al. (2011). In this paper, we pursue an alternative potentially promising, way out of the omitted variables problem by exploiting the strong cross-sectional dependence observed in macroeconomic data (see e.g. Coakley et al., 2006; Westerlund and Edgerton, 2008) to identify the common component in TFP. Parente and Prescott (2002) argue that there is a set of globally available production technologies but country-specific institutional and political factors may prevent firms from adopting the most efficient ones. This common set of production technologies implies that TFP is strongly correlated across countries, but due to different absorptive capacities TFP may grow at different rates across countries. This way of looking at TFP fits perfectly in the recent panel data literature (see e.g. Bai and Ng, 2004; Coakley et al., 2006; Pesaran, 2006) which assumes that cross-sectional dependence stems from omitted common variables or global shocks (like the worldwide level of technology) that affect each country differently (cfr. absorptive capacity). Therefore, we model TFP as having a common factor structure with country-specific factor loadings. More specifically, we use the Common Correlated Effects Pooled (CCEP) estimator of Pesaran (2006), which controls for unobserved common factors by adding cross-sectional averages of the data. As shown by Kapetanios et al. (2011) this approach is also valid in a non-stationary panel context. A second contribution of this paper is that we allow and model time-variation in the access of countries to worldwide technology. Next to direct effects of fiscal policy variables in the augmented production function, this opens the possibility for indirect effects. Parente and Prescott (2002) argue that country-specific institutions and political factors determine the absorptive capacity of a country. To the extent that these factors change over time, absorptive capacity is also time-varying.

The role of institutions for a country’s access to world technology has also been emphasized by Alfaro et al. (2008), Coe et al. (2009) and Faria and Mauro (2009). We explicitly allow for time-varying absorptive capacity by making the factor loadings a function of country-specific explanatory variables, among which fiscal policy variables. It is precisely by allowing for this extra source of heterogeneity, compared to a time fixed effects or to the standard CCEP specification, that we are able to identify indirect effects of fiscal policy on TFP. These effects run through its impact on absorptive capacity. The time-varying factor loadings imply that we cannot use the standard CCEP estimator. Instead, we propose and use a non-linear CCEP estimator, denoted CCEPnl. We further suggest to test for cointegration using the Panel Analysis of Non-stationarity in Idiosyncratic and Common Components (PANIC) on the composite error terms from the CCEP regressions. The small sample properties of our CCEPnl estimator and PANIC cointegration test are demonstrated using a small-scale Monte Carlo simulation tailored to our empirical specification and to the data we have available.

Our results strongly confirm earlier findings by Fischer (1993) that budget deficits harm TFP. Other robust conclusions concern the direct impact of a change in the structure of government expenditures. Shifting expenditures towards more productive categories has positive effects on TFP whereas a shift towards social security expenditures reduces TFP. Through the indirect channel, we find that reducing barriers to trade stimulates the absorptive capacity of a country. Finally our results show that the statutory corporate tax rate is an effective fiscal policy tool for increasing a country’s access to global technology.

The remainder of this paper is organized as follows. Section 2 describes and models the direct and indirect effects of fiscal policy on TFP. Section 3 discusses the properties of the data. Section 4 outlines the econometric model and methodology. Section 5 includes and discusses our empirical results. Section 6 concludes.

2 Empirical specification

In this section we model the impact of fiscal policy on TFP and output using a production function approach. We allow for both direct and indirect effects of fiscal policy. The indirect effects run via a country’s access to the unobserved worldwide available level of technology. To be able to interpret our results, we explicitly take into account the government budget constraint.

2.1 Aggregate production function and modeling TFP

We model production in country i at time t using a standard Cobb-Douglas production function

$$Q_{it} = A_{it} K_{it}^{\alpha_1} G_{it}^{\alpha_2} H_{it}^{\alpha_3}, \quad (1)$$

where Q_{it} is real output, A_{it} is TFP, K_{it} is aggregate private capital, G_{it} is public capital and H_{it} is total hours worked. The level of TFP captures the contribution to output of the overall level of efficiency, technology and knowledge. Given our specification of the production function, A_{it} also incorporates advances in human capital.

Rewriting equation (1) in logs yields

$$\ln Q_{it} = \ln A_{it} + \alpha_1 \ln K_{it} + \alpha_2 \ln G_{it} + \alpha_3 \ln H_{it}. \quad (2)$$

The key variable of interest in equation (2) is the level of TFP. As A_{it} is not observed, we model it through a common factor specification

$$A_{it} = e^{\gamma_i + w_{it}\delta + F_t\lambda_{it} + \varepsilon_{it}}, \quad (3)$$

in which we disentangle TFP into (i) a country-specific time-invariant unobserved technology term γ_i , (ii) a vector of country-specific observable variables w_{it} (expressed in logs) with homogeneous impact δ , (iii) an unobserved common factor F_t (expressed in logs) which represents the worldwide available level of technology and knowledge, (iv) a country-specific and time-varying factor loading λ_{it} which captures country i 's access to world technology F_t and (v) an idiosyncratic random error term ε_{it} .

Common factor specifications for TFP, similar to equation (3), can also be found in Costantini and Destefanis (2009) and Eberhardt and Teal (2013). The main difference is that we allow for time-varying factor loadings λ_{it} to capture shifts in a country's access to worldwide technology. This is inspired by Parente and Prescott (2002) who argue that world technology is commonly available but that access may differ across countries and time because country-specific fundamentals and policies lead to barriers that prevent firms from adopting more productive technologies. As these country-specific fundamentals and policies can also change over time, we model λ_{it} as

$$\lambda_{it} = \lambda_{i0} + z_{it}\lambda, \quad (4)$$

such that country i 's access to world technology consists of a time-invariant part λ_{i0} and a part that depends on time-varying (policy and fundamental) variables z_{it} (expressed in logs). Note that in contrast to a general common factor specification, we impose the restriction that there is only one common factor. This is because the econometric approach to estimating the model with a time-varying factor loading λ_{it} (see Section 4.2) requires a decision on the number of common factors. We justify our choice of a single common factor when discussing the results in Section 5.1.

2.2 Measuring direct and indirect effects of fiscal policy

The empirical specification in equations (2)-(4) allows fiscal policy to have both direct and indirect effects on TFP. Country-specific fiscal policy variables that are thought to influence TFP directly are included in w_{it} . Their impact is measured by δ . The indirect effects of fiscal policy on TFP run via its influence on countries' access to world technology. Relevant variables are included in z_{it} and their impact is measured by λ . Our specification imposes homogeneity in the impact of fiscal variables across countries. This assumption is fully supported by recent work of Gemmell et al. (2011)¹. Moreover, the alternative of parameter heterogeneity would come at the cost of drastically

¹These authors test the assumption of long-run homogeneity (pooled mean group estimation) versus long-run heterogeneity (mean group estimation) for the impact of fiscal policy variables on growth in a highly similar panel

reducing degrees of freedom. In what follows, we discuss the fiscal variables that we include in w_{it} and z_{it} relying on the recent literature.

2.2.1 Direct effects of fiscal policy on TFP

When analyzing the direct effects of fiscal policy on economic growth and/or output, many studies (e.g. Agell et al., 1997, 1999; Folster and Henrekson, 1999, 2001) focus on the effect of government size. Depending on methods used and on countries studied, the obtained results are highly contradictory. However, as pointed out by Bergh and Henrekson (2011), focusing on OECD countries and relying on panel data estimations reveals a more consistent picture. Correlation between government size and economic growth is negative and the sign seems not to be an unintended consequence of reverse causality. In explaining this negative relationship, most arguments rely on distortionary effects of taxes and/or expenditures. Thus, obviously of more importance than the mere size of the government is the composition of taxes and/or expenditures. Knowing the effects of the various components of the government budget on output and growth is very important for policy makers as political decisions are typically aimed at specific tax and expenditure items. Therefore, in measuring the direct impact of fiscal policy on TFP, we do not only look at government size ($=TotalExp_{it}$), but also at the composition of total expenditures and taxes.

On the expenditure side, we distinguish between productive and unproductive expenditures. As productive expenditures ($=ProdExp_{it}$) we include government financed R&D, education expenditures and infrastructure investment (see also Kneller et al., 1999). There is a clear consensus in the literature that an increase in, or a shift towards, more productive expenditures raises output and/or growth for given hours worked and input of physical capital. First, public sector R&D is found to be a significant determinant of long-term output. One of the channels through which public R&D affects TFP is through its positive impact on private R&D spending (see among others Guellec and de la Potterie, 2004; Gonzalez and Pazo, 2008). Second, positive effects of education expenditures on productivity and growth are obtained in both theoretical (e.g. Glomm and Ravikumar, 1997; Docquier and Michel, 1999; Dhont and Heylen, 2009) and empirical work (e.g. Nijkamp and Poot, 2004; Blankenau et al., 2007). Finally, public investment in infrastructure has robust positive effects on aggregate productivity (e.g. Munnell, 1992; Easterly and Rebelo, 1993).

As unproductive expenditures we include government consumption net of education ($=GovCons_{it}$) and social security expenditures ($=SocialExp_{it}$). All other unproductive expenditures are labeled other expenditures ($=OtherExp_{it}$). Overall effects of government consumption are typically found to be very small. Concerning the impact of social security expenditures on TFP, there is no agreement in the literature. Some empirical studies find a negative effect, e.g. Hansson and Henrekson (1994), Arjona et al. (2003) and Romero-Avila and Strauch (2008), while others obtain a positive impact, e.g. Hecce et al. (2001) and Zhang and Zhang (2004). One of the explanations for the negative effect 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). One reason why the impact may be positive is that lower inequality may lead to a more cohesive society. Such societies may be better able to make difficult political or economic decisions that promote

of 17 OECD countries for the period 1970-2004. Their Hausman test implies that the assumption of long-run homogeneity cannot be rejected (see their Table 2).

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).

On the revenue side of fiscal policy, we analyze the impact of the total tax burden ($=Taxburden_{it}$) and its decomposition into corporate ($=CorporateTax_{it}$), personal ($=PersonalTax_{it}$), consumption ($=ConsTax_{it}$) and other ($=OtherTax_{it}$) taxes. The latter category contains mainly property taxes. The literature shows overall consensus that the impact of corporate and personal taxes on TFP is negative, whereas the effects of other taxes are less clear. High corporate taxes are expected to reduce the incentives for firms to invest in innovative activities as it reduces 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 investment in schooling, thus resulting in less accumulation of human capital (Ferreira and Pessoa, 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 and may therefore promote schooling (Heylen and Van de Kerckhove, 2013). Finally, a shift towards consumption taxes is expected to have positive effects as this tax category is considered to be the least distortionary (Cournède et al., 2013).

We also analyze the direct effect on TFP of the overall government budget balance ($=BudgetBalance_{it}$). A negative budget balance (deficit) is expected to have a negative impact on TFP. The resulting debt accumulation can be associated with higher future taxes, lower future productive expenditures and more uncertainty and instability. Elaborating on the above mentioned arguments, this will hinder improvements in technology and efficiency (Fischer, 1993; Kumar and Woo, 2010).

2.2.2 Indirect effects of fiscal policy on TFP

Many authors (e.g. Van Pottelsberghe and Lichtenberg, 2001; Keller, 2010) show that incoming foreign direct investment (FDI) has an important influence on a country's absorptive capacity and access to global technology. A policy variable that is potentially important for attracting FDI is a country's corporate tax rate. A high corporate tax rate reduces the after-tax return from investing in a country and may therefore discourage the inflow of FDI (de Mooij and Ederveen, 2003; Hajkova et al., 2006). As such, the first variable we include in z_{it} is a country's relative statutory corporate tax rate (STR) ($=StrRelative_{it}$). The relative STR of a particular country is the STR of that country as a percentage of the average of the STR's of all other countries. Benassy-Quere et al. (2005) show that for attracting foreign investors by means of tax signals, the relative corporate tax rate is the most informative variable.

Another crucial factor driving access to worldwide available technology is a country's level of human capital. This has been demonstrated in various studies (among others Nelson et al., 1966; Coe et al., 2009; Faria and Mauro, 2009). The argument is that in order to be able to successfully adopt foreign technology, a country needs to have a certain level of skills. Governments can promote human capital formation, and thereby access to available technology, by increasing their public education expenditures. To assess the impact of human capital on λ_{it} , we therefore include the fraction of population with a tertiary degree ($=HCap_{it}$) in z_{it} .

Finally, international trade (especially imports) is an important channel of knowledge and technology transfers across countries (e.g. Coe and Helpman, 1995; Acharya and Keller, 2009; Coe et al., 2009). As shown by Madsen

(2007), there is a robust relationship between TFP and the transmission of knowledge through trade. Furthermore, he also indicates that knowledge spillovers have been an important contributing factor behind TFP convergence among OECD countries. When countries reduce barriers to trade, the import of embodied technology will be facilitated and access to global technology will rise. Therefore, imports as a percentage of GDP ($=Import_{it}$) are included in z_{it} .

2.3 Taking into account the government budget constraint

As all elements of the government budget are included in w_{it} , one element must be omitted in order to avoid perfect collinearity. The omitted variable then serves as the implicit financing category within the government's budget constraint. As highlighted by Kneller et al. (1999), this approach affects the interpretation of the estimated coefficients on the included fiscal variables. The coefficients should be seen as the effect of a change in the relevant variable offset by a change in the omitted category. Altering the omitted category will change the estimated coefficients for the included variables and their interpretation. In our empirical analysis we will consider four different specifications, which differ in the variables included in w_{it} and therefore also in the implicit financing category:

- Specification 1 (=S1): w_{it} includes $TotalExp_{it}$, $ProdExp_{it}$, $SocialExp_{it}$ and $BudgetBalance_{it}$. First, by keeping total government expenditures constant we measure the impact of a shift in government expenditures from government consumption and other expenditures towards productive and social security expenditures respectively. Second, by including $BudgetBalance_{it}$, the coefficient on $TotalExp_{it}$ represents the impact of a rise in government consumption and other expenditures, paid by increasing the overall tax burden.
- Specification 2 (=S2): w_{it} consists of $ProdExp_{it}$, $SocialExp_{it}$, $GovCons_{it}$, $OtherExp_{it}$ and $Taxburden_{it}$. As the total tax burden is kept constant, this specification allows to analyze the impact of a rise in each of the four different government expenditure categories financed by accumulating more debt.
- Specification 3 (=S3): Variables included in w_{it} are $TotalExp_{it}$, $Taxburden_{it}$, $PersonalTax_{it}$ and $CorporateTax_{it}$. First, by keeping the total tax burden constant, we measure the effect of a shift in the tax structure from $OtherTax_{it}$ and $ConsTax_{it}$ towards more personal and more corporate taxes. Second, by including $TotalExp_{it}$, this variable shows the effect of an increase in total expenditures financed by issuing more debt.
- Specification 4 (=S4): w_{it} now includes $ProdExp_{it}$, $BudgetBalance_{it}$, $PersonalTax_{it}$, $CorporateTax_{it}$, $ConsTax_{it}$ and $OtherTax_{it}$. By including $BudgetBalance_{it}$ and $ProdExp_{it}$, we can quantify the impact of a rise in each of the four tax categories used to finance an increase in non-productive government expenditures.

3 A first look at the data

3.1 Data and sources

We use data for a panel of 15 OECD countries over the period 1970-2012.² We distinguish between three categories of variables. The first category includes standard variables that are included in every specification: log real GDP ($\ln Q_{it}$), log real private non-residential net capital stock ($\ln K_{it}$), log real government net capital stock ($\ln G_{it}$) and log total hours worked ($\ln H_{it}$). The second category contains the fiscal policy variables that influence TFP directly and is represented by the vector w_{it} . All variables in w_{it} are expressed as a percentage of GDP and in logarithms. The third category, represented by the vector z_{it} , consists of policy variables that influence TFP indirectly through their impact on a country's access to worldwide technology. In each of our four specifications, z_{it} includes the variables $StrRelative_{it}$, $HCap_{it}$ and $Import_{it}$. These variables are also expressed in logarithms. A detailed description of the data and their sources can be found in Appendix A.

In the remainder of this section we focus on the construction of the tax variables. The tax measures included in w_{it} 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, here GDP. Taxes are constructed that way to fit in the government budget constraint (see Section 2.3). This approach, however, also comes at a cost. The reason is that macro backward-looking indicators may not be the best proxies for the actual tax rates that firms and individuals take into account when taking decisions. This is especially the case for the corporate tax rate indicator. 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 and the taxable profit. This is a serious drawback, as Devereux (2007) and Backus et al. (2008) point out. Corporate tax receipts as a percentage of GDP may rise even when tax rates are reduced. Devereux (2007) concludes that there is no straightforward relationship between the two.³ It should then come as no surprise that the correlation between corporate income tax receipts as a percentage of GDP and tax rates themselves is very low. In Appendix B we report correlation coefficients of the Statutory corporate Tax Rate (STR) with 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 Tax Rates (EMTR) and Effective Average Tax Rates (EATR) that firms can actually expect for several types of hypothetical investments. Correlation over all countries and available years between STR, EMTR and EATR is above 0.6. However, the correlation (reported in Appendix B) of each of these three tax indicators with corporate tax receipts as a percentage of GDP always remains below 0.09. It goes without saying that these findings are a reason for caution when we interpret our results on the direct impact of the corporate tax rate (included in w_{it}) on TFP in the next section.

Note that there is also a corporate tax rate indicator included in z_{it} to capture its impact on the access to

²The selection of countries and time coverage is driven by data availability. The included countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Italy, Japan, Netherlands, Norway, Spain, Sweden, United Kingdom and United States.

³As an example, consider a government who chooses to lower the effective corporate tax rate. To do that, it has two options: (i) opting for a lower statutory corporate tax rate or (ii) choosing a smaller tax base. Both options will stimulate investment and raise profits. As a consequence revenues from corporate taxation could rise because of more taxable profits. This means that a lower effective corporate tax rate could result in a higher macro-backward looking indicator.

worldwide technology. As there is no need to take the government budget constraint into account in z_{it} , from the above arguments we should ideally use the relative EMTR or EATR. However, as for these indicators data availability is limited, we use the relative statutory corporate tax rate. As can be seen in Appendix B, the STR shows strong positive correlation with the EMTR and EATR, such that it should be considered to be an adequate proxy.

3.2 Properties of the data

As a guide to selecting the most appropriate estimation method in Section 4 below, we first look at two important properties of the data: the degree of cross-sectional dependence and the order of integration.

3.2.1 Cross-sectional dependence

The modeling and identification of each country's TFP in equation (3) relies on the assumption that there is a worldwide level of technology that affects each country differently. This should show up as strong cross-sectional dependence in the data. Table 1 therefore reports the average pairwise correlation coefficient ($\bar{\rho}$) and the cross-sectional dependence (CD) test of Pesaran (2004). As all series are potentially non-stationary, we also report results for the first-differenced data to avoid spurious non-zero correlation. For the identification of worldwide technology, especially the cross-sectional dependence in output is important. For completeness we also report the test results for each of the explanatory variables.

The results in Table 1 show that most variables exhibit considerable positive cross-sectional correlation. Concentrating on the first-differenced data, strong cross-sectional dependence is found for $\ln Q_{it}$, $\ln K_{it}$, $\ln G_{it}$, $\ln H_{it}$, $\ln TotalExp_{it}$, $\ln SocialExp_{it}$, $\ln GovCons_{it}$, $\ln BudgetBalance_{it}$, $\ln HCap_{it}$ and $\ln Import_{it}$. For the other variables, cross-sectional correlation is only moderate. Looking at the CD test, the null hypothesis of no cross-sectional dependence is strongly rejected in all cases. The finding of significant cross-sectional dependence implies that we need to take this into account when estimating our empirical model. However, rather than treating cross-sectional dependence as a nuisance which needs correction, we will use it to identify unobserved TFP.

Table 1: Cross-sectional dependence in the data

Sample period: 1970 -2012, 15 OECD countries

	Levels			First-differences				Levels			First-differences		
	$\bar{\hat{\rho}}$	CD	[p-value]	$\bar{\hat{\rho}}$	CD	[p-value]		$\bar{\hat{\rho}}$	CD	[p-value]	$\bar{\hat{\rho}}$	CD	[p-value]
$\ln Q_{it}$	0.98	66.14	[0.00]	0.53	35.07	[0.00]	$\ln BudgetBalance_{it}$	0.44	29.44	[0.00]	0.43	28.45	[0.00]
$\ln K_{it}$	0.97	65.37	[0.00]	0.43	28.88	[0.00]	$\ln Taxburden_{it}$	0.58	38.64	[0.00]	0.12	7.91	[0.00]
$\ln G_{it}$	0.76	51.11	[0.00]	0.35	23.03	[0.00]	$\ln PersonalTax_{it}$	0.39	26.05	[0.00]	0.13	8.55	[0.00]
$\ln H_{it}$	0.28	19.04	[0.00]	0.32	21.54	[0.00]	$\ln CorporateTax_{it}$	0.30	19.93	[0.00]	0.19	12.51	[0.00]
$\ln TotalExp_{it}$	0.61	40.72	[0.00]	0.45	29.9	[0.00]	$\ln ConsTax_{it}$	0.11	7.57	[0.00]	0.09	6.07	[0.00]
$\ln ProdExp_{it}$	0.07	4.77	[0.00]	0.15	10.06	[0.00]	$\ln OtherTax_{it}$	0.33	22.48	[0.00]	0.07	4.33	[0.00]
$\ln SocialExp_{it}$	0.68	45.51	[0.00]	0.47	31.03	[0.00]	$\ln StrRelative_{it}$	-0.06	-3.95	[0.00]	-0.06	-3.99	[0.00]
$\ln GovCons_{it}$	0.52	35.02	[0.00]	0.38	25.35	[0.00]	$\ln HCap_{it}$	0.94	63.00	[0.00]	0.27	18.00	[0.00]
$\ln OtherExp_{it}$	0.51	34.08	[0.00]	0.19	12.47	[0.00]	$\ln Import_{it}$	0.59	39.95	[0.00]	0.58	38.71	[0.00]

Notes: The average cross-correlation coefficient $\bar{\hat{\rho}} = (2/N(N-1)) \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}$ is the average of the country-by-country cross-correlation coefficients $\hat{\rho}_{ij}$ (for $i \neq j$). *CD* is the Pesaran (2004) test defined as $\sqrt{2T/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}$, which is asymptotically standard normal under the null of cross-sectional independence. *p*-values are reported in square brackets.

3.2.2 Time series properties

The statistical properties of the below proposed estimators depend on the order of integration of the data. In this section we analyze the time series properties of each of the variables used. Panel unit root tests allowing for cross-sectional dependence have been proposed by, most notably, Pesaran (2007), Moon and Perron (2004) and Bai and Ng (2004). These tests are similar in that they assume an observed variable x_{it} to have the following common factor structure

$$x_{it} = d_{it} + f_t \pi_i + \xi_{it}, \tag{5}$$

where f_t is an $r \times 1$ vector of r common factors with country-specific factor loadings π_i , ξ_{it} is an idiosyncratic error term and d_{it} is a deterministic component which can be (i) zero, $d_{it} = 0$, (ii) an idiosyncratic intercept, $d_{it} = d_{0i}$, or (iii) an idiosyncratic intercept and idiosyncratic linear trend $d_{it} = d_{0i} + d_{1i}t$. Cross-sectional dependence stems from the component $f_t \pi_i$ which is correlated over countries as it includes the common factors f_t . The series x_{it} is non-stationary if at least one of the common factors in f_t is non-stationary, or the idiosyncratic error ξ_{it} is non-stationary, or both. The above mentioned panel unit root tests differ in the allowed number and order of integration of the unobserved common factors and in the way these factors are eliminated.

The most general approach is the PANIC unit root test of Bai and Ng (2004) as this is the only one that allows for non-stationarity in either the common factors, or in the idiosyncratic errors or in both. Rather than testing the order of integration using the observed data, x_{it} is first decomposed according to the structure in equation (5). By applying the method of principal components to the first-differenced data, the common and idiosyncratic components in first-differences can be estimated consistently, irrespectively of their orders of integration. Next, these components are accumulated to obtain the corresponding level estimates \hat{f}_t^{pc} and $\hat{\xi}_{it}^{pc}$. These components can then be tested separately for unit roots. When there is only one factor, testing for a unit root in \hat{f}_t^{pc} can be done

using a standard augmented Dickey-Fuller (ADF)-type test (with deterministic terms according to the specification of d_{it}). For multiple common factors, the $MQ_c^{c,\tau}$ and $MQ_f^{c,\tau}$ statistics (see Bai and Ng, 2004, for details) are designed to determine the number of independent stochastic trends $r_1 \leq r$ in \widehat{f}_t^{pc} . As under the appropriate choice for the number of common factors, $\widehat{\xi}_{it}^{pc}$ by design satisfies the cross-sectional independence assumption required for pooling, the Maddala and Wu (1999) (MW) panel unit root test can be used on $\widehat{\xi}_{it}^{pc}$. This consists of combining p -values for the ADF tests (with no deterministic terms) on the idiosyncratic error $\widehat{\xi}_{it}^{pc}$. The relevant distributions for the ADF tests on \widehat{f}_t^{pc} and $\widehat{\xi}_{it}^{pc}$, for the intercept only and the linear trend model, can be found in Bai and Ng (2004).

Monte Carlo simulation results in Bai and Ng (2004), for samples as small as ($T=100, N=40$), and in Gutierrez (2006), for samples as small as ($T=50, N=20$), show that the PANIC approach performs well in small samples. The ADF test on the common factor and on the MW test on the idiosyncratic error terms both have an actual size close to the 5% nominal level and have adequate power. Applications of the PANIC approach to unit root testing using a similar data span as ours ($T=43, N=15$) can be found in, among others, Huang (2011), Byrne et al. (2011), Costantini and Destefanis (2009) and Costantini et al. (2013).

The results of the PANIC unit root test are reported in Table 2. For each of the variables we estimate the number of common factors r using one of the information criteria suggested by Bai and Ng (2002). Based on their simulation results, we prefer BIC_3 because it outperforms the other information criteria in the smallest samples they consider. This is also stressed by Moon and Perron (2007) who state that BIC_3 performs better in selecting the number of factors when $\min(N, T)$ is small (≤ 20), as is the case in our application. The specification of the deterministic component d_{it} is chosen from the observed trending behavior of the variables. The results show that, except for $\ln Budgetbalance_{it}$ and $\ln CorporateTax_{it}$, each of the variables is found to be non-stationary at the 5% level of significance. For $\ln GovCons_{it}$ and $\ln StrRelative_{it}$ non-stationarity is induced by the idiosyncratic component only while for $\ln K_{it}$, $\ln G_{it}$ and $\ln HCap_{it}$ non-stationarity is induced by the common factor only. For the other 11 variables ($\ln Q_{it}$, $\ln H_{it}$, $\ln TotalExp_{it}$, $\ln ProdExp_{it}$, $\ln SocialExp_{it}$, $\ln OtherExp_{it}$, $\ln Taxburden_{it}$, $\ln PersonalTax_{it}$, $\ln ConsTax_{it}$, $\ln OtherTax_{it}$, $\ln Import_{it}$), both the common factor and the idiosyncratic error are found to be non-stationary.⁴

Taking into account the non-stationary of the data and the presence of significant cross-sectional dependence, an appropriate estimation method and panel cointegration test are discussed in the next section.

⁴The overall conclusion that most variables are non-stationary does not change when changing the number of common factors or the specification of the deterministic component.

Table 2: PANIC unit root tests

Sample period: 1970 -2012, 15 OECD countries

	\widehat{f}_t^{pc}			$\widehat{\xi}_{it}^{pc}$			\widehat{f}_t^{pc}			$\widehat{\xi}_{it}^{pc}$	
	Det	r	r_1	MW-test			Det	r	r_1	MW-test	
$\ln Q_{it}$	d_{it}	1	1	27.52	[0.60]	$\ln BudgetBalance_{it}$	d_{0i}	1	0	66.13	[0.00]
$\ln K_{it}$	d_{it}	2	2	61.62	[0.00]	$\ln Taxburden_{it}$	d_{it}	0	0	8.92	[1.00]
$\ln G_{it}$	d_{it}	3	3	137.90	[0.00]	$\ln PersonalTax_{it}$	d_{it}	0	0	7.46	[1.00]
$\ln H_{it}$	d_{it}	1	1	28.58	[0.54]	$\ln CorporateTax_{it}$	d_{0i}	0	0	62.71	[0.00]
$\ln TotalExp_{it}$	d_{it}	1	1	38.02	[0.15]	$\ln ConsTax_{it}$	d_{0i}	0	0	27.21	[0.62]
$\ln ProdExp_{it}$	d_{0i}	0	0	32.37	[0.35]	$\ln OtherTax_{it}$	d_{0i}	0	0	36.86	[0.18]
$\ln SocialExp_{it}$	d_{it}	1	1	33.64	[0.30]	$\ln StrRelative_{it}$	d_{0i}	0	0	34.41	[0.26]
$\ln GovCons_{it}$	d_{0i}	1	0	39.09	[0.12]	$\ln HCap_{it}$	d_{it}	3	3	47.09	[0.02]
$\ln OtherExp_{it}$	d_{0i}	0	0	29.01	[0.52]	$\ln Import_{it}$	d_{it}	1	1	42.36	[0.07]

Notes: ‘Det’ indicates the deterministic component of the model, i.e. d_{0i} for the intercept only model and $d_{it} = d_{0i} + d_{1i}t$ for the linear trend model. The number of common factors is estimated using the BIC_3 of Bai and Ng (2002). When $r = 1$, the number of non-stationary factors r_1 is determined using the ADF-GLS test of Elliott et al. (1996) with deterministic terms according to the specification of d_{it} . When $r > 1$, r_1 is determined using the MQ_C^c (intercept only model) or MQ_C^t (linear trend model) statistic of Bai and Ng (2004). The panel unit root test on the estimated idiosyncratic errors is the Maddala and Wu (1999) (MW) test (with no deterministic terms). The null hypothesis for each of these tests is that the series has a unit root. p -values are reported in square brackets.

4 Econometric methodology

The empirical model outlined in Section 2 allows fiscal policy to have both direct and indirect effects on TFP. In this section we outline our econometric methodology for estimating these effects. We start with a simplified specification by restricting the indirect effects to be absent. This results in a linear model that can be estimated using the standard CCEP estimator of Pesaran (2006), which is discussed in Section 4.1. Next, we show how a model including also indirect effects can be estimated using a non-linear version of the CCEP estimator, denoted CCEPnl. This is described in Section 4.2. Section 4.3 outlines our PANIC approach to testing for cointegration from the linear and non-linear CCEP estimates. The small sample properties of the newly proposed CCEPnl estimator and of the PANIC cointegration test are analyzed using Monte Carlo simulations in Section 4.4.

4.1 CCEP estimator for model with time-invariant factor loadings

We start with a simplified specification by restricting fiscal policy to have only direct effects on TFP, i.e. setting $\lambda = 0$ in equation (4) such that $\lambda_{it} = \lambda_{i0}$. Under this restriction, the empirical model can be obtained by substituting equation (3) into (2)

$$y_{it} = \gamma_i + F_t \lambda_{i0} + x_{it} \beta + \varepsilon_{it}, \quad (6)$$

where $y_{it} = \ln Q_{it}$, $x_{it} = (\ln K_{it}, \ln G_{it}, \ln H_{it}, w_{it})$ and $\beta = (\alpha_1, \alpha_2, \alpha_3, \delta)'$. The idiosyncratic error term ε_{it} is assumed to be a zero mean stationary random term which is uncorrelated over cross-section units and distributed independently of x_{it} and F_t .

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

$$\bar{y}_t = \bar{\gamma} + F_t \bar{\lambda}_0 + \bar{x}_t \beta + \bar{\varepsilon}_t, \quad (7)$$

where $\bar{y}_t = \frac{1}{N} \sum_{i=1}^N y_{it}$ and similarly for $\bar{\gamma}$, $\bar{\lambda}_0$, \bar{x}_t and $\bar{\varepsilon}_t$. For notational convenience we assume a single common factor ($r = 1$) but the results straightforwardly generalize to multiple factors (see Pesaran, 2006). Equation (7) can then be solved for F_t as

$$F_t = \frac{1}{\bar{\lambda}_0} (\bar{y}_t - \bar{\gamma} - \bar{x}_t \beta - \bar{\varepsilon}_t), \quad (8)$$

which yields \widehat{F}_t^{ca1}

$$\widehat{F}_t^{ca1} = \frac{1}{\bar{\lambda}_0} (\bar{y}_t - \bar{\gamma} - \bar{x}_t \beta), \quad (9)$$

as a proxy for F_t . Given the assumption that ε_{it} is a zero mean stationary error term which is uncorrelated over cross-section units, implying that $\text{plim}_{N \rightarrow \infty} \bar{\varepsilon}_t = 0$ for each t , we have that $\widehat{F}_t^{ca1} \xrightarrow{p} F_t$ for $N \rightarrow \infty$. This is the main result in Pesaran (2006) that the cross-sectional averages of the observed data can be used as observable proxies for F_t . Although the construction of \widehat{F}_t^{ca1} as a consistent estimator for F_t in equation (9) requires knowledge of the unknown underlying parameters, Pesaran (2006) shows that these parameters can be estimated from an augmented model obtained by replacing the unobserved F_t in equation (6) by the cross-sectional averages of the observed data using equation (8)

$$y_{it} = \gamma_i + (\bar{y}_t - \bar{\gamma} - \bar{x}_t \beta - \bar{\varepsilon}_t) \frac{\lambda_{i0}}{\bar{\lambda}_0} + x_{it} \beta + \varepsilon_{it}, \quad (10)$$

$$= \gamma_i^+ + \bar{y}_t \lambda_{i1} + \bar{x}_t \lambda_{i2} + x_{it} \beta + \varepsilon_{it}^+, \quad (11)$$

where $\gamma_i^+ = \gamma_i - \bar{\gamma} \lambda_{i0} / \bar{\lambda}_0$, $\lambda_{i1} = \lambda_{i0} / \bar{\lambda}_0$, $\lambda_{i2} = \lambda_{i0} / \bar{\lambda}_0 \beta$ and $\varepsilon_{it}^+ = \varepsilon_{it} - \lambda_{i0} / \bar{\lambda}_0 \bar{\varepsilon}_t$. Since $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$ for $N \rightarrow \infty$, the augmented model in equation (11) - ignoring any parameter restrictions - can be estimated with least squares (LS), an approach referred to as the CCEP estimator.⁵

Pesaran (2006) shows that, under appropriate regularity conditions, the CCEP estimator is consistent and asymptotically normal in stationary panel regressions. Kapetanios et al. (2011) show that these asymptotic results continue to hold in non-stationary panels provided that the idiosyncratic error term ε_{it} is stationary. We outline our approach for testing whether this assumption (of cointegration) is satisfied in Section 4.3 below.

⁵Although equation (11) is derived, for notational convenience, under the assumption of a single factor, exactly the same augmented form is obtained for multiple common factors (see Pesaran, 2006).

4.2 CCEPnl estimator for model with time-varying factor loadings

Allowing for a time-varying access to unobserved worldwide technology yields, from substituting equations (3) and (4) in (2), the following final empirical specification

$$y_{it} = \gamma_i + F_t (\lambda_{i0} + z_{it}\lambda) + x_{it}\beta + \varepsilon_{it}. \quad (12)$$

Again taking cross-sectional averages

$$\bar{y}_t = \bar{\gamma} + F_t (\bar{\lambda}_0 + \bar{z}_t\lambda) + \bar{x}_t\beta + \bar{\varepsilon}_t, \quad (13)$$

and solving for F_t

$$F_t = \frac{1}{\bar{\lambda}_0 + \bar{z}_t\lambda} (\bar{y}_t - \bar{\gamma} - \bar{x}_t\beta - \bar{\varepsilon}_t), \quad (14)$$

now yields \widehat{F}_t^{ca2}

$$\widehat{F}_t^{ca2} = \frac{1}{\bar{\lambda}_0 + \bar{z}_t\lambda} (\bar{y}_t - \bar{\gamma} - \bar{x}_t\beta), \quad (15)$$

as a proxy for F_t . From $\text{plim}_{N \rightarrow \infty} \bar{\varepsilon}_t = 0$ for each t , we again have that $\widehat{F}_t^{ca2} \xrightarrow{p} F_t$ for $N \rightarrow \infty$ such that the main result in Pesaran (2006) that the cross-sectional averages of the observed data can be used as observable proxies of F_t continues to hold. Inserting equation (14) in (12) and using \widehat{F}_t^{ca2} defined in equation (15) as a proxy for F_t yields

$$y_{it} = \gamma_i + \frac{1}{\bar{\lambda}_0 + \bar{z}_t\lambda} (\bar{y}_t - \bar{\gamma} - \bar{x}_t\beta - \bar{\varepsilon}_t) \lambda_{it} + x_{it}\beta + \varepsilon_{it}, \quad (16a)$$

$$= \gamma_i + \widehat{F}_t^{ca2} (\lambda_{i0} + z_{it}\lambda) + x_{it}\beta + \varepsilon_{it}^+, \quad (16b)$$

where $\varepsilon_{it}^+ = \varepsilon_{it} - (\lambda_{i0} + z_{it}\lambda) / (\bar{\lambda}_0 + \bar{z}_t\lambda) \bar{\varepsilon}_t$. We still have that $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$ for $N \rightarrow \infty$, but the main difference compared to the ‘unrestricted’ augmented model in equation (11) is that the time-varying factor loading λ_{it} requires estimating the ‘restricted’ augmented form in equation (16) which (i) implies making an assumption on the number of common factors and (ii) cannot be estimated using the standard CCEP estimator because it is non-linear in the parameters. In Section 5.1 below we show that one common factor is sufficient to model the cross-sectional dependence in the data. Assuming a single factor, we then estimate the unknown parameters in equation (16a) by minimizing the non-linear LS objective function

$$S_{NT}(\lambda, \beta, (\gamma_1, \dots, \gamma_N), (\lambda_{10}, \dots, \lambda_{N0})) = \sum_{i=1}^N \sum_{t=1}^T \varepsilon_{it}^+ \varepsilon_{it}^+. \quad (17)$$

We label this non-linear procedure the CCEPnl estimator.

Asymptotic theory for our non-linear CCEP estimator is currently not yet available and deriving limit distribution theory for non-linear regressions with integrated variables is very cumbersome.⁶ In a pure time series context there is already quite some literature on non-linear cointegration analysis, i.e. asymptotic theory for non-linear

⁶Note that Wan (2012, chapter 5) provides some heuristic asymptotic results for a CCEP estimator with non-linear transformations of $I(1)$ variables but which is still linear in the coefficients.

regression with integrated processes was developed by, among others, Park and Phillips (2001) and extended to a fairly general non-linear model by Saikkonen and Choi (2004). However, in a panel data context literature is much more scarce. Very similar to our model, though, González et al. (2005) estimate a fixed effects smooth transition panel cointegration model in which the regression coefficients vary across individuals and time as a function of an observable variable. They suggest to estimate the resulting non-linear model using a combination of fixed effects and LS. More specifically, as the individual means depend on the unknown parameters they first condition on the unknown parameters to calculate and remove the individual means and next use the demeaned series to estimate the unknown parameters with LS. This procedure is then iterated until convergence. They further argue that for normally distributed errors this non-linear procedure is equivalent to maximum likelihood (ML) and conjecture that this ML estimator is consistent and asymptotically normal. Palm et al. (2012) formalize this estimator as the pooled non-linear least squares dummy variable estimator and derive its asymptotic properties, confirming the conjecture of González et al. (2005).

Similar to the estimation procedure in González et al. (2005), estimating the unknown parameters from the non-linear LS objective function in equation (17) can also be done by first calculating \widehat{F}_t^{ca2} from equation (15), conditional on the unknown coefficients, and next estimating the augmented linear model in equation (16b), conditional on \widehat{F}_t^{ca2} , using a linear LS-type estimator. Iterating over these two steps is equivalent to the CCEPnl estimator defined above. The main difference with the standard CCEP estimator is that instead of augmenting the model with cross-sectional averages of the data, we augment the regression with an estimate of a single unobserved factor obtain from the cross-sectional averages of the data conditional on the unknown coefficients. As the error $\bar{\varepsilon}_t$ in the approximation of F_t by \widehat{F}_t^{ca2} shrinks to zero as $N \rightarrow \infty$, we conjecture that this non-linear procedure yields a consistent estimator for (λ, β) . The small sample properties of the proposed CCEPnl estimator are illustrated in Section 4.4 using a Monte Carlo simulation.

One additional complication is that the model is not identified as λ_{it} and \widehat{F}_t^{ca2} are not identified separately, only their product is. For instance, multiplying λ_{it} by a constant a while dividing \widehat{F}_t^{ca2} by the same constant, which implies that λ_{i0} , $\bar{\lambda}_0$ and λ are multiplied by the constant a , leaves the model in equation (16) unchanged as $(\widehat{F}_t^{ca2}/a)(a\lambda_{it}) = \widehat{F}_t^{ca2}\lambda_{it}$ or equivalently $\frac{a\lambda_{i0}+z_{it}a\lambda}{a\bar{\lambda}_0+\bar{z}_{it}a\lambda} = \frac{\lambda_{i0}+z_{it}\lambda}{\bar{\lambda}_0+\bar{z}_{it}\lambda}$. To solve this identification problem, we impose $\bar{\lambda}_0 = 1$, i.e. we normalize the average over all countries of the country-specific time-invariant access to worldwide technology to be one.

4.3 Testing for cointegration from the CCEP and CCEPnl estimates

The consistency and asymptotic normality of the above presented CCEP estimators relies on the assumption that the idiosyncratic error term ε_{it} in equation (6) or (12) is stationary (Kapetanios et al., 2011). This implies that there is cointegration (i) between (y_{it}, x_{it}) if $F_t \sim I(0)$ or (ii) between (y_{it}, x_{it}, F_t) in the linear case and between $(y_{it}, x_{it}, F_t, z_{it}F_t)$ in the non-linear case if $F_t \sim I(1)$. In this section we outline our approach to testing for cointegration from the CCEP(nl) estimation results.

Panel cointegration tests based on the CCEP estimator have been suggested by Banerjee and Carrion-i-Silvestre (2011) and Everaert (2014). Banerjee and Carrion-i-Silvestre (2011) first extend the results in Kao (1999) and

Phillips and Moon (1999) to panels with cross-sectional dependence by showing that under the null of no cointegration, the linear CCEP estimator allows for consistent estimation of the homogeneous coefficients β but not for the heterogeneous coefficients (γ_i, λ_{i0}) . Given this result, they suggest to obtain a consistent estimate for the composite error term $e_{it} = \gamma_i + F_t \lambda_{i0} + \varepsilon_{it}$ as

$$\widehat{e}_{it} = y_{it} - x_{it} \widehat{\beta} = (\gamma_i + F_t \lambda_{i0} + \varepsilon_{it}) \widehat{}, \quad (18)$$

and test for cointegration using a panel unit root test on \widehat{e}_{it} that takes into account the cross-sectional dependence induced by the unobserved common factors F_t . To this end, they suggest to use the cross-section augmented ADF (CADF) panel unit root test of Pesaran (2007). Although this approach can effectively sweep out a single common factor, F_t is restricted to have the same order of integration as the idiosyncratic error term ε_{it} . This rules out that $F_t \sim I(1)$ and $\varepsilon_{it} \sim I(0)$, i.e. cointegration between (y_{it}, x_{it}, F_t) in the linear model, a case which is of particular interest to us as F_t is included in our empirical model to capture worldwide technology, which is most likely non-stationary. Since the structure of the composite error term $e_{it} = \gamma_i + \lambda_i F_t + \varepsilon_{it}$ aligns with the general factor structure of equation (5), an obvious alternative to the CADF test is to apply the PANIC approach of Bai and Ng (2004).⁷ This allows to consistently decompose \widehat{e}_{it} in a set of common factors, denoted \widehat{F}_t^{pc} , and an idiosyncratic error term, labeled $\widehat{\varepsilon}_{it}^{pc}$, which can then be separately tested for unit roots (see PANIC approach outlined in Section 3.2.2). The main advantage of this approach is that the test whether the idiosyncratic errors ε_{it} are stationary or not does not depend on the order of integration of F_t . As such, testing for cointegration from the CCEP estimation results boils down to testing whether there is a unit root in $\widehat{\varepsilon}_{it}^{pc}$, for which the MW panel unit root test can be used. Note that although cointegration only requires the idiosyncratic errors to be $I(0)$, the integration properties of the common factors provide additional interesting information, i.e. when $F_t \sim I(0)$ there is cointegration between (y_{it}, x_{it}) while for $F_t \sim I(1)$ there is cointegration between (y_{it}, x_{it}, F_t) . When running the PANIC unit root test on \widehat{e}_{it} , we use the linear trend model specification of Bai and Ng (2004). The reason for this is that the common factor \widehat{F}_t^{pc} identified below (see Section 5.1) shows a clear upward trend. With no loss of generality (also see Bai and Ng, 2004, p. 1138) this can be modeled by including an idiosyncratic linear trend, i.e. setting $d_{it} = d_{i0} + d_{i1}t$ in the general common factor structure presented in equation (5).

A cointegration test for the CCEPnl estimator for the model in equation (12) has not yet been developed. In line with the results in Kao (1999) and Phillips and Moon (1999), for a model with no cross-sectional dependence, and in Banerjee and Carrion-i-Silvestre (2011), for a model with cross-sectional dependence as in equation (6), we conjecture that the CCEPnl estimator yields consistent estimates for the homogenous coefficients β and λ and therefore, using equation (15), also for F_t ⁸. This implies that we can obtain a consistent estimate for the composite

⁷Using the PANIC approach to testing for panel cointegration in the presence of common factors has also been suggested by Gengenbach et al. (2006), Banerjee and Carrion-i-Silvestre (2006) and Bai and Carrion-i-Silvestre (2013). The main difference between these approaches and ours lies in the estimation of the unknown coefficients in the cointegrating relation, for which we use the CCEP estimator while the above references estimate a model in first-differences with the common factors and factor loadings estimated using principal components.

⁸Note that $\widehat{\lambda}$ and \widehat{F}_t^{ca2} are only identified up to scale (see discussion in Section 4.2) but their product used in equation (19) is identified.

error term $e_{it} = \gamma_i + F_t \lambda_{i0} + \varepsilon_{it}$ as

$$\widehat{e}_{it} = y_{it} - x_{it} \widehat{\beta} - z_{it} \widehat{\lambda} \widehat{F}_t^{ca2} = (\gamma_i + F_t \lambda_{i0} + \varepsilon_{it}) \widehat{}, \quad (19)$$

from which we again test for cointegration using the PANIC approach in the same way as in the linear model. If the idiosyncratic error $\widehat{\varepsilon}_{it}^{pc}$ is found to be stationary, there is cointegration between (y_{it}, x_{it}) when $F_t \sim I(0)$ or between $(y_{it}, x_{it}, F_t, z_{it} F_t)$ when F_t is found to be $I(1)$. In the next subsection, we provide numerical support for our conjecture that the CCEPnl estimator is consistent under the null hypothesis of no cointegration and analyse the size and power properties of the PANIC approach applied to the CCEPnl composite error term in equation (19).

4.4 Monte Carlo simulation

The small sample behavior of the CCEP estimator is analyzed by Pesaran (2006) for stationary panel regressions and extended to non-stationary panels by Kapetanios et al. (2011). Both Monte Carlo studies show that the small sample properties in the case ($T=30, N=20$) are satisfactory. However, as we extend their settings to a non-linear model, in this section we present Monte Carlo simulation results to examine the small sample properties of the CCEPnl estimator.

The actual size and power of a PANIC cointegration test on the composite error term of a linear CCEP regression have already been analyzed by Everaert (2014). He finds that this is an adequate approach to testing for cointegration between (y_{it}, x_{it}, F_t) . In our Monte Carlo experiment we further analyze the size and power of the PANIC cointegration test and extend the analysis to testing for cointegration in the CCEPnl regressions. Although we are mainly interested in the properties for the small sample we have available ($T=43, N=15$), we also present results for larger sample sizes to illustrate the more general properties of the CCEPnl estimator and PANIC cointegration test.

4.4.1 Simulation tailored to the actual data for $T=43$ and $N=15$

Design

To make sure that our simulation results are relevant for putting the estimates presented in Section 5 in perspective, we simulate data for exactly the same sample size ($T=43, N=15$) 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 simulate artificial data for y_{it} from its DGP, specified in equations (6) and (12) for the linear and non-linear model respectively, using the observed data for x_{it} and z_{it} . We conduct a separate experiment for each of the four different specifications we consider. The population parameters $\gamma_i, \lambda_{i0}, \lambda, \beta$ and the common factor F_t in the DGP of y_{it} are taken from the CCEP and CCEPnl estimation results (Table 8 in Section 5 below), when simulating according to the linear and non-linear DGP respectively. The idiosyncratic error term ε_{it} is generated from the following AR(1) specification

$$\varepsilon_{it} = \theta \varepsilon_{i,t-1} + \psi_{it}, \quad \psi_{it} \sim N(0, \sigma_\psi^2), \quad (20)$$

for various values of θ . To analyze the power of the PANIC cointegration test outlined in Section 4.3, we set $\theta = \{0; 0.8; 0.9\}$. This yields three different stationary processes for ε_{it} . As our estimate for the unobserved common factor F_t is found to be non-stationary (see Section 5.1), these values for θ imply that there is cointegration between (y_{it}, x_{it}, F_t) in the linear model (CCEP estimator) and between $(y_{it}, x_{it}, F_t, z_{it}F_t)$ in the non-linear model (CCEPnl estimator). To analyze the actual size of the PANIC cointegration test, we generate ε_{it} from a random walk process by setting $\theta = 1$ such that there is no cointegration. Using equation (20), we calibrate parameter values for σ_ψ over the different values of θ by setting σ_ψ equal to the sample standard deviation of $\widehat{\varepsilon}_{it} - \theta\widehat{\varepsilon}_{i,t-1}$, with $\widehat{\varepsilon}_{it}$ being the estimated error term from the CCEPnl estimator in Table 8. In the baseline simulation with $\theta = 0$, σ_ψ is calibrated to be 0.02.⁹ The other calibrated values for σ_ψ are reported in the note to Table 4. For analyzing the power of the PANIC cointegration test, the nominal size is fixed at 5%. To get a more complete picture for the actual size of the test, we consider three different values for the nominal size (i.e. 5%, 2.5% and 1%). Each experiment is based on 1000 iterations.

Small sample properties of the CCEPnl estimator

The simulation results for the small sample properties of the CCEPnl estimator for the non-linear model in our baseline design ($\theta = 0$) can be found in Table 3.¹⁰ We report the (i) mean bias (bias), (ii) standard deviation (stdv), (iii) mean of the estimated standard errors (stde) of the coefficient estimates and (iv) actual size (size). The actual size is calculated for a two-sided hypothesis test at the 5% nominal level of significance for the null hypothesis that the estimated coefficient equals the population parameter. The general picture that emerges from Table 3 is that despite the limited sample size (i) the bias in estimating the coefficients is negligibly small, (ii) the mean of the estimated standard errors is fairly close to the actual standard deviation of the estimates and (iii) the actual size is close to the nominal level of 5%. These results imply that the CCEPnl estimator allows for reliable estimation and valid inference in the non-linear specification in equation (12) even in our limited sample ($T=43, N=15$).

Small sample properties of the PANIC cointegration test

The simulation results for the power and size of the PANIC cointegration test are reported in Table 4. Starting with the power, this is found to be close to 100% for both the CCEP and CCEPnl estimator when ε_{it} is a white noise error term ($\theta = 0$). In the setting where $\theta = 0.8$, power is lower but still sufficiently high, certainly when taking into account that we consider a fairly small sample ($T=43, N=15$). Power decreases further when setting $\theta = 0.9$. Turning to the actual size, the PANIC cointegration test tends to be somewhat oversized. For the CCEP estimator in the linear model, the size distortion is not too big, though. However, for the CCEPnl estimator in the non-linear model, the actual size at the 5% nominal level varies between 7.5% and 17.7%. Reducing the nominal size to 1% yields an actual size between 2.4% and 7.5%.

⁹Since $\theta = 0$ we also have $\sigma_\varepsilon = 0.02$ in this case. As the dependent variable $\ln Q_{it}$ is log real GDP, $\sigma_\varepsilon = 0.02$ implies that 95% of the generated error terms ε_{it} are between -4% and 4% of real GDP.

¹⁰Simulation results for the CCEP estimator are available on request.

Table 3: Monte Carlo simulation results for the CCEPnl estimator ($T=43, N=15$)

S1					S3				
	bias	stdv	stde	size		bias	stdv	stde	size
$\ln K_{it}$	-0.006	0.019	0.020	0.016	$\ln K_{it}$	-0.001	0.016	0.019	0.056
$\ln G_{it}$	0.001	0.014	0.013	0.048	$\ln G_{it}$	0.002	0.013	0.015	0.039
$\ln H_{it}$	0.003	0.021	0.025	0.048	$\ln H_{it}$	0.007	0.017	0.024	0.016
$\ln TotalExp_{it}$	0.002	0.032	0.033	0.047	$\ln TotalExp_{it}$	-0.001	0.048	0.053	0.042
$\ln ProdExp_{it}$	-0.002	0.012	0.012	0.057	$\ln Taxburden_{it}$	0.000	0.032	0.036	0.037
$\ln SocialExp_{it}$	-0.001	0.017	0.017	0.048	$\ln PersonalTax_{it}$	0.000	0.005	0.006	0.049
$\ln BudgetBalance_{it}$	0.002	0.049	0.051	0.048	$\ln CorporateTax_{it}$	-0.002	0.018	0.020	0.036
$\ln StrRelative_{it}$	0.020	0.090	0.096	0.030	$\ln StrRelative_{it}$	-0.048	0.102	0.1362	0.085
$\ln HCap_{it}$	0.010	0.049	0.054	0.048	$\ln HCap_{it}$	0.025	0.056	0.074	0.074
$\ln Import_{it}$	-0.010	0.050	0.057	0.048	$\ln Import_{it}$	-0.028	0.056	0.075	0.086
S2					S4				
	bias	stdv	stde	size		bias	stdv	stde	size
$\ln K_{it}$	-0.008	0.019	0.021	0.040	$\ln K_{it}$	-0.008	0.015	0.020	0.034
$\ln G_{it}$	0.002	0.014	0.015	0.044	$\ln G_{it}$	0.001	0.012	0.014	0.028
$\ln H_{it}$	0.004	0.021	0.026	0.017	$\ln H_{it}$	0.005	0.017	0.024	0.018
$\ln ProdExp_{it}$	-0.001	0.015	0.015	0.058	$\ln ProdExp_{it}$	0.000	0.013	0.013	0.047
$\ln SocialExp_{it}$	0.001	0.011	0.011	0.065	$\ln BudgetSurplus_{it}$	-0.002	0.005	0.005	0.055
$\ln GovCons_{it}$	0.004	0.014	0.014	0.045	$\ln PersonalTax_{it}$	-0.001	0.014	0.014	0.037
$\ln OtherExp_{it}$	0.000	0.005	0.005	0.058	$\ln CorporateTax_{it}$	-0.001	0.005	0.005	0.047
					$\ln ConsTax_{it}$	0.002	0.036	0.037	0.053
$\ln Taxburden_{it}$	-0.001	0.023	0.021	0.066	$\ln OtherTax_{it}$	0.001	0.011	0.011	0.058
$\ln StrRelative_{it}$	0.026	0.097	0.109	0.082	$\ln StrRelative_{it}$	-0.028	0.075	0.093	0.071
$\ln HCap_{it}$	0.014	0.056	0.051	0.071	$\ln HCap_{it}$	0.016	0.045	0.054	0.066
$\ln Import_{it}$	-0.017	0.053	0.060	0.095	$\ln Import_{it}$	-0.017	0.041	0.051	0.084

Notes: Data for y_{it} are simulated from the DGP in equation (12) using population parameters for the coefficients taken from the CCEPnl estimation results in Table 8. We further set $\theta = 0$ and $\sigma_\psi = 0.020$ in the DGP for the idiosyncratic error term ε_{it} in equation (20). Each experiment is based on 1000 iterations.

4.4.2 Simulation for varying values of T and N

Important for our PANIC cointegration test procedure is that the CCEPnl estimator is consistent under the null of no cointegration. In this section, we therefore analyse the statistical properties of the CCEPnl estimator for varying

Table 4: Power and actual size of the PANIC cointegration test ($T=43, N=15$)

	Nominal size	CCEP estimates				CCEPnl estimates			
		S1	S2	S3	S4	S1	S2	S3	S4
Power									
$\theta = 0.0$	5.0%	100.0%	99.7%	99.8%	99.5%	100.0%	100.0%	100.0%	99.9%
$\theta = 0.8$	5.0%	80.0%	77.6%	79.2%	76.1%	97.9%	97.9%	98.3%	98.7%
$\theta = 0.9$	5.0%	22.0%	15.0%	22.0%	21.0%	57.0%	54.0%	60.0%	64.0%
Actual Size									
$\theta = 1.0$	5.0%	7.0%	7.2%	8.7%	8.5%	17.7%	15.2%	7.5%	15.9%
$\theta = 1.0$	2.5%	4.2%	3.9%	4.8%	5.1%	12.6%	10.1%	4.9%	11.2%
$\theta = 1.0$	1.0%	2.8%	2.4%	2.5%	2.5%	6.6%	5.9%	2.4%	7.5%

Notes: Data for y_{it} are simulated from the DGP in equation (6) for the linear model, estimated using the CCEP estimator, and from equation (12) for the non-linear model, estimated using the CCEPnl estimator. Population parameters for the coefficients in each of the four specifications are taken from the CCEP and CCEPnl estimation results in Table 8. When varying θ over the four cases $\theta = \{0; 0.8; 0.9; 1\}$ we calibrate σ_ψ from equation (20) as $\sigma_\psi = \{0.020; 0.012; 0.012; 0.013\}$. Reported are rejection frequencies of a panel MW test for the null hypothesis of a unit root in the idiosyncratic error term $\hat{\varepsilon}_{it}^c$, which is obtained from using PANIC on the composite error term \hat{e}_{it} of the CCEP and CCEPnl estimates in the four different specifications. Each experiment is based on 1000 iterations.

values of T and N . Given that the PANIC cointegration test on the composite error terms of the CCEPnl was found to be somewhat oversized for a sample with $T=43$ and $N=15$, we further check whether this size distortion disappears for larger values of T and N . As a benchmark, we also include results for the CCEP estimator in the linear model.

Design

When considering larger sample sizes, we can no longer use the actual data for x_{it} and z_{it} and the proxy for the common factor F_t from the CCEP(nl) estimation results. Therefore, we now simulate data using $x_{it} = x_{i,t-1} + e_{it}^x$, $z_{it} = z_{i,t-1} + e_{it}^z$ and $F_t = 0.1 + F_{t-1} + e_t^F$, with $e_{it}^x \sim N(0, 1)$, $e_{it}^z \sim N(0, 1)$ and $e_t^F \sim N(0, 1)$. Using these data, we then generate y_{it} from its DGP, specified in equations (6) and (12) for the linear and non-linear model respectively, with $\beta = 1$, $\lambda = 0.1$, $\gamma_i \sim N(0, 1)$, $\lambda_{i0} \sim N(1, 0.5)$ and the idiosyncratic error term ε_{it} generated from the AR(1) specification in equation (20) with $\psi_{it} \sim N(0, 1)$. We again vary the values for θ to analyse the size and power properties of the PANIC cointegration test.

Properties CCEPnl estimator and PANIC cointegration test

The simulation results for the CCEPnl estimator are reported in Table 5. As can be seen, the mean of the estimated coefficients is always close to their true population value with a standard error that decrease in the sample size. Note that this main result holds irrespectively of the value for θ . Only for the sample $T=43$ and $N=15$, there is a small downward bias in the estimates for λ when $\theta = 1$ but this disappears as the sample size grows larger. These results support our conjecture in Section 4.3 that the CCEPnl estimator is consistent even under the null of no cointegration.

The simulation results for the PANIC cointegration test on the CCEP and CCEPnl estimates are reported in Table 6. In line with the results in Section 4.4.1, especially the PANIC cointegration test using the CCEPnl estimates is somewhat oversized for the sample size $T=43$ and $N=15$. However, this size distortion disappears as

Table 5: CCEPnl estimates for varying T and N

T/N	$\hat{\beta}$			$\hat{\lambda}$		
	43/15	100/40	100/100	43/15	100/40	100/100
$\theta = 0.0$	1.000 (0.024)	1.000 (0.005)	1.000 (0.003)	0.100 (0.022)	0.100 (0.012)	0.100 (0.007)
$\theta = 0.8$	1.000 (0.071)	1.000 (0.022)	1.000 (0.013)	0.099 (0.032)	0.100 (0.013)	0.100 (0.008)
$\theta = 0.9$	0.999 (0.099)	1.000 (0.036)	1.000 (0.022)	0.098 (0.037)	0.100 (0.014)	0.100 (0.009)
$\theta = 1.0$	0.999 (0.166)	1.000 (0.097)	1.000 (0.059)	0.091 (0.057)	0.099 (0.021)	0.100 (0.013)

Notes: Data for y_{it} are simulated from the DGP in equation (6) for the linear model and from equation (12) for the non-linear model, with $\beta = 1$, $\lambda = 0.1$, $\gamma_i \sim N(0, 1)$, $\lambda_{i0} \sim N(1, 0.5)$ and the idiosyncratic error term ε_{it} generated from the AR(1) specification in equation (20) with $\psi_{it} \sim N(0, 1)$. Reported are the mean of the coefficient estimates and their standard deviation (in parentheses). Each experiment is based on 1000 iterations.

the sample size increases. This provides additional support for the validity of our PANIC cointegration test.

Table 6: Power and actual size of the PANIC cointegration test for varying T and N

T/N	Nominal size	CCEP estimates			CCEPnl estimates		
		43/15	100/40	100/100	43/15	100/40	100/100
Power							
$\theta = 0.0$	5.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
$\theta = 0.8$	5.0%	94.0%	100.0%	100.0%	93.5%	100.0%	100.0%
$\theta = 0.9$	5.0%	37.4%	100.0%	100.0%	40.0%	100.0%	100.0%
Actual Size							
$\theta = 1.0$	5.0%	6.7%	5.9%	5.3%	9.1%	7.7%	5.8%
$\theta = 1.0$	2.5%	3.6%	3.1%	2.6%	5.5%	4.4%	3.2%
$\theta = 1.0$	1.0%	1.5%	1.3%	1.0%	2.3%	1.7%	1.3%

Notes: See note to Table 5 for how the data were generated. Reported are rejection frequencies of a panel MW test for the null hypothesis of a unit root in the idiosyncratic error term $\hat{\varepsilon}_{it}^{pc}$, which is obtained from using PANIC on the composite error term \hat{e}_{it} of the CCEP and CCEPnl estimates. Each experiment is based on 1000 iterations.

The overall picture that emerges from the simulation results is that a PANIC cointegration test on the composite error term \hat{e}_{it} of the CCEP-type estimators is an adequate approach to testing for cointegration in our setting. However, it also shows that care should be taken when interpreting p -values in a sample as small as ours as the PANIC test is somewhat oversized. This suggests that we should be a bit more conservative and reject the null of no cointegration only at sufficiently low levels of significance.

5 Estimation results

Our estimation results are reported in Table 8. As outlined in Section 2.3 we consider four different specifications depending on the variables included in w_{it} . In the first four columns of Table 8, we report CCEP estimation results

for the linear model in equation (6). Using these results we can thus only test the direct effects of fiscal policy on TFP. In the last four columns of Table 8, we report CCEPnl estimates for the non-linear model in equation (12). This approach allows for time-variation in countries' access to world technology and thus for fiscal policy to have also indirect effects. In what follows, we first motivate some of the basic choices that we made in our estimations. Then we discuss our results for the direct and the indirect effects of fiscal policy on TFP.

5.1 Basic Choices

The non-linear specification in equation (12) is richer than the linear specification in (6) since it explores the time-variation in countries' access to global technology. However, the CCEPnl estimator used to estimate the non-linear model requires a decision on the total number of unobserved common factors. Therefore, we first look at the empirical relevance of the common factors in the CCEP composite error term \widehat{e}_{it} defined in equation (18). Panel (a) in Table 7 reports the cross-sectional correlation in output $\ln Q_{it}$ and in the CCEP composite error term \widehat{e}_{it} after taking out the contribution of $r = (0, 1, 2, 3)$ common factors. For $r = 0$, this is the cross-sectional correlation in the original series, while for $r > 0$ this is the cross-sectional correlation in the idiosyncratic part calculated using PANIC with $r = (1, 2, 3)$. The results show that one factor seems to be sufficient to remove the cross-sectional dependence from output and the CCEP composite error term. To analyse the contribution of the estimated common factors, panel (b) of Table 7 reports the fraction of the total variance explained by the common factors for different values of r . The results show that the first factor explains about 50% of the variation. When adding a second factor, this fraction increases to 60%. As the explanatory power by construction increases with the number of factors, information criteria with an appropriate penalization for the number of factors are provided by Bai and Ng (2002). As outlined above, we prefer their BIC_3 . The results reported in panel (c) of Table 5 clearly point to one common factor in the error terms of each of the four specifications. As such, in the remainder we assume a single common factor when using CCEPnl. To visualize our proxy for the unobserved worldwide available level of technology, Figure 1 plots the estimated common component from the CCEPnl estimator in specification 1. It exhibits clear non-stationary behavior, with an annual growth rate of 1.23% over the period 1970-2012.

Table 7: Determining the number of relevant common factors

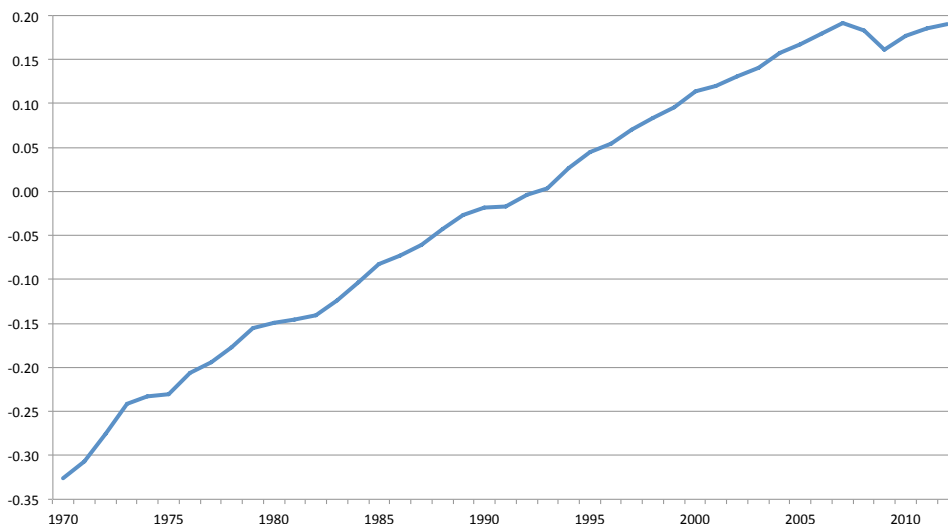
Sample period: 1970-2012, 15 OECD countries

(a) Cross-sectional correlation left after taking out r factors										
	$\ln Q_{it}$	\hat{e}_{it}^{S1}	\hat{e}_{it}^{S2}	\hat{e}_{it}^{S3}	\hat{e}_{it}^{S4}	$\Delta \ln Q_{it}$	$\Delta \hat{e}_{it}^{S1}$	$\Delta \hat{e}_{it}^{S2}$	$\Delta \hat{e}_{it}^{S3}$	$\Delta \hat{e}_{it}^{S4}$
$r = 0$	0.98	0.99	0.99	0.98	0.99	0.53	0.45	0.46	0.36	0.45
$r = 1$	-0.05	-0.06	-0.06	-0.06	-0.06	-0.06	-0.03	-0.01	-0.02	-0.04
$r = 2$	-0.06	-0.06	-0.06	-0.06	-0.05	-0.05	-0.03	-0.01	-0.03	-0.03
$r = 3$	-0.04	-0.05	-0.05	-0.06	-0.06	-0.06	-0.05	-0.04	-0.05	-0.06

(b) Variation explained by r factors					(c) BIC_3					
	$\Delta \ln Q_{it}$	$\Delta \hat{e}_{it}^{S1}$	$\Delta \hat{e}_{it}^{S2}$	$\Delta \hat{e}_{it}^{S3}$	$\Delta \hat{e}_{it}^{S4}$	$\Delta \ln Q_{it}$	$\Delta \hat{e}_{it}^{S1}$	$\Delta \hat{e}_{it}^{S2}$	$\Delta \hat{e}_{it}^{S3}$	$\Delta \hat{e}_{it}^{S4}$
$r = 0$	-	-	-	-	-	0.98	0.98	0.98	0.98	0.98
$r = 1$	0.56	0.49	0.50	0.40	0.49	0.56*	0.66*	0.65*	0.78*	0.66*
$r = 2$	0.64	0.58	0.59	0.49	0.56	0.58	0.73	0.72	0.86	0.72
$r = 3$	0.72	0.65	0.65	0.59	0.66	0.64	0.82	0.81	0.96	0.80

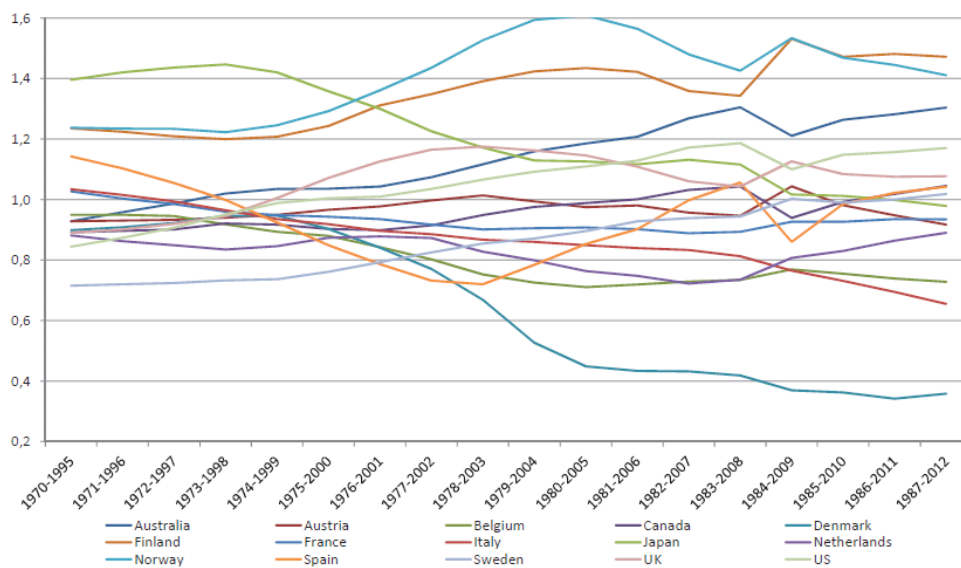
Notes: \hat{e}_{it}^{S1} , \hat{e}_{it}^{S2} , \hat{e}_{it}^{S3} and \hat{e}_{it}^{S4} are the CCEP composite error terms, defined in equation (18), taken from specification S1, S2, S3 and S4 respectively. Panel (a) reports the average cross-correlation $\bar{\rho}$ (see Table 1 for the definition) after taking out r common factors using PANIC. Panel (b) reports the average, over the N cross-sections, fraction of variation in the data explained by the first r factors. Panel (c) reports the BIC_3 of Bai and Ng (2002). The optimal number of common factors \hat{r} is selected using $\arg \min_{0 \leq r \leq 3} BIC_3(r)$ and is indicated with a ‘*’.

Figure 1: Common component from CCEPnl estimator



Notes: The common component is calculated by averaging $\hat{\lambda}_{it}^{\hat{r}ca2}$ from equation (16b) over the N cross-sections using the CCEPnl estimation results for specification S1. When using S2, S3 or S4 we get highly similar results.

Figure 2: Time-varying pattern for λ_i from rolling CCEP regressions



Notes: Time-varying estimates for λ_i are obtained from estimating equation (10) using a 26 years rolling window assuming a single common factor and normalizing $\bar{\lambda} = 1$. Reported are the results for specification S1. Similar results are obtained for S2, S3 and S4.

For most variables in Table 8 the estimated effects are quite similar for the CCEP and CCEPnl estimator, which explains why we prefer a single discussion of these effects below. For two reasons, we give a much larger weight to the CCEPnl results however. First, as already mentioned, the CCEPnl estimator allows for time-variation in countries' access to worldwide technology and therefore also for richer fiscal policy effects. Figure 2 demonstrates the relevance of this time-variation. In this figure we plot rolling window estimates for the factor loading λ_i computed from the CCEP estimates. More specifically, we estimate the restricted model in equation (10) assuming a single common factor and normalizing $\bar{\lambda} = 1$. Countries like Finland, Sweden and Norway show a clear upward trend in their absorptive capacity while others like Belgium, Denmark, Japan and Italy have experienced a notable drop in their access to world technology. By estimating the model in equation (12) we try to link this time-variation to a number of explanatory variables. A second reason for focusing on the CCEPnl estimation results is that the PANIC cointegration test results in Table 8 show that for the CCEP estimates we cannot reject the presence of a unit root in $\hat{\varepsilon}_{it}^{PC}$.¹¹ Note that despite this finding, we believe it is still useful to report these results as Banerjee and Carrion-i-Silvestre (2011) show that pooled CCEP coefficients can be estimated consistently even if there is no cointegration. For the CCEPnl estimates, the p -value for our cointegration test vary between 0.6 % and 3.7%. Taking into account the analysis of the small sample properties of the PANIC cointegration test in Section 4.4, we should be a bit careful with the interpretation of these p -values, though. However, given the very low p -values we obtain, especially for S1 and S4, we are fairly confident that, despite the fact that the PANIC test is somewhat oversized, we can reject the null hypothesis of no cointegration at a reasonably low level of significance. Note that

¹¹Allowing for more than one common factor in the PANIC cointegration test on the CCEP composite error terms does not yield a different conclusion, i.e. setting $r = 2$ yields p -values for the MW test on $\hat{\varepsilon}_{it}^{PC}$ equal to 0.47, 0.48, 0.85 and 0.16 in S1, S2, S3 and S4 respectively.

the results also show that we cannot reject a unit root in the common factor F_t^{pc} at the 5% significance level. This is an interesting result as it implies that in the non-linear case there is cointegration between $(y_{it}, x_{it}, F_t, z_{it}F_t)$ but not between (y_{it}, x_{it}) .

5.2 Direct effects of fiscal policy

Turning to the estimation results, we first discuss our parameter estimates for the standard factors of production, hours worked and private and public capital, before turning to the direct effects of fiscal policy. The indirect effects will be discussed in Section 5.3.

The results in Table 8 show decreasing returns to private and public capital and labor. Concentrating on the CCEPnl results, both the output elasticity to private physical capital and the output elasticity to hours worked are about 0.4. The output elasticity to public capital takes a positive and statistically significant value of about 0.06. These values are within the range of existing estimates in the literature, although for hours worked they are at the lower end.

The estimation results further reveal significant direct effects of fiscal policy on TFP. Very few exceptions notwithstanding, we observe consistency in the sign of the included fiscal variables when comparing the CCEP and CCEPnl results. As has been argued, we focus on the CCEPnl results. A number of interesting conclusions can be drawn. A first one concerns the key role of the budget balance. Our results strongly confirm earlier findings by Fischer (1993) that budget deficits harm TFP. In this respect, S2 reveals the impact of a rise in each of the four different government spending categories, and of a fall in the overall tax burden, financed by a change in the government budget balance (i.e. financed by borrowing). Both policies have significant negative effects. The only exception is the effect of a deficit financed increase in productive expenditures. There we observe no effect on TFP meaning that the positive effect of more productive expenditures counterbalances the negative impact on TFP of building up more debt¹². The results in S3 imply similar conclusions. Higher overall expenditures and a reduction of the tax burden, again financed by a lower budget balance, are associated with a significant fall in TFP. Note that since we control for personal and corporate taxes in S3, a tax reduction, which results in higher deficits, must be due to either lower consumption or other taxes. Finally, S4 also illustrates the key role for the budget balance. In this specification the coefficient on the budget balance measures the effect of an increasing budget balance (or deficit reduction) financed by a cut in unproductive government expenditures. This is found to have strong positive effects on TFP.

A second range of robust conclusions concerns the effects of changes in the structure of government expenditures or taxes, for given total expenditures and tax burden. S1 is informative on the TFP effects of restructuring on the expenditure side. Controlling for total expenditures, we observe a significant positive effect when shifting expenditures from consumption or other expenditures to productive expenditures. S4 confirms this result. As in this specification we keep the budget balance and tax burden constant, the implicit financing element is a shift

¹²For a correct interpretation of the results, note that the estimated coefficients are long-run elasticities. They indicate the percentage change in real output associated with a one percentage change in the share of a tax or expenditure category in GDP. To obtain the percentage change in output due to a one percentage point change in a tax or expenditure share, the estimated elasticity should be divided by the level of the tax or expenditure share. We report these shares for our sample in 2012 in Appendix A, where we discuss the construction of the data

Table 8: Regression results

Dependent variable: $\ln Q_{it}$		Sample period: 1970-2012, 15 OECD countries							
		CCEP				CCEPnl			
		S1	S2	S3	S4	S1	S2	S3	S4
Coefficient estimates									
<u>Standard Variables</u>									
$\ln K_{it}$	0.20*** (0.03)	0.17*** (0.03)	0.25*** (0.03)	0.19*** (0.03)	0.38*** (0.02)	0.40*** (0.02)	0.42*** (0.02)	0.44*** (0.02)	
$\ln G_{it}$	0.04 (0.03)	0.01 (0.03)	0.07*** (0.03)	-0.05 (0.03)	0.05*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	
$\ln H_{it}$	0.37*** (0.04)	0.34*** (0.04)	0.45*** (0.04)	0.45*** (0.04)	0.28*** (0.02)	0.38*** (0.02)	0.39*** (0.02)	0.40*** (0.02)	
<u>Direct effects</u>									
$\ln TotalExp_{it}$	-0.03 (0.04)		-0.15*** (0.02)		0.10*** (0.03)		-0.09*** (0.02)		
$\ln ProdExp_{it}$	0.05*** (0.01)	0.03** (0.01)		0.04*** (0.01)	0.02* (0.01)	0.001 (0.01)		0.02* (0.01)	
$\ln SocialExp_{it}$	-0.16*** (0.02)	-0.14*** (0.02)			-0.07*** (0.02)	-0.07*** (0.01)			
$\ln GovCons_{it}$		-0.06*** (0.02)				-0.03** (0.01)			
$\ln OtherExp_{it}$		-0.01* (0.01)				-0.01** (0.005)			
$\ln BudgetBalance_{it}$	0.02 (0.05)			0.29*** (0.05)	0.34*** (0.05)			0.27*** (0.03)	
$\ln Taxburden_{it}$		0.5 (0.04)	0.01 (0.06)			0.12*** (0.02)	0.12*** (0.04)		
$\ln PersonalTax_{it}$			-0.03 (0.03)	-0.07*** (0.02)			-0.03 (0.03)	-0.002 (0.01)	
$\ln CorporateTax_{it}$			-0.001 (0.004)	-0.01** (0.004)			0.01 (0.005)	0.01** (0.004)	
$\ln ConsTax_{it}$				0.01 (0.02)				0.08*** (0.01)	
$\ln OtherTax_{it}$				-0.01 (0.005)				-0.01** (0.005)	
<u>Indirect effects</u>									
$\ln StrRelative_{it}$					-0.61*** (0.15)	-0.65*** (0.17)	-0.79*** (0.20)	-0.60*** (0.15)	
$\ln HCap_{it}$					-0.37*** (0.08)	-0.37*** (0.09)	-0.42*** (0.10)	-0.38*** (0.08)	
$\ln Import_{it}$					0.31*** (0.11)	0.30*** (0.12)	0.33*** (0.13)	0.27*** (0.10)	
PANIC cointegration test (one common factor)									
ADF-GLS on \hat{F}_t^{pc}	-1.63 [0.77]	-2.05 [0.56]	-1.13 [0.91]	-1.59 [0.78]	-1.92 [0.63]	-2.05 [0.56]	-2.35 [0.40]	-2.15 [0.50]	
MW on \hat{e}_{it}^{pc}	30.92 [0.42]	30.72 [0.43]	27.47 [0.60]	21.08 [0.88]	52.7*** [0.006]	46.09** [0.03]	45.26** [0.037]	51.78*** [0.008]	

Notes: Standard errors are in parentheses, p -values are in square brackets. * ** and *** indicate significance at the 10%, 5% and 1% level respectively. Also see the notes to Table 2 for the PANIC test.

within expenditures. The coefficient on productive expenditures therefore captures the positive effect of a shift in expenditures towards more productive categories. Opposite results arise when shifting expenditures towards more social security expenditures. In S1 we find that this kind of shift has a negative impact on TFP. This is also

confirmed in S2, in which higher social expenditures are financed by building up debt. Finally, S2 also confirms that a restructuring from either social, consumption or other expenditures to productive expenditures would raise TFP. The former three categories have significantly negative elasticities, while the elasticity to productive expenditures is positive but not significant. The positive effect of productive expenditures on TFP is a well-established result in the literature (see Section 2.2 for references). The existing literature is much more ambiguous, however, about the effect of higher social expenditures. Our results support earlier findings by, among others, Hansson and Henrekson (1994) and Arjona et al. (2003). On the tax side, S3 reveals a negative effect on TFP when shifting consumption or other taxes towards more personal taxes. This is in line with existing literature (see among others Ferreira and Pessoa, 2007; Cournède et al., 2013). Note, however, that in S3 the effect is not statistically significant. S4 confirms the differential effects of different tax categories. The positive and significant effect on the share of consumption taxes in combination with the (insignificant) negative effect on personal income taxes, provides a clear indication for the potential gain in TFP from shifting personal income taxes to consumption taxes. As a final observation, our findings for corporate income taxes in S3 and S4 are counter-intuitive. According to our results in S3, shifting taxes to corporate income has a positive (although not significant) impact on TFP. This goes against the consensus in the literature (see e.g. Arnold et al., 2011). A possible explanation lies in the construction of the tax rates, as discussed in Section 3, which implies that the incentives for firms may not be adequately captured by the ratio of corporate income tax receipts to GDP.

Final results concerning the direct effects of fiscal policy on TFP relate to changes in the overall level of taxes and government expenditures, for a given budget balance. In S1, where the tax burden is the implicit financing element, the coefficient on total expenditures reveals the effect of a tax financed increase in government consumption and other expenditures as these variables are not controlled for in this regression. Although somewhat surprisingly, this coefficient shows up statistically significant and positive. One reason for this positive effect can be the financing element. Instead of being financed by building up debt, the increase in unproductive expenditures is explicitly financed by revenues. A complementary explanation is given by Angelopoulos et al. (2008), who show that an increase of government size may be growth promoting when public efficiency is high. This specific result of S1 is further analyzed in S4, where we see that the choice of tax instrument, to pay for these unproductive expenditures, is very important. An increase in unproductive expenditures financed by consumption taxes has a significant positive effect on TFP whereas when financed by other taxes (mainly property taxes) or personal taxes, the effect on TFP turns negative. These results are in line with the findings of Cournède et al. (2013) and further confirm that an appropriate classification into various categories is important when analyzing the impact of taxes.

5.3 Indirect effects of fiscal policy

In the non-linear case we explicitly allow for time-varying factor loadings by making them a function of country-specific variables. Each of the four different CCEPnl specifications includes three variables that are expected to drive a country's access to global technology. One of these variables is the relative statutory corporate tax rate, $StrRel_{it}$. In all non-linear estimations $StrRel_{it}$ has a significant negative indirect effect on TFP. Reducing the corporate tax rate therefore seems to be an effective fiscal policy tool for a country to stimulate its absorptive capacity and raise

TFP (at least if other countries do not respond by changing their tax rate accordingly). In this sense, our results are in line with earlier work by e.g. Hajkova et al. (2006). Significant positive effects on a country’s access to global technology also follow from an increase in openness, i.e. a higher import share in GDP. If countries reduce barriers to trade, the import of embodied technology will be facilitated and access to world technology will be higher. This will enhance TFP. Our evidence here confirms the importance of international R&D spillovers via imports of goods emphasized before by among others Coe et al. (2009). Finally, and unexpectedly, our results point to a negative effect from the share of tertiary educated people in a country on its capacity to absorb world technology. Given the existing literature (e.g. Nelson et al., 1966; Coe et al., 2009), this result is most surprising. A possible reason for this could be the limited time variation observed in $HCap_{it}$ in OECD countries meaning that the effect of human capital on λ_{it} may (to a large extent) already be captured by the time-invariant part, λ_{i0} . Moreover, due to a lack of data no measure for the quality of schooling could be included. This further weakens the relevance of our human capital measure $HCap_{it}$.

6 Conclusion

An important issue in the growth literature is the fact that TFP is largely unobserved. Existing empirical work on fiscal policy and economic activity typically employs ad hoc proxies for technology. We pursue an alternative, potentially promising way out of the omitted variables problem by exploiting the strong cross-sectional correlation observed in our data to identify TFP. We further explore the time-variation in a country’s access to a worldwide available level of technology. As such, next to direct effects we are able to identify indirect effects of fiscal policy on TFP through its impact on absorptive capacity. To deal with these indirect effects, we propose and implement a non-linear CCEP estimator.

Our estimation results demonstrate the key role of fiscal policy in the development of TFP. We find robust evidence for both direct and indirect effects, with the latter operating via countries’ access to the world level of technology and knowledge. A number of clear policy implications emerge, which we now briefly summarize. A first implication concerns the importance of sound fiscal policies, meaning budget balance (or even surplus) in the long-run. Expenditures have to be financed by government revenues. The only exception concerns deficit financed productive expenditures. According to our evidence, these contribute to public capital, and as a result raise the productivity of private capital and labor without harming TFP. A second key implication is that policy makers should not only strictly monitor the level of government expenditures and taxes, but also their structure. Our results support a restructuring of outlays from social transfers and public consumption to productive expenditures, and a shift of revenues from personal income taxes and corporate taxes to consumption taxes. The evidence that we obtain in favor of reducing corporate taxes mainly concerns the possibility of increasing a country’s capacity to absorb world technology. As to the latter, a clear final policy implication of our results is the importance to promote openness to world trade.

We end up with a number of nuances, induced by the fact that our analysis focuses on productivity and efficiency in the long-run. First of all, this focus implies that our evidence offers no guidance for fiscal policy, e.g. the use of deficit spending, as a stabilization instrument. Second, aggregate productivity is only one (although very

important) indicator of countries' performance. According to our evidence, a reduction of social transfers to finance higher productive expenditures or corporate tax cuts enhances productivity. It is up to policy makers, however, to evaluate also the possible negative effects on social cohesion and protection against poverty that may come with this productivity gain. A final element is the importance of cross-country coordination. Our evidence illustrates the possibility of a race to the bottom in corporate tax rates. By attracting FDI and improving a country's access to world technology, a corporate tax rate reduction may enhance the development of TFP. If other countries respond by also reducing corporate tax rates, however, this gain disappears. What remains are negative effects on the budget balance, which harm TFP.

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Appendix A Construction of data and data sources

Table A-1: Construction of data and data sources

Standard Variables			Data Sources
Name	Notation	Construction	Data Sources
Real GDP	Q_t	Original data	OECD, Economic Outlook 91, series GDPV
Private non-residential net capital stock	K_t	To construct private non-residential capital stocks, we use the perpetual inventory method as described in Kamps (2006)	OECD, Economic Outlook 91, series IBV
Real government net capital stock	G_t	To construct real government net capital stocks we use the perpetual inventory method as described in Kamps (2006)	OECD, Economic Outlook 91, series IGV
Total annual hours worked in the economy	H_t	Original data	The Conference Board, Total Economy Database, January 2013
Policy variables included in w_{it}			
Name	Notation	Construction	Data Sources
Total government expenditures as % of GDP	$TotalExp_{it}$	Expressed as a percentage of GDP	OECD Economic Outlook 91, series YPGT and GDP Average value in 2012: 48.14 % GDP
Productive gov. expenditures as % of GDP	$ProdExp_{it}$	Sum of nominal public expenditures on education, government fixed capital formation and government financed R&D, expressed as a percentage of GDP	Berger and Heylen (2011). See their appendix for further description. We update their data to 2012.
Gov. social security expenditures % of GDP	$SocialExp_{it}$	Nominal social security benefits paid by general government, as a percentage of GDP	Average value in 2012: 9.67 % GDP OECD Economic Outlook 91, series SSPG and GDP
Government consumption as % of GDP	$GovCons_{it}$	Government final consumption net of final cons. expenditures in education, expressed as a percentage of GDP	Average value in 2012: 15.42 % GDP Berger and Heylen (2011). See their appendix for further description. We update their data to 2012.
Government other expenditures as % of GDP	$OtherExp_{it}$	$TotalExp_{it} - ProdExp_{it} - SocialExp_{it} - GovCons_{it}$	Average value in 2012: 16.02 % GDP
Total Tax burden as % of GP	$Taxburden_{it}$	Total nominal tax revenues of general gov. expressed as a percentage of GDP	Average value in 2012: 7.02 % GDP OECD.Stat, Financial and Fiscal Affairs
Government budget balance as % of GDP	$BudgetBalance_{it}$	$Taxburden_{it} - TotalExp_{it}$	Average value in 2012: 37.57% GDP As this variable can be negative, we take the log of 1 plus the gov budget balance Average value in 2012 of 0.89

To be continued on the next page

Name	Notation	Construction	Data Sources
Personal taxes as % of GDP	$PersonalTax_{it}$	Total nominal tax revenues of general gov. of categories 1100 (taxes on income, profits and capital gains of individuals) 2000 (social sec. contributions) and 3000 (payroll taxes) of the OECD classification of taxes expressed as a percentage of GDP	OECD.Stat, Financial and Fiscal Affairs
Corporate taxes as % of GP	$CorporateTax_{it}$	Total nominal tax revenues of general gov. of category 1200 (corporate taxes on income, profits and capital gains) of the OECD classification of taxes expressed as a percentage of GDP	Average value in 2012: 21.36 % GDP OECD.Stat, Financial and Fiscal Affairs
Consumption taxes	$ConsTax_{it}$	Total nominal tax revenues of general gov. of category 5000 (taxes on goods and services) of the OECD classification of taxes expressed as a percentage of GDP	Average value in 2012: 3.27 % GDP OECD.Stat, Financial and Fiscal Affairs
Other Taxes as % of GDP	$OtherTax_{it}$	$Taxburden_{it} - PersonalTax_{it} - CorporateTax_{it} - ConsTax_{it}$	Average value in 2012: 10.3 % GDP Average value in 2012: 2.63 % GDP
Policy variables included in w_{it}			
Name	Notation	Construction	Data Sources
Statutory corporate income tax rate	STR_{it}	Combined corporate income tax rate, including both central and sub-central government taxes. Data on STR_{it} are used to construct $StrRel_{it}$	OECD Tax Database, Table II.1 for data starting in 1981 Data for 1970-1980 is taken from Berger and Heylen (2011)
Fraction of population with a higher degree	$HCap_{it}$	Tertiary level completed in % of population aged 15 and over	Barro and Lee (2010). Data are available for 1970, 1975, 1980, ..., 2010 Data for the intermediate years are calculated by interpolation
Import Share as a % of GDP	$Import_{it}$	Imports of goods and services expressed as a % of GDP	and data is extrapolated for 2011 and 2012 OECD Economic Outlook 91, series MGS and GDP

Appendix B Coefficients of correlation between corporate tax rate indicators

Table B-1: Correlation matrix

<i>Corp.taxreceipts</i> <i>GDP</i>	<i>Corp.taxreceipts</i> <i>GDP</i>	STR	EMTR	EATR
<i>Corp.taxreceipts</i> <i>GDP</i>	1.00			
STR	-0.17	1.00		
EMTR	0.08	0.64	1.00	
EATR	0.07	0.65	0.93	1.00

Note: Correlation across 15 countries over period 1981-2005.

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