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# Empirical essays on fiscal policy, growth and consumption

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To Sarah, Finn and Jack

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*Ruben Schoonackers*

# Nederlandstalige samenvatting

De financiële crisis die in de loop van 2007 uitbrak en in 2008 verscherpte, en de eruit voortvloeiende economische recessie hebben de overheidsfinanciën in de meeste geavanceerde economieën uitermate zwaar getroffen. Daardoor zijn in die landen, waaronder België, het financieringstekort en de schuld van de overheid fors gestegen. Sedertdien hebben vrijwel alle landen aanzienlijke inspanningen inzake begrotingsconsolidatie geleverd teneinde de onhoudbare ontwikkelingen een halt toe te roepen. Een terugkeer naar een situatie van houdbare overheidsfinanciën zal echter de komende jaren in de meeste landen nog extra inspanningen vereisen. Die nood aan extra saneringsmaatregelen heeft bij velen de vrees aangewakkerd voor een nog diepere en langere economische recessie.

De economische literatuur biedt echter geen eenduidig antwoord op de vraag naar het verband tussen het budgettair beleid en de economische bedrijvigheid. Belangrijk is om een onderscheid te maken tussen de impact op korte termijn en die op lange termijn. Zo blijkt op lange termijn een begrotingsconsolidatie vaak positieve gevolgen te hebben op de economische activiteit. De grootte van deze effecten hangt natuurlijk af van de precieze omstandigheden en de aard van de genomen consolidatie-maatregelen.

Het eerste hoofdstuk van dit proefschrift analyseert daarom de impact van diverse saneringsmaatregelen op de economische groei via het kanaal van de totale factorproductiviteit (TFP). Dit gebeurt voor een groep van 15 OESO landen over de periode 1970-2012, met behulp van een geaggregeerde productiefunctiebenadering. Aangezien het niet vanzelfsprekend is om de TFP in een economie te kwantificeren, staat of valt de adequaatheid van de empirische analyse met hoe hiermee wordt omgegaan. Zo leidt het buiten beschouwing laten van de TFP tot inconsistente ramingen indien de TFP gecorreleerd is met de waargenomen verklarende variabelen en zelfs tot een *spurious regression* probleem indien ze niet stationair is. In bestaand empirisch werk over begrotingsbeleid en economische groei wordt doorgaans gebruik gemaakt van ad hoc proxies voor technologie (bijvoorbeeld een gemeenschappelijke tijdstrend). In dit hoofdstuk wordt een alternatieve, mogelijks veelbelovende, oplossing naar voren geschoven voor het probleem van de meetbaarheid van de TFP. Concreet wordt gebruik gemaakt van de aanwezigheid van de sterke cross-sectionele correlatie in de gegevens om de TFP te identificeren. Dit laat ons toe om het wereldwijd beschikbaar niveau van technologie en kennis te vatten. Verder wordt voor dit wereldwijde technologieniveau zowel de landspecifieke toegang als de variatie hiervan over de tijd onderzocht. Op die manier kunnen naast de directe effecten van het begrotingsbeleid op de TFP ook indirecte effecten worden geïdentificeerd. Deze lopen namelijk via de impact van het budgettair beleid op het vermogen van een land om wereldwijde technologie te absorberen.

De resultaten van het gevoerde empirisch onderzoek onderstrepen de sleutelrol van het begrotingsbeleid in de ontwikkeling van de TFP. We vinden sterke bewijzen van zowel directe als indirecte effecten en er komen een aantal duidelijke beleidsimplicaties naar voren. Een eerste betreft het belang van een gezond begrotingsbeleid, waarmee wordt bedoeld dat de begroting op lange termijn in evenwicht is (of zelfs in overschot). Uitgaven moeten worden gefinancierd met overheidsontvangsten. Productieve uitgaven (zoals overheidsinvesteringen, onderwijs en R&D uitgaven) vormen hierop een uitzondering. Zij kunnen ook met schuldopbouw gefinancierd worden. Een tweede belangrijke implicatie is dat beleidsmakers niet alleen strikt zouden moeten toezien op het niveau van overheidsbestedingen en belastingen, maar ook op de structuur ervan. Onze resultaten verdedigen een verschuiving van de uitgaven van sociale overdrachten en de overheidsconsumptie naar meer productieve uitgaven, en een verschuiving van de inkomsten- en de vennootschapsbelasting naar verbruiksbelastingen. Het bewijs dat geleverd wordt ten gunste van een verlaging van de vennootschapsbelasting heeft voornamelijk te maken met het verhogen van het vermogen van een land om wereldwijde beschikbare technologie te absorberen. In verband hiermee is een laatste duidelijke beleidsimplicatie dat openheid voor de wereldhandel absoluut moet worden aangemoedigd. Het stimuleren en bestendigen van de landspecifieke toegang tot wereldwijd beschikbare technologie leidt immers tot een duurzame groei van de TFP en dus ook van de economische groei.

De effecten van het begrotingsbeleid via het kanaal van de TFP zijn invloedrijk aangezien op lange termijn de TFP de belangrijkste determinant is van de economische groei. Tijdens de voorbije decennia is de stijging van de welvaart per capita in geavanceerde economieën grotendeels toe te schrijven aan de algemene productiviteitstoename. Echter, in de ontwikkelde landen is de groei van de TFP reeds enkele jaren aan het vertragen. Die vertraging brengt uiteraard grote bezorgdheid teweeg, aangezien zo het toekomstig groeipotentieel van de economie wordt aangetast. Om de tendens te keren kunnen beleidsmakers inzetten op onderzoek en ontwikkeling (O&O). De rol van O&O als stimulans voor groei en technologische vooruitgang is gekend. Die stimulans is zowel direct, via de impact van O&O kapitaal op de evolutie van de TFP en innovatie binnen een land, als indirect, door de absorptiecapaciteit van landen te vergroten en zo de transfer van wereldtechnologie te stimuleren.

In de huidige context van budgettaire saneringen en toenemende efficiëntiedruk stelt zich de vraag welke beleidsopties het meest effectief zijn in het stimuleren van private O&O-investeringen. Dit wordt onderzocht in hoofdstuk 2 voor een groep van 14 OESO landen. De vraag is relevant, ook omdat de voorgestelde beleidsopties talrijk zijn. Zo kunnen overheden gebruik maken van een breed arsenaal aan steunmaatregelen gaande van directe subsidies of publieke O&O-uitgaven tot meer indirecte fiscale stimuli. De effectiviteit van deze beleidsinstrumenten werd reeds uitgebreid empirisch onderzocht, ook aan de hand van macrodata. Echter, in de bestaande empirische literatuur wordt één belangrijke potentiële determinant van O&O bedrijfsinvesteringen vaak vergeten nl. de mate van loondruk of loonmatiging in een economie.

Het debat rond de wenselijkheid van loonmatiging is in landen als België en Nederland soms erg heftig en vormt vaak het centrum van conflict tussen werknemers en werkgevers. Voorstanders wijzen traditioneel op de positieve effecten op werkgelegenheid, competitiviteit en exportprestaties. Vanuit een langetermijnperspectief is echter ook de impact van loonmatiging op de innovatie-inspanningen in een economie belangrijk. Zo argumenteren voorstanders dat loonmatiging noodzakelijk is om bedrijfswinsten op peil te houden en aldus voldoende incentives en middelen te vrijwaren voor O&O-investeringen. Anderen betwisten evenwel deze visie. Zij stellen dat een focus op loonmatiging de overlevingskansen van niet-innovatieve bedrijven verhoogt, en aldus het proces van *creative destruction* verlamt. Een regime van hoge loondruk zou veeleer gunstig zijn voor innovatie. Niet innoveren zou dan immers geen optie meer zijn. De economische theorie biedt dus geen uitsluitsel over de impact van loonmatiging op private O&O-uitgaven. Maar wat tonen onze resultaten?

Een empirische analyse over de periode 1981-2012 duidt aan dat loonmatiging niet langer kan ingeroepen vanuit de idee dat dit de O&O-bedrijfsinvesteringen stimuleert. In de Europese (Belgische, Nederlandse) context van open economieën en rigide arbeidsmarkten geldt eerder het omgekeerde nl. overdreven loonmatiging ontmoedigt innovatie. Dit impliceert evenwel niet dat een toename van de loondruk dient aangemoedigd te worden. Excessieve loondruk kan immers nadelig zijn op andere vlakken, zeker op korte en middellange termijn (concurrentiekracht, tewerkstelling). Alternatieve instrumenten om O&O-bedrijfsinvesteringen te stimuleren dragen dus de voorkeur. Idealiter wordt eerder gebruik gemaakt van fiscale maatregelen of gerichte investeringen in hoger onderwijs. Publieke of universitaire O&O-investeringen zijn op hun beurt dan weer neutraal voor private initiatieven: er is *crowding out* noch additionaliteit. Tot slot tonen onze resultaten opnieuw het belang aan van het vermogen van een economie om wereldwijd beschikbare technologie te absorberen. Voor de Europese landen is dit namelijk een belangrijke determinant in het verklaren van verschillen in innovatie-investeringen tussen landen.

Hoofdstuk 1 en 2 bespreken beiden beleidsopties ter stimulering van duurzame langetermijn economische groei. Uiteraard dient niet louter gefocust te worden op de lange termijn. Op korte termijn kunnen bepaalde budgettaire keuzes en saneringsinspanningen nadelige gevolgen hebben op de welvaart binnen een land. Zo blijkt uit de budgettaire multiplicatoreffecten dat op de korte termijn consolidatiemaatregelen een remmend effect hebben op de economische bedrijvigheid. De exacte grootte van de multiplicatoren is afhankelijk van de specifieke maatregelen en omstandigheden. Zo wordt de impact o.a. beïnvloed door de mate waarin huishoudens en ondernemingen te maken hebben met liquiditeits- of kredietbeperkingen. Een groter aandeel van de zogeheten niet-Ricardiaanse huishoudens zal leiden tot sterkere negatieve effecten op korte termijn. Niet-Ricardiaanse huishoudens zijn dus huishoudens die niet in staat zijn hun consumptie in de tijd af te vlakken teneinde het hoofd te bieden aan een daling van hun beschikbaar inkomen als gevolg van sommige consolidatiemaatregelen.

Een mogelijke invalshoek om het aandeel niet-Ricardiaanse agenten te vatten is om de gevoeligheid van de geaggregeerde consumptiegroei ten opzichte van de verwachte beschikbare inkomensgroei te bepalen, ook gekend als *excess sensitivity.* Indien alle huishoudens Ricardiaans zijn en dus hun permanente inkomen consumeren dan is de consumptiegroei onvoorspelbaar. Echter, indien economische huishoudens te maken hebben met liquiditeits- of kredietbeperkingen, indien ze aan voorzorgsparen doen of zich enkel op de korte termijn richten, dan zal de verwachte inkomensgroei mede de consumptiegroei voorspellen.

In hoofdstuk 3 trachten we dan ook de *excess sensitivity* te schatten voor de Verenigde Staten aan de hand van kwartaaldata over de periode 1954-2014 om zo een beeld te krijgen van het aandeel niet-Ricardiaanse huishoudens in de economie. Zowel de financiële liberalisatie als de deregulering van de financiële markten zouden aanleiding moeten geven tot een daling van de *excess sensitivity* over de tijd. Dit zou dan ook kleinere kortetermijn begrotingsmultiplicatoren impliceren en dus budgettaire saneringen minder pijnlijk maken. Via Bayesiaanse modelselectie wordt in dit hoofdstuk nagegaan of dit effectief klopt en of de waargenomen daling relevant is. Onze empirische resultaten spreken deze daling over de tijd tegen en wijzen eerder op een stabiele *excess sensitivy* parameter van ongeveer 0.23.

Dit impliceert dat begrotingsconsolidaties op korte termijn een grotere negatieve impact hebben op de economische bedrijvigheid. Financiële liberalisatie heeft volgens onze resultaten geen verzachtende invloed uitgeoefend op het aandeel niet-Ricardiaanse economische agenten. Interessant voor toekomstig werk is om na te gaan of dit resultaat extrapoleerbaar is naar de Europese setting.

# Contents



[1]This chapter is joint work with Gerdie Eveaert and Freddy Heylen and is published in Empirical Economics, 49(2), p. 605-640.

[2]This chapter is joint work with Tim Buyse and Freddy Heylen.

[3]This chapter is joint work with Gerdie Everaert and Lorenzo Pozzi.

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# Chapter 0

# Introduction

The financial crisis that erupted during 2007 and intensified in 2008, and the ensuing economic recession, caused a marked deterioration in the public finances of most of the advanced economies. That resulted in a sharp increase in the financing requirement and public debt in those countries. Since then, almost all countries have made a considerable effort to achieve fiscal consolidation in order to end the unsustainable developments. However, restoring sustainable public finances will entail additional efforts in most countries in the years ahead. At the same time, fear has risen that all these consolidation programs may undermine domestic demand and prolong the weakness in economic activity.

The economic literature on the effects of fiscal consolidation is very extensive. However, it does not offer a clear answer to the question of the link between fiscal policy and economic activity. The impact in fact depends very much on circumstances, which may vary considerably over time and from one country to another. It is also crucial to distinguish between the short-term and the long-term impact. In the long run fiscal consolidation has undeniable positive effects on economic growth. Of course, the magnitude of these effects depends on the characteristics of the implemented measures.

In the first chapter of this dissertation, we therefore analyse the impact of different budgetary instruments, used to continue consolidating public finances, on long-run output per capita via the transmission channel of total factor productivity. This is done for a panel of 15 OECD countries over the period 1970-2012, using an aggregate production function framework. An important issue when estimating a production function 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 (such as a common time trend). Here, we pursue an alternative and promising way out of the omitted variables problem by exploiting the strong cross-sectional dependence observed in our data. This enables us to capture the common component in TFP, which represents the world available level of technology and knowledge. This way of looking at TFP is inspired by Parente and Prescott (2002) who 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. So, although there is a common worldwide technology level, TFP may grow at different rates across countries due to differences in countries' absorptive capacity. These differences can be explained by country-specific institutions and political factors. To the extend that these factors change over time, absorptive capacity is also time-varying. As such, next to direct effects of fiscal policy on TFP, our empirical analysis also allows for indirect effects. These indirect effects run through the impact of fiscal policy on a country's absorptive capacity.

Methodologically, to capture both direct and indirect effects we propose and implement a nonlinear version of the CCEP estimator of Pesaran (2006). We further suggest to test for cointegration using the panel analysis of nonstationarity in idiosyncratic and common components (PANIC) on the composite error terms from the CCEP regressions. A small-scale Monte Carlo simulation shows that our proposed estimator has satisfactory small sample properties.

The results of the empirical analysis demonstrate the key role of fiscal policy in the development of TFP. We find robust evidence for both direct and indirect effects and a number of clear policy implications emerge. A first implication concerns the importance of sound fiscal policies, meaning government budget should be in balance (or even surplus) in the long run. Expenditures thus have to be financed by government revenues. The only exception concerns deficit financed productive expenditures (like public investment, R&D expenditures, schooling). 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 analysis supports 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. This result also points to the necessity of cross-country tax coordination because our evidence illustrates the possibility of a race to the bottom in corporate tax rates. By attracting foreign direct investments and improving 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, this gain disappears. What then remains are negative effects on the budget balance which harm TFP and output per capita. Finally, our results point to an average annual growht rate of 1.23 % for the common component of TFP. Increasing access to this source of sustainable growth is thus very fruitful and should be a priority for policy makers. Related to that, a clear final policy implication to increase a country's absorptive capacity is to promote openness to world trade.

The impact of fiscal policy on TFP is very important as in the long run TFP is the sole sustainable source of economic growth. However, for some years now TFP growth has been slowing down at macroeconomic level in all developed countries, and particularly in Europe. This deceleration is a source of major concern, because it affects not only the current situation of our economies but also their future growth potential. To restore TFP growth, policy makers should focus on stimulating research and development (R&D). This was already stressed by (Griliches, 1979, p.115) who points to R&D as “one of the few variables which public policy can affect in the future”. Boosting R&D intensity is indeed one of the top priorities of OECD countries today. For example, the Europe 2020 targets include that 3 % of the EU's GDP has to be invested in R&D and innovation (public and private combined) by 2020. The role of R&D in enhancing TFP and economic growth is well known i.e. in addition to stimulating growth directly through innovations, it increases a country's absorptive capacity which encourages international technology transfers.

Nevertheless, in the current environment of restoring sustainability of public finances and search for an increasing efficiency of public policy, the question arises which policy options are most effective in stimulating private R&D investment. Chapter 2 of this dissertation therefore analyses the effects of different policies on aggregate business funded and performed R&D investment in a panel of 14 OECD countries since 1981. To stimulate private R&D intensity, governments have a whole set of different instruments at their disposal. They can be subvidided in direct support (such as public sector R&D and direct R&D subsidies) and indirect support (such as R&D tax incentives).

However, one possible determinant of private R&D spending is often forgotten, i.e. the impact of wage pressure. The monitoring of wage formation is an important feature of many OECD countries' economic policy as it has a direct impact on employment an a country's competiveness. An important additional element, especially from a long-run perspective, is the possible impact of wage formation on a country's innovative capacity. Arguments in favour of wage moderation come mostly from an employer perspective and point to wage moderation as an important factor to maintain firm probability, which is a key condition for investment in R&D. Others have argued that an excessive focus on wage moderation may kill incentives to innovate as this increases the survival probability of the least innovative firms and retard the process of creative destruction. Using the framework of Ulph and Ulph (1994), we can reconcile both arguments. In the Ulph and Ulph (1994) - model, the main factor driving firms' innovation efforts is the expected difference between the profits that the firm can earn once it has successfully innovated and the profits that it would earn otherwise. In this setup high (excessive) wages represent a 'tax' that unions impose on the investment and the success of the firm. Lower R&D investment would be the result. However, we argue that in some cases high wage pressure no longer reduces, but raises the profit differential between innovating and not innovating. The reason is the very negative outcome in the non-innovating case. We expect this positive effect of high wage pressure to exist mainly in a very competitive environment and when firms lack the flexibility to adjust their (expensive) labour force. It will be exactly in such an environment that high wages and lack of innovation imply huge losses and the risk of bankruptcy. In these economies innovation will be firms' only competitive strategy.

To measure the impact of wage moderation and other more traditional policies on business R&D, wee also need to control for technology and knowledge spillovers. These spillovers affect firms' private returns to R&D and thus business R&D investment. Therefore, to capture the largely unobserved world level of technology and knowledge the same approach is used as in chapter 1, i.e. the unobserved common component is captured by exploiting the strong cross-sectional dependece present in the data.

Our empirical analysis shows that stimulating private R&D intensity can no longer be invoked to justify wage moderation. The policy implications of our results include a warning against excessive wage moderation in highly open economies with rigid labour markets. Even though wage moderation may promote employment in the short run, it may undermine the economy's innovative capacity and productivity in the long run. However, in our view our findings also provide no arguments in favour of excessive wage pressure. In rigid labour markets the loss of employment that excessive wages may cause in the short run, may persist in the longer run due to for example hysteresis effects in bad times. To promote business investment in R&D, our empirical results suggest better alternatives, in particular tax incentives, well-chosen innovation subsidies and the development of high skilled human capital. Finally and in line with chapter 1, the analysis reveals the importance of a country's capacity to absorb world technology. The results show that, especially for the European countries, acces to the unobserved common component is an important factor in explaining innovation differences across countries. Chapter 1 points to corporate tax policy and reducing barriers to trade as strategies to increase the absorptive capacity but given its high relevance, additional research should be done to determine all possible determinants of the capacity to absorb world technology.

Chapter 1 and 2 both discuss policy options to promote long-term sustainable growth. However, the short-run implications of these policy measures should also be analysed as certain budgetary choices and consolidation measures could hurt economic activity in the short run. Most econometric models and empirical studies show that the fiscal multipliers, which indicate the extent to which a particular fiscal stimulus influences the growth of activity, have a positive sign in the short term. Generally, an expansionary fiscal policy can stimulate economic activity in the short term, while consolidation measures have a negative impact. However the short-term multiplier effects vary according to the different instruments and the specific circumstances. As such, the scale of the short-term multipliers is also influenced by the degree to which households and businesses face liquidity or credit constraints. A larger proportion of non-Ricardian households is reflected in higher fiscal multipliers. Non-Ricardian households are households which cannot smooth out their consumption over time in response to a decline in their disposable income resulting from certain consolidation measures.

A potential angle to capture the proportion of non-Ricardian households is to measure the sensitivity of aggregate consumption growth with respect to expected disposable income growth. Traditional permanent income and life cycle models of consumption predict that aggregate consumption growth should follow a random walk. However, when economic agents face liquidity constraints, are myopic or have precautionary saving motives, aggregate consumption growth is excessively sensitive to anticipated disposable income growth.

In chapter 3 we will estimate this degree of excess sensitivity (ES) to get an idea on the importance of the fraction of non-Ricardian consumers. This is done for the United States using quarterly data since 1954. More specifically, we relax the assumption of a constant ES parameter in favor of a time-varying specification. The reason being that financial liberalisation and the development of financial markets could have led to a decrease in ES over time. Further on, and following the recent literature, we take into account other forms of aggregate consumption predictability and we adequately deal with both measurement error and time aggregation to obtain valid estimates of the ES parameter. Finally we test whether the time variation in the degree of ES is relevant, using Bayesian model selection for unobserved components in state space models.

Our results show that when estimating our empirical specification, the excess sensitivity parameter turns out to be stable around 0.23 over the entire sample period. This implies that financial liberalisation and the deregulation of financial markets had no mitigating effect on the proportion of non-Ricardian consumers in the economy. Moreover, this result has also implications for the short-term impact of consolidation measures. In this scenario, a reduction in transfers, such as social benefits, has a much more negative effect compared to the scenario where the proportion of non-Ricardian households would have been absent. Of course, additional research would be interesting to test whether the ES results for the United States can be extrapolated to Europe.

# Chapter 1

# Fiscal policy and TFP in the OECD: measuring direct and indirect effects [1]

This chapter 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 modeling 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.

## 1.1 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

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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 Domenech (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 chapter 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, Bleaney, and Gemmell (1999), Romero-Avila (2006) and Arnold, Brys, Heady, Johansson, Schwellnus, and Vartia (2011). In this chapter, 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, Fuertes, and Smith, 2006; Westerlund, 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, Fuertes, and Smith, 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, Pesaran, and Yamagata (2011) this approach is also valid in a non-stationary panel context. A second contribution of this chapter 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, Kalemh-Ozcan, and Volosovych (2008), Coe, Helpman, and Hoffmaister (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 chapter is organized as follows. Section 1.2 describes and models the direct and indirect effects of fiscal policy on TFP. Section 1.3 discusses the properties of the data. Section 1.4 outlines the econometric model and methodology. Section 1.5 includes and discusses our empirical results. Section 1.6 concludes.

## 1.2 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.

### 1.2.1 Aggregate production function and modeling TFP

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

$$Q_{it} = A_{it} K_{it}^{\alpha_1} G_{it}^{\alpha_2} H_{it}^{\alpha_3}, \tag{1.1}$$

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 (1.1) in logs yields

$$\ln Q_{it} = \ln A_{it} + \alpha_1 \ln K_{it} + \alpha_2 \ln G_{it} + \alpha_3 \ln H_{it}. \tag{1.2}$$

The key variable of interest in equation (1.2) is the level of TFP. As $A_{it}$ is not observed, we model it through a common factor specification

$$A_{it} = e^{\gamma_i + w_{it}\delta + F_t \lambda_{it} + \varepsilon_{it}}, \tag{1.3}$$

in which we disentangle TFP into (i) a country-specific time-invariant unobserved technology term $\gamma_i$, (ii) a vector of country-specific observable variables $w_{it}$ (expressed in logs) with homogeneous impact $\delta$, (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 $\lambda_{it}$ which captures country $i$'s access to world technology $F_t$ and (v) an idiosyncratic random error term $\varepsilon_{it}$.

Common factor specifications for TFP, similar to equation (1.3), 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 $\lambda_{it}$ 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 $\lambda_{it}$ as

$$\lambda_{it} = \lambda_{i0} + z_{it}\lambda, \tag{1.4}$$

such that country $i$'s access to world technology consists of a time-invariant part $\lambda_{i0}$ 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 $\lambda_{it}$ (see Section 1.4.2) requires a decision on the number of common factors. We justify our choice of a single common factor when discussing the results in Section 1.5.1.

### 1.2.2 Measuring direct and indirect effects of fiscal policy

The empirical specification in equations (1.2)-(1.4) 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 $\delta$. 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 $\lambda$. Our specification imposes homogeneity in the impact of fiscal variables across countries. This assumption is fully supported by recent work of Gemmell, Kneller, and Sanz (2011)[2]. Moreover, the alternative of parameter heterogeneity would come at the cost of drastically 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.

#### 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, Lindh, and Ohlsson, 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, Bleaney, and Gemmell, 1999). There

[2]These 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 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).

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, Simpson, and Tomljanovich, 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, Ladaique, and Pearson (2003) and Romero-Avila and Strauch (2008), while others obtain a positive impact, e.g. Herce, Sosvilla-Rivero, and de Lucio (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 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, Brys, Heady, Johansson, Schwellnus, and Vartia, 2011). In line with the arguments raised by Arjona, Ladaique, and Pearson (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, Goujard, and Pina, 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).

### 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, Nicoletti, Vartia, and Yoo, 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, Fontagne, and Lahreche-Revil (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, Denison, Sato, and Phelps, 1966; Coe, Helpman, and Hoffmaister, 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 $\lambda_{it}$, 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, Helpman, and Hoffmaister, 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 $z_{it}$.

### 1.2.3 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, Bleaney, and Gemmell (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.

## 1.3 A first look at the data

### 1.3.1 Data and sources

We use data for a panel of 15 OECD countries over the period 1970-2012.[3] 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 1.B.

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 1.2.3). 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, Henriksen, and Storesletten (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.[4] 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 1.A 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

[3]The 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 Kingom and United States.

[4]As 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.

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 1.A) 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 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 1.A, the STR shows strong positive correlation with the EMTR and EATR, such that it should be considered to be an adequate proxy.

### 1.3.2 Properties of the data

As a guide to selecting the most appropriate estimation method in Section 1.4 below, we first look at two important properties of the data: the degree of cross-sectional dependence and the order of integration.

#### Cross-sectional dependence

The modeling and identification of each country's TFP in equation (1.3) 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 1.1 therefore reports the average pairwise correlation coefficient ($\overline{\hat{\rho}}$) 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 1.1 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 1.1:** Cross-sectional dependence in the data

Sample period: 1970 -2012, 15 OECD countries

| | Levels | | | First-differences | | | | Levels | | | First-differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\widehat{\overline{\rho}}$ | CD | | $\widehat{\overline{\rho}}$ | CD | | | $\widehat{\overline{\rho}}$ | CD | | $\widehat{\overline{\rho}}$ | CD | |
| $\ln Q_{it}$ | 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 $\widehat{\overline{\rho}} = (2/N(N-1)) \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij}$ is the average of the country-by-country cross-correlation coefficients $\widehat{\rho}_{ij}$ (for $i \neq j$). $CD$ is the Pesaran (2004) test defined as $\sqrt{2T/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{ij}$, which is asymptotically standard normal under the null of cross-sectional independence. $p$-values are reported in square brackets.

### 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

$$x_{it} = d_{it} + f_t \pi_i + \xi_{it}, \tag{1.5}$$

where $f_t$ is an $r \times 1$ vector of $r$ common factors with country-specific factor loadings $\pi_i$, $\xi_{it}$ 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 $\xi_{it}$ 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 (1.5). 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 $\widehat{f}_t^{pc}$ and $\widehat{\xi}_{it}^{pc}$. These components can then be tested separately for unit roots. When there is only one factor, testing for a unit root in $\widehat{f}_t^{pc}$ 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, Fiess, and Ronald (2011), Costantini and Destefanis (2009) and Costantini, Demetriades, James, and Lee (2013).

**Table 1.2:** 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, Rothenberg, and Stock (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 $MQ_c^\tau$ (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.

The results of the PANIC unit root test are reported in Table 1.2. 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 ($\leq$ 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.[5]

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.

## 1.4 Econometric methodology

The empirical model outlined in Section 1.2 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 1.4.1. 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 1.4.2. Section 1.4.3 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 1.4.4.

### 1.4.1 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 (1.4) such that $\lambda_{it} = \lambda_{i0}$. Under this restriction, the empirical model can be obtained by substituting equation (1.3) into (1.2)

$$y_{it} = \gamma_i + F_t \lambda_{i0} + x_{it}\beta + \varepsilon_{it}, \tag{1.6}$$

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 $\varepsilon_{it}$ 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, Pesaran, and Yamagata (2011), we identify the unobserved common factors $F_t$ from the cross-section dimension of the data. Taking cross-sectional

[5] The 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.

averages of the model in equation (1.6) yields

$$\overline{y}_t = \overline{\gamma} + F_t\overline{\lambda}_0 + \overline{x}_t\beta + \overline{\varepsilon}_t, \tag{1.7}$$

where $\overline{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ and similarly for $\overline{\gamma}$, $\overline{\lambda}_0$, $\overline{x}_t$ and $\overline{\varepsilon}_t$. For notational convenience we assume a single common factor ($r = 1$) but the results straightforwardly generalize to multiple factors (see Pesaran, 2006). Equation (1.7) can then be solved for $F_t$ as

$$F_t = \frac{1}{\overline{\lambda}_0}\left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta - \overline{\varepsilon}_t\right), \tag{1.8}$$

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

$$\widehat{F}_t^{ca1} = \frac{1}{\overline{\lambda}_0}\left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta\right), \tag{1.9}$$

as a proxy for $F_t$. Given the assumption that $\varepsilon_{it}$ is a zero mean stationary error term which is uncorrelated over cross-section units, implying that $\operatorname*{plim}_{N\to\infty} \overline{\varepsilon}_t = 0$ for each $t$, we have that $\widehat{F}_t^{ca1} \xrightarrow{p} F_t$ for $N \to \infty$. 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 (1.9) 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 (1.6) by the cross-sectional averages of the observed data using equation (1.8)

$$y_{it} = \gamma_i + \left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta - \overline{\varepsilon}_t\right)\frac{\lambda_{i0}}{\overline{\lambda}_0} + x_{it}\beta + \varepsilon_{it}, \tag{1.10}$$

$$= \gamma_i^+ + \overline{y}_t\lambda_{i1} + \overline{x}_t\lambda_{i2} + x_{it}\beta + \varepsilon_{it}^+, \tag{1.11}$$

where $\gamma_i^+ = \gamma_i - \overline{\gamma}\lambda_{i0}\left/\overline{\lambda}_0\right.$, $\lambda_{i1} = \lambda_{i0}\left/\overline{\lambda}_0\right.$, $\lambda_{i2} = \lambda_{i0}\left/\overline{\lambda}_0\right.\beta$ and $\varepsilon_{it}^+ = \varepsilon_{it} - \lambda_{i0}\left/\overline{\lambda}_0\right.\overline{\varepsilon}_t$. Since $\varepsilon_{it}^+ \xrightarrow{p} \varepsilon_{it}$ for $N \to \infty$, the augmented model in equation (1.11) - ignoring any parameter restrictions - can be estimated with least squares (LS), an approach referred to as the CCEP estimator.[6]

Pesaran (2006) shows that, under appropriate regularity conditions, the CCEP estimator is consistent and asymptotically normal in stationary panel regressions. Kapetanios, Pesaran, and Yamagata (2011) show that these asymptotic results continu to hold in non-stationary panels provided that the idiosyncratic error term $\varepsilon_{it}$ is stationary. We outline our approach for testing whether this assumption (of cointegration) is satisfied in Section 1.4.3 below.

[6] Although equation (1.11) 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).

### 1.4.2 CCEPnl estimator for model with time-varying factor loadings

Allowing for a time-varying access to unobserved worldwide technology yields, from substituting equations (1.3) and (1.4) in (1.2), the following final empirical specification

$$y_{it} = \gamma_i + F_t \left(\lambda_{i0} + z_{it}\lambda\right) + x_{it}\beta + \varepsilon_{it}. \tag{1.12}$$

Again taking cross-sectional averages

$$\overline{y}_t = \overline{\gamma} + F_t \left(\overline{\lambda}_0 + \overline{z}_t\lambda\right) + \overline{x}_t\beta + \overline{\varepsilon}_t, \tag{1.13}$$

and solving for $F_t$

$$F_t = \frac{1}{\overline{\lambda}_0 + \overline{z}_t\lambda} \left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta - \overline{\varepsilon}_t\right), \tag{1.14}$$

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

$$\widehat{F}_t^{ca2} = \frac{1}{\overline{\lambda}_0 + \overline{z}_t\lambda} \left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta\right), \tag{1.15}$$

as a proxy for $F_t$. From $\operatorname*{plim}_{N\to\infty} \overline{\varepsilon}_t = 0$ for each $t$, we again have that $\widehat{F}_t^{ca2} \xrightarrow{p} F_t$ for $N \to \infty$ 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 (1.14) in (1.12) and using $\widehat{F}_t^{ca2}$ defined in equation (1.15) as a proxy for $F_t$ yields

$$y_{it} = \gamma_i + \frac{1}{\overline{\lambda}_0 + \overline{z}_t\lambda} \left(\overline{y}_t - \overline{\gamma} - \overline{x}_t\beta - \overline{\varepsilon}_t\right)\lambda_{it} + x_{it}\beta + \varepsilon_{it}, \tag{1.16a}$$

$$= \gamma_i + \widehat{F}_t^{ca2} \left(\lambda_{i0} + z_{it}\lambda\right) + x_{it}\beta + \varepsilon_{it}^{+}, \tag{1.16b}$$

where $\varepsilon_{it}^{+} = \varepsilon_{it} - \left(\lambda_{i0} + z_{it}\lambda\right) / \left(\overline{\lambda}_0 + \overline{z}_t\lambda\right) \overline{\varepsilon}_t$. We still have that $\varepsilon_{it}^{+} \xrightarrow{p} \varepsilon_{it}$ for $N \to \infty$, but the main difference compared to the 'unrestricted' augmented model in equation (1.11) is that the time-varying factor loading $\lambda_{it}$ requires estimating the 'restricted' augmented form in equation (1.16) 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 1.5.1 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 (1.16a) by minimizing the non-linear LS objective function.

$$S_{NT}\left(\lambda, \beta, \left(\gamma_1, \ldots, \gamma_N\right), \left(\lambda_{10}, \ldots, \lambda_{N0}\right)\right) = \sum_{i=1}^{N} \sum_{t=1}^{T} \varepsilon_{it}^{+'} \varepsilon_{it}^{+}. \tag{1.17}$$

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.[7] In a pure time series context there is already quite some literature on non-linear cointegration analysis, i.e. asymptotic theory for non-linear 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, Teräsvirta, and van Dijk (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, Urbain, and Wan (2012) formalize this estimator as the pooled non-linear least squares dummy variable estimator and derive its asymptotic properties, confirming the conjecture of González, Teräsvirta, and van Dijk (2005).

Similar to the estimation procedure in González, Teräsvirta, and van Dijk (2005), estimating the unknown parameters from the non-linear LS objective function in equation (1.17) can also be done by first calculating $\widehat{F}_t^{ca2}$ from equation (1.15), conditional on the unknown coefficients, and next estimating the augmented linear model in equation (1.16b), 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

[7] Note 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.

the unknown coefficients. As the error $\bar{\varepsilon}_t$ in the approximation of $F_t$ by $\widehat{F}_t^{ca2}$ shrinks to zero as $N \to \infty$, we conjecture that this non-linear procedure yields a consistent estimator for $(\lambda, \beta)$. The small sample properties of the proposed CCEPnl estimator are illustrated in Section 1.4.4 using a Monte Carlo simulation.

One additional complication is that the model is not identified as $\lambda_{it}$ and $\widehat{F}_t^{ca2}$ are not identified separately, only their product is. For instance, multiplying $\lambda_{it}$ by a constant $a$ while dividing $\widehat{F}_t^{ca2}$ by the same constant, which implies that $\lambda_{i0}$, $\overline{\lambda}_0$ and $\lambda$ are multiplied by the constant $a$, leaves the model in equation (1.16) unchanged as $\left(\widehat{F}_t^{ca2}/a\right)(a\lambda_{it}) = \widehat{F}_t^{ca2}\lambda_{it}$ or equivalently $\frac{a\lambda_{i0}+z_{it}a\lambda}{a\overline{\lambda}_0+\bar{z}_t a\lambda} = \frac{\lambda_{i0}+z_{it}\lambda}{\overline{\lambda}_0+\bar{z}_t\lambda}$. To solve this identification problem, we impose $\overline{\lambda}_0 = 1$, i.e. we normalize the average over all countries of the country-specific time-invariant access to worldwide technology to be one.

### 1.4.3 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 $\varepsilon_{it}$ in equation (1.6) or (1.12) is stationary (Kapetanios, Pesaran, and Yamagata, 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 $\beta$ but not for the heterogeneous coefficients $(\gamma_i, \lambda_{i0})$. 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

$$\widehat{e}_{it} = y_{it} - x_{it}\widehat{\beta} = (\gamma_i + F_t\lambda_{i0} + \varepsilon_{it})\widehat{\ }, \qquad (1.18)$$

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 $\varepsilon_{it}$. 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 (1.5), an obvious alternative to the CADF test is to apply the PANIC approach of Bai and Ng (2004).[8] 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 1.3.2). The main advantage of this approach is that the test whether the idiosyncratic errors $\varepsilon_{it}$ 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 1.5.1) 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 (1.5).

A cointegration test for the CCEPnl estimator for the model in equation (1.12) 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 (1.6), we conjecture that the CCEPnl estimator yields consistent estimates for the homogenous coefficients $\beta$ and $\lambda$ and therefore, using equation (1.15), also for $F_t$[9]. This implies that we can obtain a consistent estimate for the composite error term $e_{it} = \gamma_i + F_t\lambda_{i0} + \varepsilon_{it}$ as

$$\widehat{e}_{it} = y_{it} - x_{it}\widehat{\beta} - z_{it}\widehat{\lambda}\widehat{F}_t^{ca2} = (\gamma_i + F_t\lambda_{i0} + \varepsilon_{it})\widehat{\ }, \tag{1.19}$$

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

[8] Using the PANIC approach to testing for panel cointegration in the presence of common factors has also been suggested by Gengenbach, Palm, and Urbain (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.

[9] Note 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 (1.19) is identified.

of the PANIC approach applied to the CCEPnl composite error term in equation (1.19).

### 1.4.4 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, Pesaran, and Yamagata (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.

**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 1.5 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 (1.6) and (1.12) 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 1.8 in Section 1.5 below), when simulating according to the linear and non-linear DGP respectively. The idiosyncratic error term $\varepsilon_{it}$ is generated from the following AR(1) specification

$$\varepsilon_{it} = \theta\varepsilon_{i,t-1} + \psi_{it}, \quad \psi_{it} \sim N(0, \sigma_\psi^2), \tag{1.20}$$

for various values of $\theta$. To analyze the power of the PANIC cointegration test outlined in Section 1.4.3, we set $\theta = \{0; 0.8; 0.9\}$. This yields three different stationary processes for $\varepsilon_{it}$. As our estimate for the unobserved common factor $F_t$ is found to be non-stationary (see Section 1.5.1), these values for $\theta$ 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 $\varepsilon_{it}$ from a random walk process by setting $\theta = 1$ such that there is no cointegration. Using equation (1.20), we calibrate parameter values for $\sigma_\psi$ over the different values of $\theta$ by setting $\sigma_\psi$ 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 1.8. In the baseline simulation with $\theta = 0$, $\sigma_\psi$ is calibrated to be 0.02.[10] The other calibrated values for $\sigma_\psi$ are reported in the note to Table 1.4. 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 1.3.[11] 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 1.3 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 (1.12) 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 1.4. Starting with the power, this is found to be close to 100% for both the CCEP and CCEPnl estimator when $\varepsilon_{it}$ 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

[10] Since $\theta = 0$ 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 $\varepsilon_{it}$ are between -4% and 4% of real GDP.

[11] Simulation results for the CCEP estimator are available on request.

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%.

**Table 1.3:** 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 (1.12) using population parameters for the coefficients taken from the CCEPnl estimation results in Table 2.4. We further set $\theta = 0$ and $\sigma_\psi = 0.020$ in the DGP for the idiosyncratic error term $\varepsilon_{it}$ in equation (1.20). Each experiment is based on 1000 iterations.

### 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 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.

**Table 1.4:** Power and actual size of the PANIC cointegration test ($T$=43, $N$=15)

| | Nominal size | CCEP estimates S1 | S2 | S3 | S4 | CCEPnl estimates 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 (1.6) for the linear model, estimated using the CCEP estimator, and from equation (1.12) 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 2.4. When varying $\theta$ over the four cases $\theta = \{0; 0.8; 0.9; 1\}$ we calibrate $\sigma_\psi$ from equation (1.20) 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 $\widehat{\varepsilon}_{it}^{pc}$, which is obtained from using PANIC on the composite error term $\widehat{e}_{it}$ of the CCEP and CCEPnl estimates in the four different specifications. Each experiment is based on 1000 iterations.

*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 (1.6) and (1.12) 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 $\varepsilon_{it}$ generated from the AR(1) specification in equation (1.20) with $\psi_{it} \sim N(0,1)$. We again vary the values for $\theta$ 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 1.5. 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 $\theta$. Only for the sample $T$=43 and $N$=15, there is a small downward bias in the estimates for $\lambda$ when $\theta = 1$ but this disappears as the sample size grows larger. These results support our conjecture in Section 1.4.3 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 1.6. In line with the results in Section 1.4.4, 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 the sample size increases. This provides additional support for the validity of our PANIC cointegration test.

**Table 1.5:** CCEPnl estimates for varying $T$ and $N$

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

Notes: Data for $y_{it}$ are simulated from the DGP in equation (1.6) for the linear model and from equation (1.12) 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 $\varepsilon_{it}$ generated from the AR(1) specification in equation (1.20) 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.

**Table 1.6:** Power and actual size of the PANIC cointegration test for varying $T$ and $N$

| | Nominal | CCEP estimates | | | CCEPnl estimates | | |
|---|---|---|---|---|---|---|---|
| $T\,/N$ | size | 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 1.5 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 $\widehat{\varepsilon}_{it}^{pc}$, which is obtained from using PANIC on the composite error term $\widehat{e}_{it}$ 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 $\widehat{e}_{it}$ 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.

## 1.5 Estimation results

Our estimation results are reported in Table 1.8. As outlined in Section 1.2.3 we consider four different specifications depending on the variables included in $w_{it}$. In the first four columns of Table 1.8, we report CCEP estimation results for the linear model in equation (1.6). Using these results we can thus only test the direct effects of fiscal policy on TFP. In the last four columns of Table 1.8, we report CCEPnl estimates for the non-linear model in equation (1.12). 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.

### 1.5.1 Basic Choices

The non-linear specification in equation (1.12) is richer than the linear specification in (1.6) 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 (1.18). Panel (a) in Table 1.7 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 1.7 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 1.7 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 1.1 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.

For most variables in Table 1.8 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 1.2 demonstrates the relevance of this time-variation. In this figure we plot rolling window estimates for the factor loading $\lambda_i$ computed from the CCEP estimates. More specifically, we estimate the restricted model in equation (1.10) assuming a single common factor and normalizing $\overline{\lambda} = 1$. Countries like Finland, Sweden and

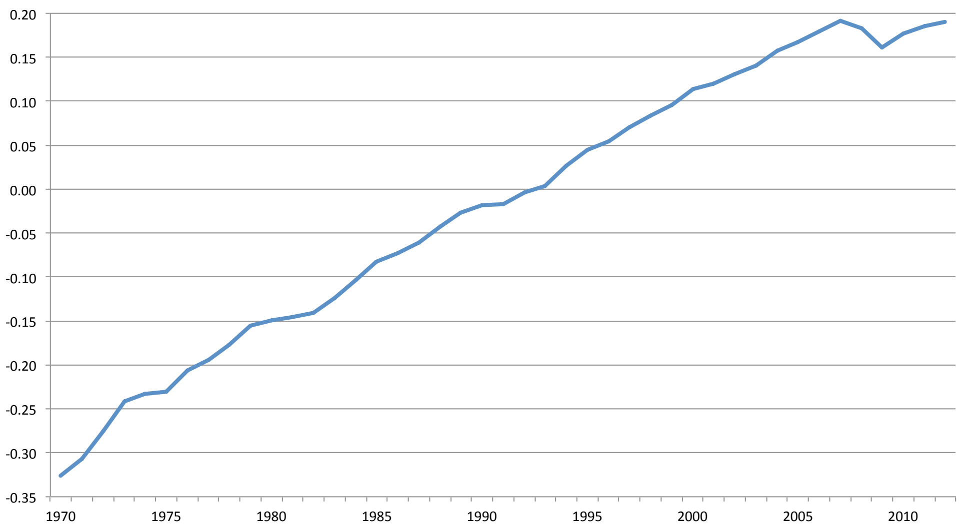
**Table 1.7:** Determining the number of relevant common factors

Sample period: 1970-2012, 15 OECD countries

| | (a) Cross-sectional correlation left after taking out $r$ factors | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\ln Q_{it}$ | $\widehat{e}_{it}^{S1}$ | $\widehat{e}_{it}^{S2}$ | $\widehat{e}_{it}^{S3}$ | $\widehat{e}_{it}^{S4}$ | $\Delta \ln Q_{it}$ | $\Delta\widehat{e}_{it}^{S1}$ | $\Delta\widehat{e}_{it}^{S2}$ | $\Delta\widehat{e}_{it}^{S3}$ | $\Delta\widehat{e}_{it}^{S4}$ |
| $r=0$ | 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) $BIC_3$ | | | | |
| | $\Delta \ln Q_{it}$ | $\Delta\widehat{e}_{it}^{S1}$ | $\Delta\widehat{e}_{it}^{S2}$ | $\Delta\widehat{e}_{it}^{S3}$ | $\Delta\widehat{e}_{it}^{S4}$ | $\Delta \ln Q_{it}$ | $\Delta\widehat{e}_{it}^{S1}$ | $\Delta\widehat{e}_{it}^{S2}$ | $\Delta\widehat{e}_{it}^{S3}$ | $\Delta\widehat{e}_{it}^{S4}$ |
| $r=0$ | - | - | - | - | - | 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: $\widehat{e}_{it}^{S1}$, $\widehat{e}_{it}^{S2}$, $\widehat{e}_{it}^{S3}$ and $\widehat{e}_{it}^{S4}$ are the CCEP composite error terms, defined in equation (2.13), taken from specification S1, S2, S3 and S4 respectively. Panel (a) reports the average cross-correlation $\bar{\bar{\rho}}$ (see Table 2.1 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 $\widehat{r}$ is selected using arg $\min_{0\leq r\leq 3} BIC_3(r)$ and is indicated with a '*'.

**Figure 1.1:** Common component from CCEPnl estimator

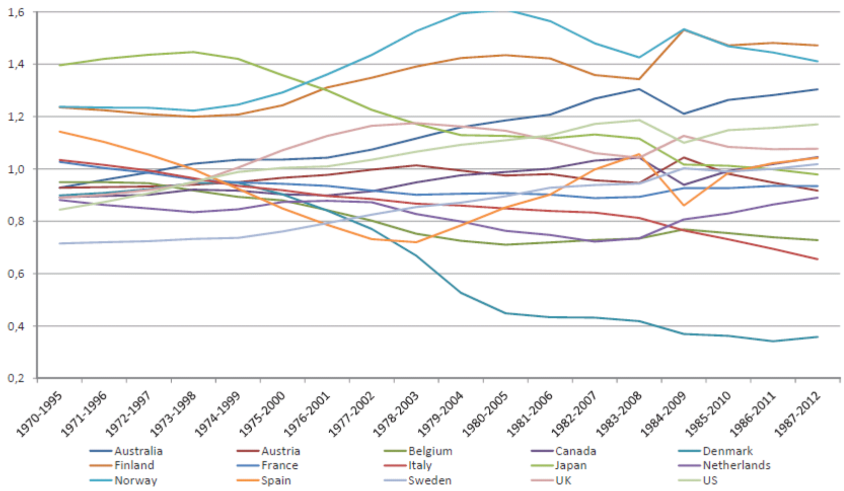



Notes: The common component is calculated by averaging $\widehat{\lambda}_{it}\widehat{F}_t^{ca2}$ from equation (1.16b) over the $N$ cross-sections using the CCEPnl estimation results for specification S1. When using S2, S3 or S4 we get highly similar results.

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 (1.12) 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 1.8 show that for the CCEP estimates we cannot reject the presence of a unit root in $\widehat{\varepsilon}_{it}^{pc}$.[12] 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

[12] Allowing 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 $\widehat{\varepsilon}_{it}^{pc}$ equal to 0.47, 0.48, 0.85 and 0.16 in S1, S2, S3 and S4 respectively.

**Figure 1.2:** Time-varying pattern for $\lambda_i$ from rolling CCEP regressions




Notes: Time-varying estimates for $\lambda_i$ are obtained from estimating equation (2.11) using a 26 years rolling window assuming a single common factor and normalizing $\overline{\lambda} = 1$. Reported are the results for specification S1. Similar results are obtained for S2, S3 and S4.

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 1.4.4, 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 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 $(y_{it}, x_{it})$.

### 1.5.2 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 1.5.3.

The results in Table 1.8 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.

**Table 1.8:** 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** | | | | | | | | |
| Standard Variables | | | | | | | | |
| $\ln K_{it}$ | $0.20^{***}$ | $0.17^{***}$ | $0.25^{***}$ | $0.19^{***}$ | $0.38^{***}$ | $0.40^{***}$ | $0.42^{***}$ | $0.44^{***}$ |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.02) | (0.02) | (0.02) | (0.02) |
| $\ln G_{it}$ | 0.04 | 0.01 | $0.07^{***}$ | $-0.05$ | $0.05^{***}$ | $0.06^{***}$ | $0.06^{***}$ | $0.06^{***}$ |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.01) | (0.01) | (0.01) | (0.01) |
| $\ln H_{it}$ | $0.37^{***}$ | $0.34^{***}$ | $0.45^{***}$ | $0.45^{***}$ | $0.28^{***}$ | $0.38^{***}$ | $0.39^{***}$ | $0.40^{***}$ |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.02) | (0.02) | (0.02) | (0.02) |
| Direct effects | | | | | | | | |
| $\ln TotalExp_{it}$ | $-0.03$ | | $-0.15^{***}$ | | $0.10^{***}$ | | $-0.09^{***}$ | |
| | (0.04) | | (0.02) | | (0.03) | | (0.02) | |
| $\ln ProdExp_{it}$ | $0.05^{***}$ | $0.03^{**}$ | | $0.04^{***}$ | $0.02^{*}$ | 0.001 | | $0.02^{*}$ |
| | (0.01) | (0.01) | | (0.01) | (0.01) | (0.01) | | (0.01) |
| $\ln SocialExp_{it}$ | $-0.16^{***}$ | $-0.14^{***}$ | | | $-0.07^{***}$ | $-0.07^{***}$ | | |
| | (0.02) | (0.02) | | | (0.02) | (0.01) | | |
| $\ln GovCons_{it}$ | | $-0.06^{***}$ | | | | $-0.03^{**}$ | | |
| | | (0.02) | | | | (0.01) | | |
| $\ln OtherExp_{it}$ | | $-0.01^{*}$ | | | | $-0.01^{**}$ | | |
| | | (0.01) | | | | (0.005) | | |
| $\ln BudgetBalance_{it}$ | 0.02 | | | $0.29^{***}$ | $0.34^{***}$ | | | $0.27^{***}$ |
| | (0.05) | | | (0.05) | (0.05) | | | (0.03) |
| $\ln Taxburden_{it}$ | | 0.5 | 0.01 | | | $0.12^{***}$ | $0.12^{***}$ | |
| | | (0.04) | (0.06) | | | (0.02) | (0.04) | |
| $\ln PersonalTax_{it}$ | | | $-0.03$ | $-0.07^{***}$ | | | $-0.03$ | $-0.002$ |
| | | | (0.03) | (0.02) | | | (0.03) | (0.01) |
| $\ln CorporateTax_{it}$ | | | $-0.001$ | $-0.01^{**}$ | | | 0.01 | $0.01^{**}$ |
| | | | (0.004) | (0.004) | | | (0.005) | (0.004) |
| $\ln ConsTax_{it}$ | | | | 0.01 | | | | $0.08^{***}$ |
| | | | | (0.02) | | | | (0.01) |
| $\ln OtherTax_{it}$ | | | | $-0.01$ | | | | $-0.01^{**}$ |
| | | | | (0.005) | | | | (0.005) |
| Indirect effects | | | | | | | | |
| $\ln StrRelative_{it}$ | | | | | $-0.61^{***}$ | $-0.65^{***}$ | $-0.79^{***}$ | $-0.60^{***}$ |
| | | | | | (0.15) | (0.17) | (0.20) | (0.15) |
| $\ln HCap_{it}$ | | | | | $-0.37^{***}$ | $-0.37^{***}$ | $-0.42^{***}$ | $-0.38^{***}$ |
| | | | | | (0.08) | (0.09) | (0.10) | (0.08) |
| $\ln Import_{it}$ | | | | | $0.31^{***}$ | $0.30^{***}$ | $0.33^{***}$ | $0.27^{***}$ |
| | | | | | (0.11) | (0.12) | (0.13) | (0.10) |
| **PANIC cointegration test (one common factor)** | | | | | | | | |
| ADF-GLS on $\widehat{F}_t^{pc}$ | $-1.63$ | $-2.05$ | $-1.13$ | $-1.59$ | $-1.92$ | $-2.05$ | $-2.35$ | $-2.15$ |
| | [0.77] | [0.56] | [0.91] | [0.78] | [0.63] | [0.56] | [0.40] | [0.50] |
| MW on $\widehat{\epsilon}_{it}^{pc}$ | 30.92 | 30.72 | 27.47 | 21.08 | $52.7^{***}$ | $46.09^{**}$ | $45.26^{**}$ | $51.78^{***}$ |
| | [0.42] | [0.43] | [0.60] | [0.88] | [0.006] | [0.03] | [0.037] | [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 2.2 for the PANIC test.

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 overal 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 debt[13]. 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 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 1.2.2 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, Ladaique, and Pearson (2003). On

[13]For 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 2.3.1, where we discuss the construction of the data

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, Goujard, and Pina, 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, Brys, Heady, Johansson, Schwellnus, and Vartia, 2011). A possible explanation lies in the construction of the tax rates, as discussed in Section 1.3, 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, Philippopoulos, and Tsionas (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, Goujard, and Pina (2013) and further confirm that an appropriate classification into various categories is important when analyzing the impact of taxes.

### 1.5.3 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, Nicoletti, Vartia, and Yoo (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, Helpman, and Hoffmaister (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, Denison, Sato, and Phelps, 1966; Coe, Helpman, and Hoffmaister, 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 $\lambda_{it}$ may (to a large extent) already be captured by the time-invariant part, $\lambda_{i0}$. 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 $HCap_{it}$.

## 1.6 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.

# Appendix

## 1.A Coefficients of correlation between corporate tax rate indicators

**Table 1.A.1:** Correlation matrix

| | $\frac{Corp.taxreceipts}{GDP}$ | STR | EMTR | EATR |
|---|---|---|---|---|
| $\frac{Corp.taxreceipts}{GDP}$ | 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.

## 1.B Construction of data and data sources

**Table 1.B.1:** Construction of data and data sources

| Name | Notation | Construction | Data Sources |
|---|---|---|---|
| | | **Standard Variables** | |
| **Name** | **Notation** | **Construction** | **Data Sources** |
| Real GDP | $Q_{it}$ | Original data | OECD, Economic Outlook 91, series GDPV |
| Private non-residential net capital stock | $K_{it}$ | 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 | $G_{it}$ | 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 | $H_{it}$ | 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<br>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.<br>We update their data to 2012.<br>Average value in 2012: 9.67 % GDP |
| Gov. social security expenditures % of GDP | $SocialExp_{it}$ | Nominal social security benefits paid by general government, as a percentage of GDP | OECD Economic Outlook 91, series SSPG and GDP<br>Average value in 2012: 15.42 % GDP |
| Government consumption as % of GDP | $CovCons_{it}$ | Government final consumption net of final cons. expenditures in education, expressed as a percentage of GDP | Berger and Heylen (2011). See their appendix for further description.<br>We update their data to 2012.<br>Average value in 2012: 16.02 % GDP |
| Government other expenditures as % of GDP | $OtherExp_{it}$ | $TotalExp_{it}$-$ProdExp_{it}$-$SocialExp_{it}$-$GovCons_{it}$ | Average value in 2012: 7.02 % GDP |
| Total Tax burden as % of GP | $Taxburden_{it}$ | Total nominal tax revenues of general gov. expressed as a percentage of GDP | OECD.Stat, Finacial and Fiscal Affairs<br>Average value in 2012:37.57% GDP |
| Government budget balance as % of GDP | $BudgetBalance_{it}$ | $Taxburden_{it}$-$TotalExp_{it}$ | As this variable can be negative, we take the log of 1 plus the gov budget balance<br>Average value in 2012 of 0.89 |

*To be continued on the next page*

*Continued from previous 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<br>Average value in 2012: 21.36 % GDP |
| 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 | OECD.Stat, Financial and Fiscal Affairs<br>Average value in 2012: 3.27 % GDP |
| 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 | OECD.Stat, Financial and Fiscal Affairs<br>Average value in 2012: 10.3 % GDP |
| Other Taxes as % of GDP | $OtherTax_{it}$ | $Taxburden_{it}$-$PersonalTax_{it}$-$CororateTax_{it}$-$ConsTax_{it}$ | 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<br>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<br>Data for the intermediate years are calculated by interpolation and data is extrapolated for 2011 and 2012 |
| Import Share as a % of GDP | $Import_{it}$ | Imports of goods and services expressed as a % of GDP | OECD Economic Outlook 91, series MGS and GDP |

# Chapter 2

# On the role of public policies and wage formation for private investment in R&D: a long-run panel analysis[1]

This chapter studies the drivers of business funded and performed R&D in a panel of 14 OECD countries since 1981. More specifically, we investigate the effects of public R&D related policies and wage formation. Following Pesaran (Econometrica, 2006) and Kapetanios et al. (Journal of Econometrics, 2011), our empirical strategy allows for cross-sectionally correlated error terms due to the presence of unobserved common factors, which are potentially non-stationary. We find that tax incentives are effective. Public funding (subsidization) of R&D performed by firms can also be effective if subsidies are not too low, neither too high. R&D performed within the government sector and within institutions of higher education is basically neutral with respect to business R&D. We find no evidence for crowding out, nor for complementarity. Using an indicator for wage pressure developed by Blanchard (Economic Policy, 2006), we find that wage moderation may contribute to innovation, but only in fairly closed economies and in economies with flexible labour markets. In highly open economies and economies with rigid labour markets rather the opposite holds. In these economies high wage pressure may enhance creative destruction and force firms to innovate as competitive strategy. Our results show that a careful treatment of the properties of the data is crucial.

[1]This chapter is joint work with Tim Buyse and Freddy Heylen.

## 2.1 Introduction

Ageing and rising pressure on the welfare state force all OECD countries to develop effective employment and growth policies. When it comes to long-run growth, both the theoretical and empirical literature recognize investment in research and development (R&D) as a major factor (see Romer, 1990; Aghion and Howitt, 1992; Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 2009). Numerous studies have therefore investigated the determinants of business investment in R&D in many countries, both at the micro and the macro level. Guellec and Van Pottelsberghe (1997, 2003) were the first to provide an explanation at the macro level in a panel of 17 OECD countries. In their seminal paper, they paid particular attention to the role of public policies organized to stimulate private R&D investment i.e. tax incentives, public funding of R&D projects in the business sector, expenditures on R&D within the government sector and R&D spending in institutions of higher education.

Our research is inspired by two gaps in the empirical macro literature on the drivers of business R&D. A first one relates to the impact of wage formation. Today, OECD countries are not only called upon to develop effective growth policies, but also to create jobs and to raise employment rates. To reach this goal, many countries adopt outspoken wage moderation policies. Interestingly, these policies also affect incentives and available resources for firms to innovate and invest in R&D. On the employer side, it is often argued that wage moderation is an important factor to maintain firm profitability, which is a key condition for investment in R&D. Several researchers have, however, argued that an excessive focus on wage moderation may kill incentives to innovate (e.g Kleinknecht, 1998). Wage moderation may for example increase the survival probability of the least innovative firms and retard the process of creative destruction. Weighing on the purchasing power of households, outspoken wage moderation may also lead to lower demand-driven innovations as demand for new products and services falls. Conversely, higher wage pressure may force firms to innovate as a key element in their competitive strategy. To the best of our knowledge, despite its theoretical importance, rigorous cross-country empirical work on these conflicting hypotheses has never been done.

A second gap in the existing empirical macro literature on the determinants of R&D investment is methodological. A key characteristic of new technology and knowledge is that it may spillover to other firms and countries, so that all may benefit from an improvement in the world level of technology, although not necessarily to the same extent (Coe, Helpman, and Hoffmaister, 2009; Everaert, Heylen, and Schoonackers, 2015). Eberhardt, Helmers, and Strauss (2013) have shown that these spillovers affect firms' private returns to R&D and therefore business R&D investment. A crucial econometric issue, however, follows from the fact that the world level of technology and knowledge is largely unobserved. Technology spillovers will then manifest themselves in standard panel R&D regressions as cross-sectional dependence in the error terms, induced by an unobserved common factor. Guellec and Van Pottelsberghe (1997, 2003) and subsequent macro research (e.g. Falk, 2006; Westmore, 2014) have neglected this issue. If omitted common factors are correlated with the included explanatory variables, estimated parameters will be biased and inconsistent. Even worse, when unobserved common factors are non-stationary, standard estimators yield spurious results.

Our contribution in this chapter is to study the determinants of business funded and performed R&D in 14 OECD countries in the period 1981-2012, with a special focus on the role of wage formation and by adopting an empirical strategy that deals with cross-sectionally correlated error terms due to the presence of unobserved common factors. For the set of countries in our empirical analysis, Figure 2.1 shows the data for business funded and performed R&D, expressed in real per capita terms and in 2010 PPP dollars. Huge cross-country differences stand out, both in the level and in the evolution of R&D, making an empirical analysis highly relevant. Next to the role of wage pressure, we also test the impact of public policies organised to stimulate private R&D investment, in line with Guellec and Van Pottelsberghe (2003). To estimate our model, we use the common correlated effects pooled (CCEP) estimator of Pesaran (2006). This estimator controls for unobserved common factors by adding cross-sectional averages of the data. As shown by Kapetanios, Pesaran, and Yamagata (2011), this approach is also valid in a non-stationary panel context.

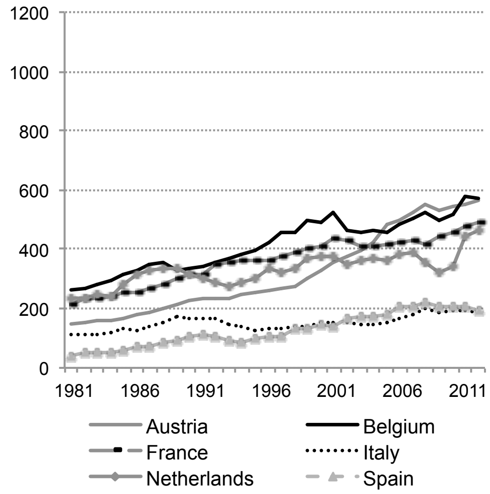
Our main findings are the following. First of all, we learn from our results that a careful treatment of the properties of the data is crucial. The empirical analysis reveals significant cross-sectional correlation in levels and in first-differences for most variables. All variables are also found to be non-stationary. For most variables the non-stationarity is induced by an (unobserved) common factor. The use of the CCEP estimator is therefore highly justified. Second, the effects of wage pressure are significant but not uniform. We find that in economies where firms face relatively little (foreign) competition and dispose of flexibility to adjust their employed labour force because employment protection legislation is soft, high wage pressure has negative effects on private R&D expenditures. In open economies where firms face sharp (foreign) competition and run their activities in a rather rigid and regulated labour environment, however, the opposite seems to happen. In such economies - think of many European economies - firms that do not innovate cannot survive when wage pressure is high. Rising wages thus enhance creative destruction and force all firms to innovate as competitive strategy. Third, our empirical analysis reveals various ways in which governments can effectively promote business R&D investment. We observe that both tax incentives and public funding (subsidization) of R&D projects in the business sector can work, if chosen carefully. This condition applies in particular to public funding. For this policy instrument, we confirm an earlier finding of Guellec and Van Pottelsberghe (2003) that the relationship between subsidization and private R&D expenditures is inverted U-shaped. That is, subsidies encourage private firms to raise their own R&D spending if these subsidies are not too low neither too high. The optimal subsidization rate may be somewhere between 6 % and 10 %. The results also show that the available stock of human capital is an important driver of business R&D investment implying that governments should invest in schooling in order to increase the percentage of population with a higher degree. Furthermore, we find that R&D investment within the government sector and within universities will also have positive effects on aggregate R&D spending. Most of our results predict a one-to-one effect from higher spending within the public sector to aggregate R&D. In other words, neither the idea that public R&D would crowd out private R&D spending, nor the idea of complementarity between the two, find support in our results.

Our focus on aggregate private R&D investment in this chapter is not common in the literature. In comparative perspective, many more studies have investigated R&D expenditures at the firm or the industry level (see e.g. the survey in David, Hall, and Toole, 2000, and our overview of the literature in Section 2.2). Yet, there are very good reasons why an analysis of macroeconomic data is important. A first one relates to the indirect effects or externalities of policies. For example, if individual firms benefit from R&D investment subsidies, this may boost their innovation activity. At the same time, however, also other firms may be affected. Competing firms may suffer because of the advantage given to a direct competitor. Due to falling rates of return they may reduce their R&D investment. Conversely, downstream customers in the supply chain may benefit from knowledge spillovers induced by the innovating firm. They may raise their R&D investment. Similar externalities can occur between industries (Guellec and Van Pottelsberghe, 2003). The potential presence of these external effects makes the case for an empirical analysis at the macro level. A second reason follows from the observation that (firms in) different industries may react differently to changes in the drivers of R&D, for example because market environment and institutions are different. In that sense, the response of R&D investment to rising wage pressure may be different in manufacturing sectors than in services. For policy makers it will be highly interesting also to know what the response is at the aggregate level.

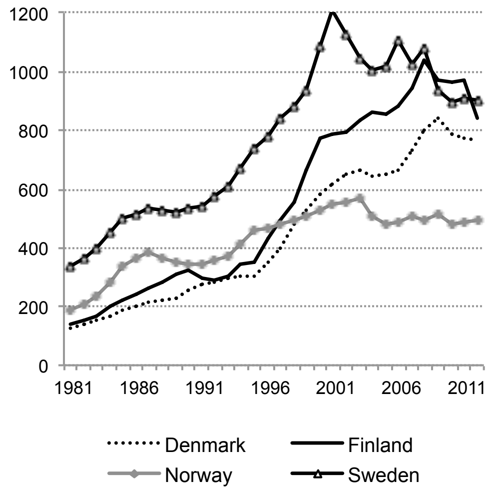
The remainder of this chapter is structured as follows. Section 2.2 contains a brief survey of the literature on public policy instruments to encourage business R&D investment, and on their effects. This section also reviews the conflicting hypotheses regarding the influence of wage formation on innovation. Section 2.3 discusses important properties of the data and sets out the empirical model. This section also discusses the econometric methodology. In Section 2.4 we report our estimation results. Section 2.5 concludes the paper.

**Figure 2.1:** Business financed and performed R&D expenditures in 14 OECD countries (real per capita, 2010 PPP dollars)

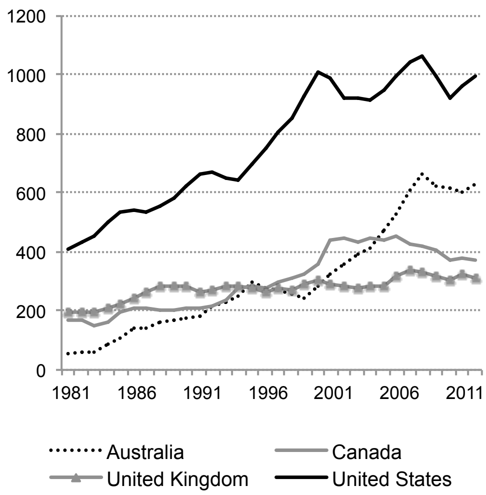
(a) Euro area countries




(b) Nordic countries




(c) Anglo-Saxon countries



## 2.2 Drivers of private R&D intensity: literature

Boosting R&D intensity is one of the top priorities of OECD countries today. The Europe 2020 targets include that 3% of the EU's GDP has to be invested in R&D and innovation (public and private combined) by 2020. To stimulate private R&D intensity, governments have different instruments at their disposal. These instruments are used to offset market failure in the allocation of resources to long-term and risky investment, which are key characteristics of R&D investment. As a result, private investment in R&D is mostly lower than socially optimal, thus justifying government support.

Section 2.2.1 discusses existing public policy instruments and some of the empirical evidence on their impact. In Section 2.2.2. we review the literature regarding the effects of wage formation and some underlying labour market characteristics on R&D investment and innovation. Various countries have institutionalized wage moderation or wage control mechanisms in the second half of the 1980s or early 1990s. Other countries have decentralized wage bargaining and introduced legislation to reduce union power, also contributing to wage moderation. While most will agree that these policies have positive effects on employment and competitiveness, at least in the short run, their possible long-run effects on a country's innovative capacity occur much less clear. In our discussion of the arguments for and against wage moderation, we also pay attention to the potential impact of the institutional environment within which wage formation takes place. We end with a brief explanation of the role of product market characteristics.

### 2.2.1 Public policy instruments

Traditionally, R&D policy can be subdivided in direct support (such as public sector R&D and direct R&D subsidies) and indirect support (such as R&D tax incentives). In addition, governments may also provide support for the university research system and the formation of high-skilled human capital as for formal R&D cooperation between institutions. In this section, we point at existing, mostly empirical, evidence on the impact of policy support measures on private R&D expenditures.

#### Public sector R&D and government funding of R&D in the business sector

Among the most frequently used public policy instruments to support R&D are public sector R&D and government funding of private investment in R&D. The former refers to direct R&D expenditures by public research institutions (intramural) and universities. The latter may either take the form of grants or subsidies, where the results of the R&D belong to the private performer, or it may concern funding aimed at the procurement of R&D, where the results belong to a recipient that is not necessarily the performer. An important question in the literature is whether these instruments are effective tools to stimulate private investment in R&D, or not. On the one hand, the public sector can stimulate private investment in R&D by lowering the cost of research for the industry. One way to achieve this is by conducting basic risk research (where the wedge between private and social returns is probably the highest) and by making its results publicly available. It can also be done more directly by providing resources that lift potential cash constraints in private firms or by providing a buffer when high financial risk is involved. Guellec and Van Pottelsberghe (2003), however, see three reasons why one may question the effectiveness of public spending on R&D. As a worst case scenario, public spending may even crowd out private R&D. First, government spending on R&D may increase the demand for researchers, which may raise these researchers' wages and make private R&D investment more expensive. This potential source of crowding out is most likely to occur if there is a shortage in the most decisive factor of the R&D process. That is if high-skilled labour is scarce. Second, public sector money can act as a substitute to private money. In other words, governments may execute or subsidize projects that would have been implemented anyway such that the same investment is performed with public instead of private money, without any increase in total R&D. Third, the allocation of funds by the government generally occurs less efficiently than by market forces, thereby distorting competition and resource allocation.

As to the empirical evidence on the effects of R&D in the public sector, Goolsbee (1998), for the United States, finds evidence of crowding out of private funding through raising wages of scientists and engineers. Guellec and Van Pottelsberghe (2003) (their Table III) report results for a panel of 17 OECD countries that are consistent with this observation. According to their findings, a one euro increase in R&D expenditures within the government sector tends to imply a 0.38 euro decline in business expenditures in the long run. Although this supports the hypothesis of crowding out, the net aggregate effect of intramural government R&D would still seem to be positive. That is, crowding out is only partial. As to R&D expenditures in universities, Guellec and Van Pottelsberghe (2003) find an effect on private spending that is basically zero, leaving an aggregate net effect of 1. Falk (2006), on the other hand, finds indications of a significant positive impact of R&D in the higher education sector on business R&D.

When it comes to the effects of direct funding by the government of R&D in the private sector, David, Hall, and Toole (2000) report that one third of available, mostly firm-level, studies find substitution effects. Overall the authors conclude that the empirical literature is inconclusive about the net impact of public R&D subsidies. Falk (2006) and Bassanini and Ernst (2002) are also inconclusive or report negligible effects. By contrast, Guellec and Van Pottelsberghe (2003) find that the net long-run impact of R&D subsidies on private R&D investment is positive. A one euro increase in government funded R&D in the business sector would induce an additional

0.7 euro of private spending. Finally, Lach (2002) also finds that public R&D subsidies stimulate private R&D expenditures in the long run.

In general, more recent research tends to find less evidence for crowding out and concludes in favour of additionality effects of public R&D subsidies (see for instance Duguet, 2004; Carboni, 2011; Czarnitzki and Hussinger, 2004; Aerts and Schmidt, 2008; Hussinger, 2008; Cerulli and Poti, 2012; Oezcelik and Taymaz, 2008; Bloch and Graversen, 2012). The effects of R&D subsidies need not be homogeneous, however. For instance, Jaumotte and Pain (2005) show that on a firm level the positive effect of R&D subsidies is more pronounced when firms are cash-constrained. In fact, there is broader empirical evidence that public subsidies are more effective drivers of R&D in small (financially constrained) firms. In the same spirit Czarnitzki and Ebersberger (2010) underscore the importance of aimed targeting of subsidies. These authors observe that in many cases most funding is awarded to larger firms that would have performed the R&D even in the absence of the public subsidy. Some studies also report heterogeneity in effects depending on the size of public subsidies. Guellec and Van Pottelsberghe (2003), for instance, find an inverted U-shape, where the strongest positive effects on private R&D can be observed for public subsidy rates of $4-11$ %, while rates that are too high (>20%) tend to generate negative (crowding-out) effects. Gorg and Strobl (2007) confirm these findings. Becker (2014) concludes that this non-linear effect suggests that it could be more effective to provide intermediate support levels to a larger number of firms than a large amount of support to fewer firms.

**R&D tax incentives**

The policy mix aimed at stimulating business R&D and innovation has seen growing use of R&D tax incentives. Such measures are indirect since the decision to use them, and the decision on how to use them, remain with the company. They are thus considered to be more market-oriented than for instance direct subsidies. Companies investing in R&D are eligible to claim tax reductions against their payable tax (Warda, 2001). As such, R&D tax incentives reduce the marginal cost of R&D spending and are also more neutral (i.e. less distortive) than direct R&D subsidies. In general, while direct subsidies are more targeted towards long-term research, R&D tax schemes are more likely to encourage short-term applied research and boost incremental innovation rather than radical breakthroughs (EC, 2003; OECD, 2014).

Fiscal incentives for R&D may take on various forms such as R&D tax credits, which are present in countries such as France, Belgium and the UK (OECD, 2014; EC, 2003). These tax credits are deducted from the corporate income tax and are applicable either to the level of R&D expenditures or to the increase in these expenditures with respect to a given base. Alternatively, some countries, such as Canada, Denmark and the UK, allow for the immediate or accelerated depreciation of investment in machinery, equipment, and buildings devoted to R&D activities

(Warda, 2013; Falk, 2006). Finally, tax incentives need not necessarily apply to the corporate income tax, but may also apply to the personal income tax, as in the Netherlands and Belgium, or to the value added tax (or other taxes such as consumption, land or property) (OECD, 2014).

An often used indicator reflecting the overall generosity of R&D tax incentives in a country is the so-called B-index (Warda, 2001). It is a composite index that is computed as the present value of income before taxes necessary to cover the initial cost of R&D investment and to pay the corporate income tax so that it becomes profitable to perform research activities (Warda, 2001). Algebraically, the B-index is equal to the after-tax cost of a one euro expenditure on R&D divided by one minus the corporate income tax rate. The after-tax cost is the net cost of investing in R&D, taking account of all available tax incentives (corporate income tax rates, R&D tax credits and allowances, depreciation rates). The more favourable a country's tax treatment of R&D investment, the lower its B-index.

Hall and Van Reenen (2000) find that most studies in the pre 2000 literature show positive effects of fiscal incentives on R&D expenditures. More recent research into the effectiveness of tax credits is even more unanimous in concluding that there are positive R&D effects (Becker, 2014). For instance, both Bloom, Griffith, and Van Reenen (2002) and Guellec and Van Pottelsberghe (2003) find significant negative coefficients on the B-index in their regressions explaining business R&D expenditures. Bloom, Griffith, and Van Reenen (2002) estimate that a 10% tax cut induced fall in the cost of R&D induces just over a 1% rise in the level of R&D in the short run, and just under a 10% rise in R&D in the long run. That is, they find a long-run elasticity of R&D with respect to the user cost of just below 1. Long-run elasticities vary between modest estimates of $-0.14$ (Bernstein and Mamuneas, 2005; Baghana and Mohnen, 2009) to $-1.5$ and over (as in Harris, Li, and Trainor, 2009; Parisi and Sembenelli, 2003). Most studies, however, find elasticities in between these extremes (Lokshin and Mohnen, 2012; Koga, 2003; Mulkay and Mairesse, 2013).

**Knowledge spillovers from the university research system and the formation of high-skilled human capital**

Governments may resort to other than the traditional policy instruments to support private R&D expenditures. Some recent studies indicate the relevance of knowledge spillovers from university research to firms, enhancing technological opportunities and the productivity of private R&D, for example through personal interactions, university spin-offs and consultancy. Most empirical studies on this topic indeed find positive (geographically localized) knowledge externalities from university research to private R&D (see for instance Jaffe, 1989; Autant-Bernard, 2001; Karlsson and Andersson, 2009). Policies may thus aim to facilitate and support the formation of regional clusters of university and private R&D activity to exploit agglomeration economies. An important role in this context is played by the (increased) availability of high-skilled personnel trained by universities. Some studies do indeed find important positive R&D effects of high-skilled human capital resources[2]. Education policies and human capital investment thus also have a role in increasing private R&D.

### 2.2.2 Wage formation, labour and product market characteristics and innovation

The monitoring of wage formation is an important feature of many OECD countries' economic policy as it has a direct impact on employment and a country's competiveness. Expected positive effects on employment generally underlie arguments in favour of wage moderation (see e.g. Bovenberg, 1997). Lower wages may increase firm profitability, generating more resources for investment. They may improve the competitiveness of domestic firms and raise exports. And they may make production more labour intensive. It then comes as no surprise that in many European countries wage moderation policies have become institutionalized. Germany's success is currently often taken as guiding inspiration (Heylen and Buyse, 2012).

An important additional element, especially from a long-run perspective, is the possible impact of wage formation on a country's innovative capacity. If high (excessive) wages reduce R&D investment, their negative effects on employment and competitiveness would be multiplied. On the other hand, if wage pressure promotes innovation, negative effects on competitiveness would be limited to the short run, whereas in the long run competitiveness and employment would rise. Theoretical arguments in favour of wage moderation come mostly from an employer perspective. That is, wage moderation would imply higher profits which can subsequently be spent on innovation activities.

If a focus on wage restraint is missing, rents from innovation may be appropriated by unions through higher wage claims. This may reduce firms' willingness and resources to innovate. An early statement of this argument was the so-called *hold-up problem* under incomplete contracts (Grout, 1984; Menezes-Filho and Van Reenen, 2003). In more recent work, Ulph and Ulph (1994) confirm this argument in a right-to-manage model where unions and firms bargain only over the wage. The main factor driving firms in their innovation efforts in their model is the expected difference between the profits that the firm can earn once it has successfully innovated and the profits that it would earn otherwise. In this setup high (excessive) wages represent a 'tax' that unions impose on the investment and the success of the firm. Lower R&D investment would be the result. Conversely, a focus on wage moderation would imply higher R&D. Other authors, however, have challenged this expectation (see e.g. Kleinknecht, 1994, 1998; Kleinknecht and Naastepad,

[2] Variables that are considered are the availability of highly qualified scientists and engineers (Adams, Chiang, and Starkey, 2001; Adams, Chiang, and Jensen, 2003; Becker and Pain, 2008), the share of the number of workers with higher education in the total number of workers (Garcia and Mohnen, 2010), the share of the population with tertiary education in the total working age population (Wang, 2010) and the years of formal schooling (Kanwar and Evenson, 2003).

2004). One of their main arguments is that wage restraint raises the survival probability of low-productive firms and non-innovators, slowing down the process of creative destruction. In a regime of wage increases and wage pressure, by contrast, the balance would shift and lack of innovation would no longer - or much less - be an option. In the framework of Ulph and Ulph (1994), this argument would imply that high wage pressure no longer reduces, but raises the profit differential between innovating and not innovating. The reason is the very negative outcome in the non-innovating case. Intuitively, this idea raises a number of interesting extensions. One would expect this positive effect of high wage pressure to exist mainly in a very competitive environment and when firms lack the flexibility to adjust their (expensive) labour force. What we have in mind are very open economies and/or economies with highly deregulated product markets, but a very regulated labour market (e.g. extensive employment protection legislation). It will be exactly in such an environment that high wages and lack of innovation imply huge losses and the risk of bankruptcy. In these economies innovation will be firms' only possible competitive strategy.

Theory being inconclusive, what do we know about the impact of wage moderation on innovation and R&D empirically? First of all, it must be said that existing empirical work directly relating wage formation and innovation is very scarce. Most studies that analyse the effect of labour markets on innovation focus on aspects of numerical flexibility, such as the existence of flexible employment contracts, or functional flexibility such as the possibility of outsourcing or temporary employment. For instance, Bassanini and Ernst (2002) have estimated the impact of labour market regulation on the industry's R&D intensity in a cross-section of 18 manufacturing industries and 18 OECD countries. More recently, Murphy, Siedschlag, and McQuinn (2012) examined the impact of the strictness of employment protection legislation on innovation intensity in the OECD. Univocal results are hard to find. Observed effects depend on the system of industrial relations and the characteristic of industries. We know of only one study that has directly analysed the impact of wage changes on innovation. Pieroni and Pompei (2008) find, for a panel of Italian manufacturing industries, that wage increases are positively related to the number of patents (their proxy for innovation). However, the authors only look at absolute wages and do not include an adequate measure of wage pressure (wage moderation) as we will do (See Section 2.3.1).

Next to the impact of labour market institutions, a growing number of researchers have studied the role of product market characteristics (in particular product market competition) on innovation. In a highly cited contribution, Aghion, Bloom, Griffith, and Howitt (2005) put forward an inverted U-shaped relationship between the degree of competition and investment in innovation. The argument goes as follows. When competition is low to begin with, the economy is expected to consist of a higher fraction of sectors with 'neck-and-neck' competing firms. Product market deregulation will induce these neck-and-neck firms to innovate in order to escape competition, since the incremental value of getting ahead rises in the degree of competition. When competition is high to begin with, however, the economy will have a higher fraction of sectors with one technological leader and many laggards. Further deregulation then has negative effects on innovation. Since more competition reduces the net rent that can be captured by laggards who succeed in catching up, the incentives for them to try will get weaker. This is the Schumpeterian effect of more competition. Although our focus in this chapter is not on product market characteristics, we will control for them in our empirical work. Moreover, as we have mentioned above, the degree of product market competition may also be a factor that changes the effect of wage pressure on firms' investment in R&D.

## 2.3 Empirical analysis

Our empirical analysis follows Guellec and Van Pottelsberghe (2003) and relies on a simple R&D investment model that considers real per capita business sector funded and performed R&D ($BERD_{it}$) to be a function of a mix of policy instruments ($POLICY_{it}$), discussed in Section 2.2, and of real per capita value added generated by the business sector ($VA_{it}$). We further build on Falk (2006) and allow for other possible determinants ($Z_{it}$) driving private R&D investment. Finally, we explicitly investigate the possible impact of wage formation ($WAGE_{it}$) on $BERD_{it}$,

$$BERD_{it} = f(VA_{it}, POLICY_{it}, Z_{it}, WAGE_{it}), \tag{2.1}$$

where subscripts $i$ and $t$ respectively denote the $i$th country and $t$th period. The exact functional form for equation (2.1) will depend on the discussion of the properties of the data in Section 2.3.1.

### 2.3.1 A first look at the data

**Data and sources**

We analyse the determinants of real per capita business sector funded and performed R&D for a group of 14 OECD countries[3] using yearly data over the period 1981-2012. An overview of the construction of all data and their sources can be found in Appendix 2.C.

When focusing on our sample of countries, figure 2.1 reports wide variation across the countries, both in the level and the evolution of business expenditure on R&D. Policy instruments included in $POLICY_{it}$ are real per capita government intramural expenditure on R&D ($GOVERD_{it}$) and real per capita expenditure on R&D in the higher education sector ($HERD_{it}$). As a measure for direct R&D subsidies ($SUBS_{it}$) we include real per capita government funded expenditure on R&D per-

[3]These countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Italy, Netherlands, Norway, Spain, Sweden, UK and US. The selection of countries has been driven by data availability.

formed in the business sector. A final measure included in $POLICY_{it}$ is the B-index ($BINDEX_{it}$), which captures direct R&D tax incentives[4]. In our empirical analysis, $VA_{it}$, $BERD_{it}$ and all variables in $POLICY_{it}$ will be expressed in logarithms.

Regarding the variables in $Z_{it}$, we focus on three possible determinants of business sector R&D, i.e. the degree of openness of the economy ($OPEN_{it}$), the available stock of human capital ($HCAP_{it}$) in a country and the degree of product market regulation ($PMR_{it}$). The degree of openness is included to account for international trade, which is an important channel of knowledge and technology transfers across countries raising the return to domestic private R&D investment (e.g. Coe and Helpman, 1995; Coe, Helpman, and Hoffmaister, 2009; Acharya and Keller, 2009). Based on this argument, we expect a positive effect from a higher degree of openness on $BERD$. The stock of human capital is considered due to its potential double impact on private R&D investment. First, human capital is an important factor reflecting the absorptive capacity of an economy with regards to international technology and knowledge (see amongst others Nelson, Denison, Sato, and Phelps, 1966; Coe, Helpman, and Hoffmaister, 2009). Second, Acemoglu (1998) shows that a high proportion of skilled workers in the economy stimulates high-skill biased technological change. As to product market regulation, it would be our basic position to expect a U-shaped relationship with R&D investment, in line with the arguments raised by Aghion, Bloom, Griffith, and Howitt (2005) that we discussed in section 2.2.2. We measure $OPEN_{it}$ as the sum of imports and exports of goods and services as a percentage of GDP. As a proxy for the stock of human capital, we use the percentage of population, aged 15 and over that has completed tertiary schooling. To capture $PMR_{it}$, the OECD economy-wide product market regulation index is employed.

As a final determinant of business funded and performed R&D, we introduce an indicator for wage pressure. Its construction is discussed below.

**An appropriate wage indicator**

To assess the impact of wage formation and wage pressure on private R&D investment, we follow Blanchard (2006) and use insights from growth theory. The approach is to compare actual (growth of) real wage costs with the so-called 'warranted' real wage (growth). The latter is determined by the rate of Harrod-neutral technical progress. In growth theory, this is the rate of real wage growth consistent with stable employment along a balanced growth path. Blanchard (2006) constructs the rate of Harrod-neutral technical progress using the Solow residual, and dividing it by the labour share. More formally, let $W_{it}$ represent real hourly labour cost in country $i$ at time $t$ and let $A_{it}$ be a measure of labour efficiency driven by technological progress. The underlying CRS production

[4]See Section 2.2.1 for more details.

function is

$$Y_{it} = K_{it}^{\alpha} G_{it}^{\beta} (A_{it} L_{it})^{(1-\alpha-\beta)}, \tag{2.2}$$

with $Y_{it}$ real output, $K_{it}$ the stock of real private physical capital, $G_{it}$ the stock of real public capital, $L_{it}$ total hours worked, and $A_{it}L_{it}$ effective labour in hours. Labour efficiency can then be computed as:

$$\ln A_{it} = \frac{1}{1-\alpha-\beta} \left[\ln Y_{it} - \alpha \ln K_{it} - \beta \ln G_{it} - (1-\alpha-\beta) \ln L_{it}\right] \tag{2.3}$$

Following Blanchard's reasoning, a suitable wage gap or wage pressure indicator will then be defined as real hourly labour cost per efficiency unit of labour, $\frac{W_{it}}{A_{it}}$. In our empirical analysis, we will express this indicator in logs, such that we get

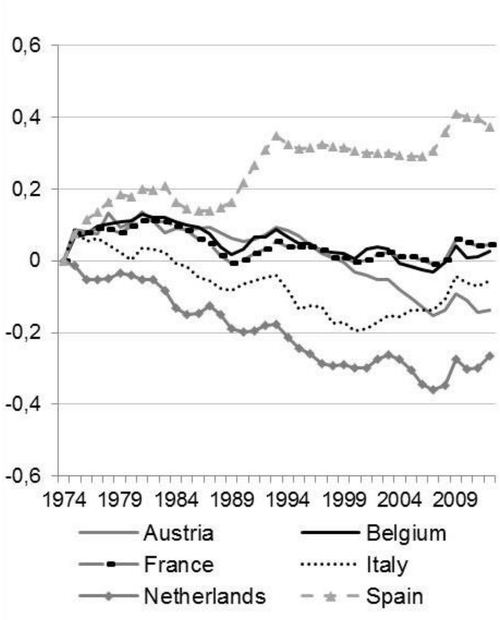
$$\ln WAGE_{it} = \ln \frac{W_{it}}{A_{it}} = \ln W_{it} - \ln A_{it} \tag{2.4}$$

As to data, $W_{it}$ represents real compensation of employees per hour. To compute $\ln A_{it}$, we estimate the production function in (2.2) for the same panel of countries that we study in our empirical analysis of private R&D investment. In line with, amongst others, Costantini and Destefanis (2009), Eberhardt and Teal (2013) and Everaert, Heylen, and Schoonackers (2015), we account for the presence of unobserved common factors that are potentially non-stationary. Estimation of this production function is similar to Everaert, Heylen, and Schoonackers (2015) and results in a share of private capital in total income ($\alpha$) of 0.20, a share of public capital ($\beta$) of 0.14, and a labour share ($1-\alpha-\beta$) of 0.66. Our estimate for $\beta$ is very close to the results reported by Bom and Ligthart (2014). Building on a meta-regression analysis, they put forward 0.11 as long-run output elasticity of public capital. Using the Blanchard indicator has the additional advantage that it is not (directly) affected by endogenous adjustment of labour productivity, as is the case for more traditional indicators that measure the wage gap by relating real labour cost to labour productivity i.e. output per hour or per worker. Such indicators will give the wrong sign when firms adjust capital intensity in response to wage changes. For example, excessive wage increases may induce firms to substitute capital for labour. The productivity of labour will then rise and excessive wage pressure may no longer show up in the data, implying measurement error.

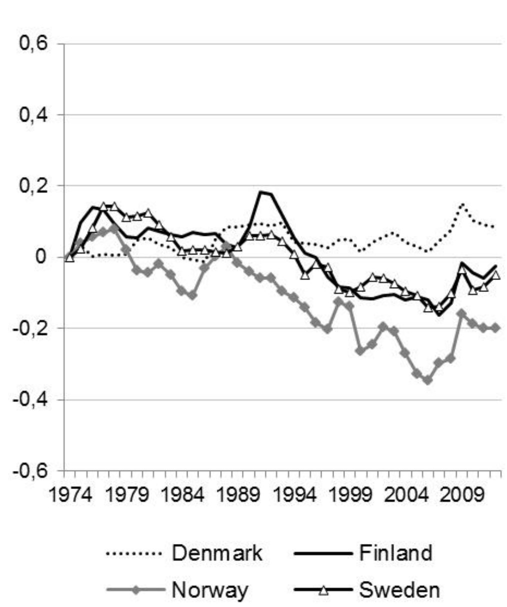
Figure 2.1 shows our indicator for wage pressure ($\ln WAGE_{it}$) in three groups of countries: six euro area countries, four Nordic countries and four Anglo-Saxon countries. Note that for each country, we normalized the wage gap to zero in 1974. Although this is obviously somewhat arbitrary, the idea is that in the early 1970s about all countries were close to full employment, so that wages must have been more or less at their 'warranted' level[5]. All in all, our indicator is very similar to the real wage gap of Arpaia and Pichelmann (2007), which is also based on the Blanchard approach.

**Figure 2.1:** Indicator of wage pressure ($\ln WAGE_{it}$) for three groups of countries

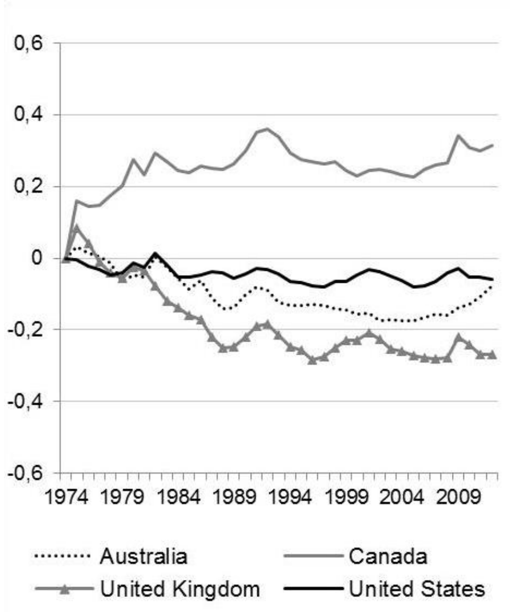
(a) Euro area countries




(b) Nordic countries




(c) Anglo-Saxon countries




[5]Even if this assumption were wrong for some countries, it will not affect our estimation results in Section 2.4, since we control for unobserved country fixed effects. What matters is the evolution of $\ln WAGE$ over time, not its initial level.

Wage pressure increased strongly in most countries throughout the second half of the 1970s, with a peak around 1982. From then onwards, the trend in the wage gap was negative in most countries for at least one decade. Many countries such as Belgium, Italy and Sweden, institutionalized mechanisms of wage restraint or wage control to keep the evolution of wages more in line with its warranted level. Other countries, like the UK, decentralised wage bargaining, and introduced tough legislation to reduce union power. The main exceptions to this overall pattern are the US, the Netherlands, Canada and Spain. The evolution of wages was exceptional in the US in that we see no excess wage growth in the 1970s. Moreover, since 1980, wage growth in the US has only been slightly smaller than its warranted level, keeping the wage gap between 0 and -8 % all of the time. The Netherlands, by contrast, shows a steady decline of wage pressure throughout almost the entire period under consideration. This confirms the strong focus on wage moderation as an important policy instrument in this country. Very influential in this respect was the so-called *Wassenaar agreement* of 1982, which initiated a series of national social compacts to restrain wage growth. Unions were convinced of the need to restrain inflationary pressure in the labour market and co-ordinated action was introduced to bring this about. Canada and Spain differ in the sense that we see no wage moderation in these countries during the last three decades. As a final observation, almost all countries show a sharp rise in wage pressure between 2008 and 2010.

In our regressions in Section 4 we will at first introduce $\ln WAGE$ as a separate variable. Building on our discussion in Section 2.2.2, however, we will soon add interaction terms with context variables that may tilt the effect of wage pressure on R&D investment. The degree of openness ($OPEN$) and the degree of product market regulation ($PMR$), already discussed above, affect the strength of the competition that firms experience. Another is the degree of employment protection legislation ($EPL$), The higher $EPL$, the more difficult it may be for firms to adapt by changing (expensive) labour. Both $OPEN$, $EPL$ and $PMR$ may thus affect the profit differential when firms do not innovate (and wage pressure rises). These considerations would suggest significant effects from these interaction terms on R&D investment.

### Properties of the data

As a guide to selecting the most appropriate estimation method in Section 2.3.3 below and to determine the optimal functional form for equation (2.1), we first look at two important properties of the data: the degree of cross-sectional dependence and the order of integration.

*Cross-sectional dependence*

Recently, the panel data literature has seen an increasing interest in models with unobserved, time-varying heterogeneity that may stem from omitted (and unobserved) common variables or global shocks that affect all units, but perhaps to a different degree (see e.g. Coakley, Fuertes, and Smith, 2002; Eberhardt and Teal, 2011; Everaert, 2014). These omitted common variables induce error cross-sectional dependence and may lead to inconsistent estimates if they are correlated with the explanatory variables and to a spurious regression problem if they are non-stationary.

At the macroeconomic level, cross-sectional dependencies are rather the rule than the exception because countries are interconnected through trade, geography, international relations etc. (Westerlund and Edgerton, 2008). When considering the potential determinants of business financed and performed R&D intensity across OECD countries, unobserved common variables are also likely to be present. A first potential common factor is a global business cycle, which results from the increased business cycle synchronization across countries. Changes in this global business cycle affect the financial constraints of both the government and the business sector and will thus have an impact on business R&D intensity (Guellec and Van Pottelsberghe, 2003). Second, and probably more important is the role of the unobserved available world level of technology which causes international technology and knowledge spillovers. These could be regarded as omitted unobserved factors for explaining business R&D expenditures. The reason being that technology spillovers affect private R&D investment as they have a positive impact on a country's absorptive capacity and affect private returns to $R\&D$ investment (Eberhardt, Helmers, and Strauss, 2013).

If these unobserved common factors have indeed an impact on private sector R&D, this should show up as strong cross-sectional dependence in the data. Table 2.1 therefore reports the average pairwise correlation coefficient ($\bar{\hat{\rho}}$) 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 nonzero correlation. To assess if common factors are really influencing private sector funded and performed R&D, especially the cross-sectional dependence in $\ln BERD_{it}$ is important. For completeness, we also report the test results for each of the explanatory variables.

**Table 2.1:** Cross-sectional dependence in the data

Sample period: 1981-2012, 14 OECD countries

| | Levels | | | First-differences | | | | Levels | | | First-differences | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\bar{\hat{\rho}}$ | CD | | $\bar{\hat{\rho}}$ | CD | | | $\bar{\hat{\rho}}$ | CD | | $\bar{\hat{\rho}}$ | CD | |
| $\ln BERD_{it}$ | 0.881 | 47.55 | [0.00] | 0.194 | 10.277 | [0.00] | $\ln BINDEX_{it}$ | 0.190 | 10.255 | [0.00] | 0.037 | 1.965 | [0.05] |
| $\ln VA_{it}$ | 0.926 | 49.955 | [0.00] | 0.575 | 30.544 | [0.00] | $OPEN_{it}$ | 0.701 | 37.830 | [0.00] | 0.669 | 35.507 | [0.00] |
| $\ln GOVERD_{it}$ | 0.051 | 2.745 | [0.01] | 0.054 | 2.87 | [0.01] | $HCAP_{it}$ | 0.930 | 50.185 | [0.00] | 0.05 | 2.656 | [0.01] |
| $\ln HERD_{it}$ | 0.961 | 51.868 | [0.00] | 0.089 | 4.771 | [0.00] | $\ln WAGE_{it}$ | 0.415 | 2.379 | [0.00] | 0.447 | 23.745 | [0.00] |
| $\ln SUBS_{it}$ | 0.027 | 1.468 | [0.14] | 0.043 | 2.262 | [0.02] | $PMR_{it}$ | 0.958 | 51.738 | [0.00] | 0.191 | 10.147 | [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.

The results in Table 2.1 show that all, but one, variables exhibit considerable positive cross-sectional correlation in levels and in first differences. $\ln SUBS_{it}$ is the exception as the null hypothesis of no cross-sectional dependence is not rejected for the variable in levels, but is rejected for the data in first differences. The finding of significant cross-sectional dependence in $\ln BERD_{it}$ implies that we need to take this into account when choosing our econometric methodology and estimating our empirical model.

*Time series properties*

We also analyse the time series properties of each of the variables used. This requires a panel unit root test allowing for cross-sectional dependence. Such panel unit root tests have been proposed by, most notably, Pesaran (2007), Moon and Perron (2004) and Bai and Ng (2004). These tests are similar in that they all assume an observed variable $x_{it}$ to have the following common factor structure

$$x_{it} = d_{it} + f_t \pi_i + \xi_{it}, \tag{2.5}$$

where $f_t$ is an $r \times 1$ vector of $r$ common factors with country-specific factor loadings $\pi_i$, $\xi_{it}$ 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 $\xi_{it}$ 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 panel unit root test allowing for cross-sectional dependence 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 (2.5). 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 $\widehat{f}_t^{pc}$ and $\widehat{\xi}_{it}^{pc}$. These components can then be tested separately for unit roots. When there is only one factor, testing for a unit root in $\widehat{f}_t^{pc}$ 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 the MW test on the idiosyncratic error terms both have an actual size close to the 5% nominal level and adequate power. Applications of the PANIC approach to unit root testing using a similar data span as ours ($T$=32, $N$=14) can be found in, among others, Byrne, Fiess, and Ronald (2011), Costantini, Demetriades, James, and Lee (2013) and Everaert, Heylen, and Schoonackers (2015).

**Table 2.2:** PANIC unit root tests

Sample period: 1981-2012, 14 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 | |
| $\ln BERD_{it}$ | $d_{it}$ | 1 | 1 | 37.907 | [0.10] | $\ln BINDEX_{0i}$ | $d_{it}$ | 0 | 0 | 17.45 | [0.93] |
| $\ln VA_{it}$ | $d_{it}$ | 3 | 3 | 24.854 | [0.64] | $OPEN_{it}$ | $d_{it}$ | 2 | 2 | 12.364 | [1.00] |
| $\ln GOVERD_{it}$ | $d_{0i}$ | 1 | 1 | 12.056 | [1.00] | $HCAP_{it}$ | $d_{it}$ | 5 | 5 | 42.238 | [0.04] |
| $\ln HERD_{it}$ | $d_{it}$ | 0 | 0 | 27.91 | [0.47] | $\ln WAGE_{it}$ | $d_{0i}$ | 3 | 3 | 21.597 | [0.80] |
| $\ln SUBS_{it}$ | $d_{it}$ | 1 | 1 | 27.868 | [0.47] | $PMR_{it}$ | $d_{it}$ | 3 | 3 | 24.572 | [0.65] |

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) with a maximum of 5 factors. When $r = 1$, the number of non-stationary factors $r_1$ is determined using the ADF-GLS test of Elliott, Rothenberg, and Stock (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 $MQ_c^\tau$ (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.

In Table 2.2 we report the results of the PANIC unit root tests. For each of the variables the number of common factors $r$ is estimated using the $BIC_3$ information criterion suggested by Bai and Ng (2002). We prefer the $BIC_3$ information criterion as based on the simulation results of Bai and Ng (2002) and Moon and Perron (2007), the $BIC_3$ outperforms other information criteria in small samples like ours. The specification of the deterministic component $d_{it}$ is chosen from the observed trending behaviour of the variables. Results show that all variables are found to be non-stationary at the 5 % level of significance. For all but two variables, the non-stationarity is induced by both the common component and idisoyncratic errors. For the variable $HCAP_{it}$ non-stationarity only stems from the presence of a set of unobserved common factors while for $\ln HERD_{it}$ non-stationarity comes from the idiosyncratic component as this variable is found to have no common factor according to the $BIC_3$ information criterion. When focusing on the main variable of interest, $\ln BERD_{it}$, the Bai and Ng (2002) test to determine the number of common factors shows the presence of 1 non-stationary common factor.

### 2.3.2 Empirical model

When choosing the optimal functional form for (2.1), Guellec and Van Pottelsberghe (2003) and Falk (2006) estimate a log linear partial adjustment model by arguing that firms do not change their R&D spending immediately following changes in direct or indirect public support for R&D or changes in the other determinants. However, both Guellec and Van Pottelsberghe (2003) and Falk (2006) did not take into account two important properties of the data, i.e. the significant degree of cross-sectional dependence due to the presence of unobserved common factors and the non-stationarity of the variables considered. In this empirical analysis we explicitly deal with these properties and consider as our basic specification the following long-run relationship for $\ln BERD_{it}$,

$$\ln BERD_{it} = \gamma_i + X_{it}\beta + \mu_{it}. \tag{2.6}$$

where $X_{it} = (\ln VA_{it}, \ln POLICY_{it}, Z_{it}, \ln WAGE_{it})$ and $\beta' = (\beta_1, \beta_2, \beta_3, \beta_4)$. In this equation, the individual effect $\gamma_i$ captures unobserved time-invariant heterogeneity.

To deal with cross-sectional correlated errors (see Section 2.3.1) we adopt a multi-factor error structure, where cross-sectional dependence is modelled to arise from unobserved common factors (see e.g. Eberhardt and Teal, 2011; Everaert, Heylen, and Schoonackers, 2015):

$$\mu_{it} = \lambda_i' f_t + \epsilon_{it}, \tag{2.7}$$

where $f_t$ is an $r$x1 vector of unobserved common factors and $\lambda_i$ an $r$x1 country-specific vector of factor loadings. The generality of the error structure in (2.7) is an advantage as it allows for an unknown (but fixed) number of unobserved common components with heterogeneous factor loadings (heterogeneous cross-sectional dependence). It thus also nests common time effects (homogeneous cross-sectional dependence) as a special case and controls for possible spatial spillovers (Pesaran and Tosetti, 2011). This last element could be important as in a recent paper Montmartin and Herrera (2015) point to the importance of spatial dependence between private R&D activities in OECD countries.

In the empirical analysis we will focus on determining the long-run drivers of business sector R&D by estimating equation (2.6). Note that when estimating this equation it is important to deal appropriately with the multi-factor error structure in (2.7) as ignoring the presence of unobserved common factors leads to inconsistent estimates if the unobserved factors are correlated with the explanatory variables and to a spurious regression problem if they are non-stationary. Finally, as all variables have a unit root we test for the existence of a cointegration relationship between the variables in (2.6).

### 2.3.3 Econometric methodology

In line with Pesaran (2006) and Kapetanios, Pesaran, and Yamagata (2011), the set of unobserved common factors $f_t$ is identified from the cross-sectional dimension of the data. Taking cross-sectional averages of the model represented by equations (2.6)-(2.7) yields

$$\overline{y}_t = \overline{\gamma} + \overline{\lambda} f_t + \overline{X}_t \beta + \overline{\epsilon}_t, \tag{2.8}$$

where $y_{it} = \ln BERD_{it}$ and where $\overline{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ and similarly for $\overline{\gamma}$, $\overline{\lambda}$, $\overline{X}_t$ and $\overline{\epsilon}_t$. For notational convenience we assume a single common factor ($r = 1$) but the results straightforwardly generalize to multiple factors (see Pesaran, 2006). Equation (2.8) can then be solved for $f_t$ as

$$f_t = \frac{1}{\overline{\lambda}} \left( \overline{y}_t - \overline{\gamma} - \overline{X}_t \beta - \overline{\epsilon}_t \right), \tag{2.9}$$

which yields $\widehat{f}_t^{ca}$

$$\widehat{f}_t^{ca} = \frac{1}{\overline{\lambda}} \left( \overline{y}_t - \overline{\gamma} - \overline{X}_t \beta \right), \tag{2.10}$$

as a proxy for $f_t$. Under the assumption that $\epsilon_{it}$ is a zero mean stationary error term which is uncorrelated over cross-section units, implying that $\underset{N\to\infty}{\text{plim}}\ \overline{\epsilon}_t = 0$ for each $t$, we have that $\widehat{f}_t^{ca} \xrightarrow{p} f_t$ for $N \to \infty$. 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 $\widehat{f}_t^{ca}$ as a consistent estimator for $f_t$ in equation (2.10) 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 (2.7) by the cross-sectional averages of the observed data using equation (2.9)

$$y_{it} = \gamma_i + \left( \overline{y}_t - \overline{\gamma} - \overline{X}_t \beta - \overline{\epsilon}_t \right) \frac{\lambda_i}{\overline{\lambda}} + X_{it}\beta + \varepsilon_{it}, \tag{2.11}$$

$$= \gamma_i^{+} + \overline{y}_t \lambda_{i1} + \overline{X}_t \lambda_{i2} + X_{it}\beta + \epsilon_{it}^{+}, \tag{2.12}$$

where $\gamma_i^{+} = \gamma_i - \overline{\gamma}\lambda_i \big/ \overline{\lambda}$, $\lambda_{i1} = \lambda_i \big/ \overline{\lambda}$, $\lambda_{i2} = \lambda_i \big/ \overline{\lambda}\, \beta$ and $\epsilon_{it}^{+} = \epsilon_{it} - \lambda_i \big/ \overline{\lambda}\, \overline{\epsilon}_t$. Since $\epsilon_{it}^{+} \xrightarrow{p} \epsilon_{it}$ for $N \to \infty$, the augmented model in equation (2.12) - ignoring any parameter restrictions - can be estimated with least squares (LS), an approach referred to as the CCEP estimator.[6] Pesaran (2006) shows that, under appropriate regularity conditions, the CCEP estimator is consistent and asymptotically normal in stationary panel regressions. Kapetanios, Pesaran, and Yamagata (2011) show that these asymptotic results continu to hold in non-stationary panels provided that the idiosyncratic error term $\epsilon_{it}$ is stationary. This implies that there is cointegration (i) between $(y_{it}, X_{it})$ if $f_t \sim I(0)$ or (ii) between $(y_{it}, X_{it}, f_t)$ if $f_t \sim I(1)$.

As our empirical analysis involves testing for cointegration, we need an appropriate panel cointegration test based on the CCEP estimator. These kind of tests have been suggested by Banerjee and Carrion-i-Silvestre (2011) and Everaert (2014). Banerjee and Carrion-i-Silvestre (2011) show that under the null of no cointegration, the linear CCEP estimator allows for consistent estimation of the homogeneous coefficients $\beta$ but not for the heterogeneous coefficients $(\gamma_i, \lambda_i)$. Given this result, they suggest to obtain a consistent estimate for the composite error term $e_{it} = \gamma_i + \lambda_i f_t + \epsilon_{it}$ as

$$\widehat{e}_{it} = y_{it} - X_{it}\widehat{\beta} = (\gamma_i + \widehat{\lambda_i f_t} + \epsilon_{it}), \tag{2.13}$$

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 set of 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 $\epsilon_{it}$. This rules out that $f_t \sim I(1)$ and $\epsilon_{it} \sim I(0)$, i.e. cointegration between $(y_{it}, x_{it}, f_t)$. Since the structure of the composite error term $e_{it} = \gamma_i + \lambda_i f_t + \epsilon_{it}$ aligns with the general factor structure of equation (2.5), 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 $\widehat{\epsilon}_{it}^{pc}$, which can then be separately tested for unit roots (see PANIC approach outlined in Section 2.3.1). The main advantage of this approach is that the test whether the idiosyncratic errors $\epsilon_{it}$ 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 $\widehat{\epsilon}_{it}^{pc}$, 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

[6] Although equation (2.12) 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).

[7] Using the PANIC approach to testing for panel cointegration in the presence of common factors has also been suggested by Gengenbach, Palm, and Urbain (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.

$(y_{it}, X_{it})$ while for $f_t \sim I(1)$ there is cointegration between $(y_{it}, X_{it}, f_t)$. In a simulation exercise both Everaert (2014) and Everaert, Heylen, and Schoonackers (2015) show that a PANIC on the composite error term $\widehat{e}_{it}$ is an appropriate approach to test for common-factor augmented panel cointegration, even in small samples as ours.

## 2.4 Estimation results

### 2.4.1 Main results

The main estimation results are reported in Table 2.2. As mentioned before, our dependent variable is the log of real per capita R&D investment financed and performed by the business sector ($\ln BERD_{it}$). We estimate 10 different specifications. We start in column (1) by considering the standard set of variables that Guellec and Van Pottelsberghe (2003) introduce in their regressions. Next to value added in the business sector ($\ln VA_{it}$), there are four policy variables: public funding of R&D projects in the business sector ($\ln SUBS_{it}$), the B-index reflecting a country's tax treatment of R&D investment ($\ln BINDEX_{it}$), direct 'intramural' government expenditures on R&D ($\ln GOVERD_{it}$) and expenditures on R&D by higher education institutions ($\ln HERD_{it}$). In columns (2)-(4) we respectively extend the set of explanatory variables by the degree of openness ($OPEN_{it}$), the stock of human capital ($HCAP_{it}$), and by our wage pressure indicator ($\ln WAGE_{it}$). Columns (5) further controls for a non-linear impact of the amount of public subsidies whereas columns (6)-(10) test for non-linear and/or heterogeneous effects of wage pressure.

In a first step each specification is tested for the existence of a cointegration relationship using the PANIC approach of Bai and Ng (2004), which requires determining the number of unobserved common factors in $\ln BERD_{it}$. The analysis in Table 2.2 points to the existence of 1 common factor in $\ln BERD_{it}$. As an additional check, Table 2.1 reports the cross-sectional correlation in $\ln BERD_{it}$ 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 confirm the presence of one common factor as this seems sufficient to remove the cross-sectional dependence from $\ln BERD_{it}$ and the CCEP composite error term.

#### FE results

To highlight the importance of dealing with cross-sectional dependence for the estimation results, we first ignore any unobserved common factors and estimate the empirical model using a standard

**Table 2.1:** Determining the number of relevant common factors

Sample period: 1981-2012, 14 OECD countries

| | Cross-sectional correlation left after taking out $r$ factors | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $r=0$ | $r=1$ | $r=2$ | $r=3$ | | $r=0$ | $r=1$ | $r=2$ | $r=3$ |
| $\ln BERD_{it}$ | 0.881 | -0.053 | -0.063 | -0.055 | $\Delta \ln BERD_{it}$ | 0.1935 | -0.048 | -0.06 | -0.059 |
| $\widehat{e}_{it}^{S}1$ | 0.549 | -0.015 | -0.017 | -0.0384 | $\Delta\widehat{e}_{it}^{S}1$ | 0.086 | -0.02 | -0.013 | -0.041 |
| $\widehat{e}_{it}^{S}2$ | 0.487 | -0.028 | -0.041 | -0.024 | $\Delta\widehat{e}_{it}^{S}2$ | 0.096 | -0.032 | -0.034 | -0.039 |
| $\widehat{e}_{it}^{S}3$ | 0.194 | -0.044 | -0.044 | -0.063 | $\Delta\widehat{e}_{it}^{S}3$ | 0.112 | -0.038 | -0.032 | -0.056 |
| $\widehat{e}_{it}^{S}4$ | 0.574 | -0.026 | -0.040 | -0.043 | $\Delta\widehat{e}_{it}^{S}4$ | 0.092 | -0.025 | -0.028 | -0.039 |
| $\widehat{e}_{it}^{S}5$ | 0.131 | -0.058 | -0.062 | -0.066 | $\Delta\widehat{e}_{it}^{S}5$ | 0.147 | -0.045 | -0.048 | -0.058 |
| $\widehat{e}_{it}^{S}6$ | 0.086 | -0.047 | -0.039 | -0.056 | $\Delta\widehat{e}_{it}^{S}6$ | 0.128 | -0.047 | -0.038 | -0.049 |
| $\widehat{e}_{it}^{S}7$ | 0.089 | -0.042 | -0.044 | -0.052 | $\Delta\widehat{e}_{it}^{S}7$ | 0.116 | -0.039 | -0.04 | -0.054 |
| $\widehat{e}_{it}^{S}8$ | 0.127 | -0.052 | -0.063 | -0.053 | $\Delta\widehat{e}_{it}^{S}8$ | 0.154 | -0.047 | -0.055 | -0.06 |
| $\widehat{e}_{it}^{S}9$ | 0.817 | -0.047 | -0.047 | -0.052 | $\Delta\widehat{e}_{it}^{S}9$ | 0.117 | -0.040 | -0.036 | -0.054 |
| $\widehat{e}_{it}^{S}10$ | 0.315 | -0.051 | -0.043 | -0.054 | $\Delta\widehat{e}_{it}^{S}10$ | 0.103 | -0.038 | -0.027 | -0.049 |

Note: $\widehat{e}_{it}^{S}1$, $\widehat{e}_{it}^{S}2$,..., $\widehat{e}_{it}^{S}8$ are the CCEP composite error terms, defined in equation (2.13) taken from specification (1),(2),...,(8) respectively. We report the average cross-correlation $\overline{\widehat{\rho}}$ (see Table 2.1 for the definition) after taking our $r$ common factors using PANIC.

FE estimator. The results can be found in Appendix 2.A. Using the FE estimator, we cannot reject the null of no cointegration for all different specifications. The PANIC cointegration test at the bottom of Table 2.A.1 shows that both the common factor and the idiosyncratic error terms are non-stationary at the 5% level of significance. This is problematic as Urbain and Westerlund (2011) show that the standard result in Phillips and Moon (1999) that panel regressions yield consistent results even if there is no cointegration, does no longer hold when the non-stationarity in the error term is induced by a common factor. This implies that the results from the FE estimator, which ignores the presence of non-stationary common factors, are spurious. As such we do not interpret these results.

### CCEP results

Turning to the CCEP estimator, which controls for unobserved common factors, the cointegration test results in Table 2.2 show that for all, but one, specifications containing our wage measure the null of no cointegration can be rejected at low levels of significance. For specifications (6) and (7), we can reject the null hypothesis at the 1% significance level while for specifications (4), (8) and (10) the null can be rejected at the 5% level. For specifications (5) and (9), the null can only be rejected at the 10 % level of significance. The importance of taking into account wage policy as a factor influencing private R&D investment is confirmed by considering the cointegration test results of specifications (1), (2) and (3). For these specficiations, the null of no cointegration cannot be rejected at the 5% level of significance, implying that our wage measure is an essential part of the cointegration relationship. Looking in detail at the PANIC cointegration test results, the time series properties of the unobserved common factor, $f_t$ reveal that this variable is part of the cointegration relationship. So there is cointegration between $(y_{it}, X_{it}, f_t)$.

Regarding the estimated coefficients, the effect of total value added on R&D investment in the business sector is robustly positive and statistically significant in all our regressions. The estimated (partial) long-run elasticity varies between 0.43 and 0.75, the median being 0.65. As to public policies, our estimation results reveal various ways in which governments can effectively promote R&D investment in a country. One approach is to give tax incentives or subsidies and grants. Another is to spend more on R&D within the public sector itself if this does not crowd out private spending. Our evidence suggests that both options can work, if chosen appropriately.

Let us start with the former. In a majority of our regressions, we observe a negative and statistically significant effect on the B-index of about -0.18, supporting the hypothesis that tax incentives encourage private R&D investment. This result is clearly in line with most of the literature that we summarized in Section 2.2.1. In some of our regressions, though, the observed negative effect is not statistically significant. For public funding of investment in the business sector ($\ln SUBS_{it}$) we always obtain positive but mostly highly insignificant elasticities. Only in specifications (9) and (10) the long-run elasticity varies around 0.4 and is significant at the 5% level. At first sight, our results therefore seems to indicate that private firms are not encouraged to raise their own R&D expenditures and undertake additional investments when some of their projects are publicly funded. Neither, however, do they cut back on their own spending. The observed positive coefficient on $\ln SUBS_{it}$ clearly challenges the hypothesis that subsidized private firms would just substitute public money for their own. Additional analysis, however, as in specification (5), reveals a much richer reality behind this general result. When we follow Guellec and Van Pottelsberghe (2003) and allow for different effects from public funding on private R&D expenditures depending on the level of the subsidization percentage, we find both at low subsidization rates (i.e. below 4%) and at high subsidization rates (above 11%) a negative elasticity of public funding[8]. At intermediate subsidization rates, however, we find this elasticity to be positive (0.076) and statistically significant. We conclude that direct government funding can be effective in promoting private R&D investment, but this funding should not be too low, neither too high. In the former case support may be too weak to help firms overcome the risks and uncertainties involved in innovation projects. In the latter case, support may be larger than the number of (new) projects that firms can develop, so that in the end they simply use public resources to finance projects that would have been done anyway. In this sense we confirm earlier evidence by Guellec and Van Pottelsberghe (2003).

[8]We follow Guellec and Van Pottelsberghe (2003) and use the share of government funded R&D in total business performed R&D as a proxy for the subsidization rate. We find this rate to be low ($<$ 4 % on average over the sample period) in Australia and Finland, and high ($>$ 11%) in France, Italy, Norway, Spain, UK and US. The other countries take intermediate positions.

**Table 2.2:** CCEP regression results

Dependent variable: $\ln BERD_{it}$

Sample period: 1981-2012, 14 OECD countries

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Coefficient estimates** | | | | | | | | | | |
| **Explanatory variables** | | | | | | | | | | |
| $\ln VA_{it}$ | $0.644^{***}$ | $0.709^{***}$ | $0.646^{***}$ | $0.459^{**}$ | $0.663^{***}$ | $0.659^{***}$ | $0.497^{**}$ | $0.742^{***}$ | $0.428^{*}$ | $0.512^{**}$ |
| | (0.18) | (0.194) | (0.187) | (0.242) | (0.227) | (0.257) | (0.249) | (0.222) | (0.230) | (0.240) |
| $\ln BINDEX_{it}$ | $-0.186^{**}$ | -0.114 | $-0.187^{**}$ | $-0.182^{**}$ | $-0.170^{**}$ | -0.103 | -0.10 | $-0.189^{**}$ | $-0.229^{***}$ | $-0.142^{*}$ |
| | (0.087) | (0.10) | (0.089) | (0.086) | (0.084) | (0.093) | (0.092) | (0.080) | (0.086) | (0.082) |
| $\ln SUBS_{it}$ | 0.004 | 0.01 | 0.017 | 0.000 | | 0.028 | 0.031 | 0.034 | $0.046^{**}$ | $0.044^{**}$ |
| | (0.002) | (0.025) | (0.024) | (0.023) | | (0.024) | (0.024) | (0.022) | (0.023) | (0.022) |
| $\ln GOVERD_{it}$ | 0.055 | 0.053 | 0.055 | 0.064 | 0.059 | $0.087^{*}$ | $0.126^{**}$ | 0.021 | 0.023 | 0.020 |
| | (0.044) | (0.045) | (0.045) | (0.044) | (0.043) | (0.046) | (0.05) | (0.042) | (0.053) | (0.049) |
| $\ln HERD_{it}$ | 0.071 | 0.063 | -0.017 | 0.096 | -0.057 | 0.042 | 0.032 | 0.074 | -0.018 | 0.022 |
| | (0.069) | (0.072) | (0.071) | (0.068) | (0.064) | (0.071) | (0.071) | (0.066) | (0.065) | (0.067) |
| $HCAP_{it}$ | | | $0.051^{***}$ | | $0.093^{***}$ | $0.06^{***}$ | $0.068^{***}$ | $0.092^{***}$ | $0.047^{***}$ | $0.067^{***}$ |
| | | | (0.010) | | (0.011) | (0.011) | (0.01) | (0.011) | (0.012) | (0.010) |
| $OPEN_{it}$ | | 0.002 | | | | $0.014^{***}$ | | | | |
| | | (0.001) | | | | (0.005) | | | | |
| $\ln WAGE_{it}$ | | | | -0.205 | 0.127 | $-1.108^{**}$ | | | -0.085 | 0.383 |
| | | | | (0.211) | (0.197) | (0.463) | | | (0.202) | (0.445) |
| $PMR_{it}$ | | | | | | | | | $0.419^{**}$ | -0.112 |
| | | | | | | | | | (0.196) | (0.154) |
| $PMR^2_{it}$ | | | | | | | | | -0.046 | |
| | | | | | | | | | (0.036) | |
| $\ln SUBS_{it} * low$ | | | | | -0.053 | | | | | |
| | | | | | (0.075) | | | | | |
| $\ln SUBS_{it} * medium$ | | | | | $0.076^{**}$ | | | | | |
| | | | | | (0.034) | | | | | |
| $\ln SUBS_{it} * high$ | | | | | $-0.087^{**}$ | | | | | |
| | | | | | (0.040) | | | | | |
| $\ln WAGE_{it} * OPEN_{it}$ | | | | | | $0.014^{**}$ | | | | |
| | | | | | | (0.006) | | | | |
| $\ln WAGE_{it} * PMR_{it}$ | | | | | | | | | | $-0.295^{*}$ |
| | | | | | | | | | | (0.172) |
| $\ln WAGE_{it} * epl_{low}$ | | | | | | | $-1.205^{***}$ | | | |
| | | | | | | | (0.447) | | | |
| $\ln WAGE_{it} * epl_{middle}$ | | | | | | | 0.134 | | | |
| | | | | | | | (0.474) | | | |
| $\ln WAGE_{it} * epl_{high}$ | | | | | | | 0.092 | | | |
| | | | | | | | (0.257) | | | |
| $\ln WAGE_{it} * anglo$ | | | | | | | | -0.639 | | |
| | | | | | | | | (0.464) | | |
| $\ln WAGE_{it} * euro$ | | | | | | | | $1.331^{***}$ | | |
| | | | | | | | | (0.338) | | |
| $\ln WAGE_{it} * nordic$ | | | | | | | | 0.27 | | |
| | | | | | | | | (0.305) | | |
| **Panic Cointegration test (one common factor)** | | | | | | | | | | |
| ADF-GLS on $\widehat{f}^{pc}_t$ | -0.699 | -1.392 | -0.931 | -0.797 | -1.455 | -2.105 | -1.55 | -2.168 | -0.073 | -0.344 |
| | [0.97] | [0.84] | [0.94] | [0.96] | [0.82] | [0.52] | [0.79] | [0.49] | [0.99] | [0.99] |
| MW on $\widehat{\epsilon}^{pc}_{it}$ | 1.23 | $1.37^{*}$ | 1.086 | $1.603^{**}$ | $1.295^{*}$ | $2.446^{***}$ | $2.918^{***}$ | $1.661^{**}$ | $11.460^{*}$ | $2.085^{**}$ |
| | [0.11] | [0.09] | [0.14] | [0.05] | [0.10] | [0.01] | [0.00] | [0.05] | [0.07] | [0.02] |

Notes: standard errors are in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively. For the panel cointegration test results, the unit root test on the common factor $\widehat{F}_t$ is a ADF-GLS test for a model with constant. The corresponding (simulated) p-values are reported in square brackets. The unit root test on the estimated idiosyncratic errors $\widehat{\epsilon}^{pc}_{it}$ is a MW test. The corresponding p-values are reported in square brackets

Results on the effects of R&D spending within the government sector ($\ln GOVERD_{it}$) and within institutions of higher education ($\ln HERD_{it}$) all go in the same direction. The effect is positive in almost all cases but small and mostly insignificant. Although this may sound poor from a statistical perspective, it is not unimportant economically. It means that each euro that the government spends on 'intramural' R&D or on R&D within universities adds one euro to aggregate spending on R&D. Our findings therefore go against the hypothesis of (weak) crowding out, for which Guellec and Van Pottelsberghe (2003) found evidence, as well as against the hypothesis of complementarity between public and private spending, as suggested by Falk (2006). Only for $\ln GOVERD_{it}$ in columns (6) and (7) we may find some weak indications in favour of complementarity. The regressions in these columns yield a long-run positive elasticity of about 0.1[9].

Important is also that governments can stimulate private R&D investment by encouraging human capital formation. This is confirmed by our empirical results which yield very robust and significant positive estimates on the stock of high skilled human capital ($HCAP_{it}$). Considering the lack of consistent findings in the existing literature (see for example Falk, 2006), this is an interesting result. We also find a positive effect from the degree of openness of the economy on business R&D spending. In column (2) this positive effect is not statistically significant. In specification (6) it is. This may point to the importance of international transfer of technology and knowledge for business R&D. However, in line with results that we discuss below for the wage gap, a complementary interpretation could be that a more open economy raises the degree of competition that firms face. Facing more competitors then seems to encourage firms to innovate.

An important potential determinant of business-funded and performed R&D is wage pressure. Theory being inconclusive, what do we learn from our results on its impact on innovation? When analyzing the basic effect in specifications (4) and (5) we do not find any significant effect from wage formation on R&D investment. In column (4) the effect is insignificantly negative whereas in column (5) it is insignificantly positive. However, a much more detailed analysis, based on the theoretical arguments in Section 2.2.2, gives a clearer view. As wage pressure has possibly positive effects in a very competitive environment, we allow in specification (6) for interaction between $\ln WAGE_{it}$ and $OPEN_{it}$. The basic impact of $\ln WAGE_{it}$ is now negative and highly significant, with an estimated long-run coefficient equal to -1.1. If wage pressure increases with 1 %point, this implies that, on average, private R&D investment drops with 1.11 %. Higher wage pressure thus seems to undermine business R&D expenditures. An obvious explanation, and in

[9] The observed elasticities allow us to compute the marginal effect on business financed R&D and on aggregate R&D spending (business + public) induced by one euro spent by the government. Considering that $BERD_{it}$ relates to $GOVERD_{it}$ as 5 to 1 and to $SUBS_{it}$ as 13 to 1 on average over all countries considered in our analysis, elasticities of 0.126 for $GOVERD_{it}$ and 0.076 for $SUBS_{it}$ (the highest we observe in our results) would imply that $\frac{\Delta BERD_{it}}{\Delta GOVERD_{it}} = 0.63$ and $\frac{\Delta BERD_{it}}{\Delta SUBS_{it}} = 0.99$. In the case of $GOVERD_{it}$, aggregate R&D spending would thus rise by 1.63 (1 euro public + 0.63 euro private) euro, in the case of $SUBS_{it}$ by 1.99 (1 euro public + 0.99 euro private) euro.

line with Ulph and Ulph (1994), would be that higher wages reduce the profit differential between innovating and not innovating. However, the basic hypothesis only seems to survive in economies where firms face relatively little (foreign) competition. In a competitive environment the wage effect may be tilted. From the interaction term in specification (6) we learn that in countries with a degree of openess higher than 80 % the global impact of wage pressure becomes positive, meaning that higher wages encourage private R&D investment. Specification (7) differentiates the effect of $\ln WAGE_{it}$ according to the level of employment protection legislation ($EPL_{it}$)[10]. In countries with low average $EPL$ a significant negative effect of wage pressure emerges, again indicating that higher wages reduces the incentive to innovate. In (very) regulated labour markets the negative impact disappears as for the other two groups of countries we observe (insignificant) positive effects of wage pressure on business R&D investment. As an additional check, the possible impact of openess and labour market characteristics are integrated in specification (8). We distinguish three groups of countries.

The first group of Anglo-Saxon countries is characterized by a relatively low degree of openness and low employment protection legislation. The estimated effect from $\ln WAGE_{it}$ is clearly negative in this group (although significant only at 20%). The second group of euro area countries is characterized by rather the opposite of a high degree of openness and rigid labour markets. Here we observe a significant positive coefficient on $\ln WAGE_{it}$. The arguments raised by Kleinknecht (1998) and co-authors that an excessive focus on wage moderation could be harmful to innovation, would thus seem to find support for this group. The third group of Nordic countries takes an intermediate position. Finally, in specifications (9) and (10) we analyse the direct impact of product market (de)regulation, $PMR_{it}$, and its possible effect on the relation between wage pressure and innovation. Following Aghion, Bloom, Griffith, and Howitt (2005), a U-shaped relationship should be expected between $PMR_{it}$ and $\ln BERD_{it}$. In specification (9) we do not find evidence for this U-shaped effect. On the contrary, results show that more regulated product markets increase firms' incentive to invest in R&D. In this view, higher product market regulation, and thus lower competition, increases firms' rents when investing in R&D. When also taking into account the possible impact of $PMR_{it}$ on the effect of wage pressure on business funded and performed R&D, which is done in specification (10), the direct impact of $PMR_{it}$ is somewhat different. Now, higher product market regulation has a negative, but insignficant, impact on the amount of business R&D expenditures. More interestingly is the interaction between $PMR_{it}$ and $\ln WAGE_{it}$. This interaction effect confirms our earlier finding. In a less competitive environment (high $PMR_{it}$), higher wage pressure reduces the incentives of firms to invest in R&D. When product markets become more deregulated, the basic negative effect disappears and in these circumstances wage pressure

[10]As time variation in $EPL_{it}$ is too limited, we cannot interact $\ln WAGE_{it}$ with $EPL_{it}$. As a solution, we differentiate the impact of $\ln WAGE_{it}$ amongst three groups of countries with different average $EPL_{it}$

can even stimulate private R&D investment.

### 2.4.2 The importance of economic and policy related variables in explaining private investment in R&D

Our empirical results in Table 2.2 help us to understand and explain important differences in the level and evolution of real business funded and performed R&D in the OECD during the last decades. In what follows, we discuss the explanatory power of our estimated empirical model and conduct a counterfactual analysis. The latter allows us to assess the contribution of changes since 1981 in public policy, wage pressure and human capital to the evolution of business R&D. What fraction of the total change in $BERD$ between 1981 and 2012 can these explanatory variables explain? Which was more important, which was less important? Are the results the same for all countries/country groups?

**Explanatory power**

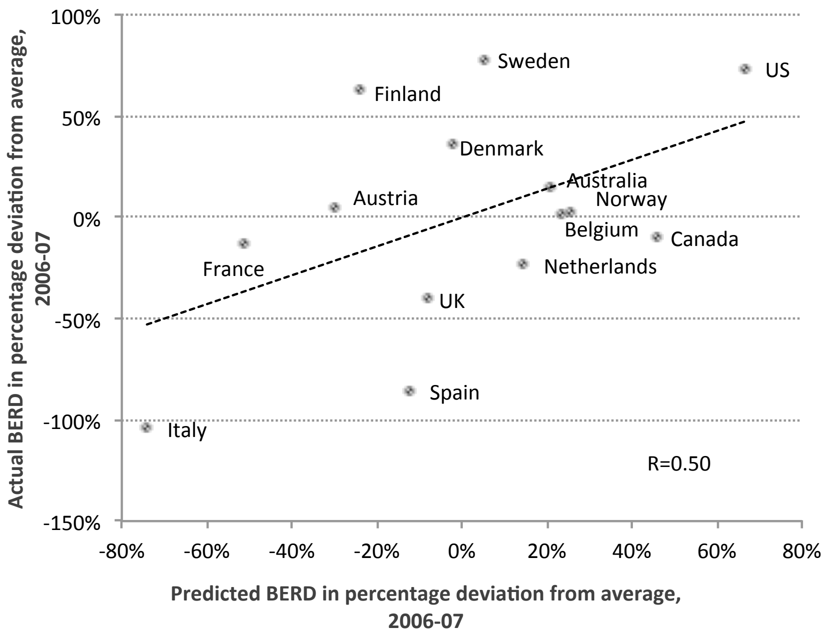
Figure 2.1 demonstrates the capacity of our empirical model to explain the variation in business R&D investment across countries and over time. We use the regression result in specification (6). The upper panel in Figure 2.1 (panel a) relates our model's prediction (economic explanation) for the *level* of business R&D expenditures in 2006-2007 to the true observation[11]. Both prediction and true observation are represented as percentage deviations from their overall country averages. The lower panel (panel b) relates predicted and observed *changes* in business funded and performed R&D between 1981 and 2007. We emphasize that our predictions in both panels have been obtained solely from using the 'economic' and 'policy related' parts of the estimated equation. They do not include the country-specific fixed effects nor the approximations for the country-specific factor loadings and unobserved common factors.

Correlation in panel (a) is 0.50. Our model correctly predicts far above average business R&D investment in 2006-2007 in the US and (far) below average R&D investment in Italy and France. The model's prediction of close to average performance in Australia, Austria, Belgium, Denmark and Norway is also quite well in line with the facts. On the other hand, using only the economic and policy related explanatory variables in the model, it is harder to match the high level of business R&D investment in 2006-2007 in Finland and Sweden. So it is to match relative low investment in Spain. It is clear that for these countries the unobserved common factor was more important than for other countries.

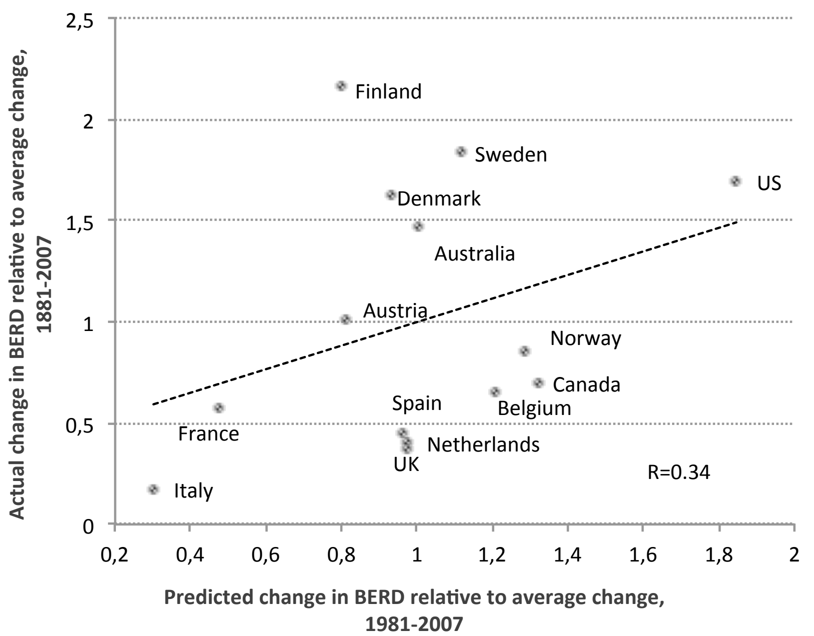
[11] We choose these years as they are the last before the outbreak of the global financial crisis. Severe shocks to firms' investment decisions during this crisis imply that the data are much less likely to match the long-run equilibrium relationship that our model captures.

**Figure 2.1:** Actual and predicted business R&D expenditure (Table 2.2, specification 6)

(a) Actual and predicted business R&D expenditure levels, 2006-2007




(b) Actual and predicted change in business R&D expenditure, 2007 versus 1981



In this respect, our results are in line with those of Everaert, Heylen, and Schoonackers (2015). Studying the drivers of TFP, they find for Finland and Sweden a relatively strong and rising absorptive capacity to the (unobserved and common) world level of technology. Stronger international technology spillovers, and their effects on the private return to R&D, may explain an important part of the above average business investment in innovation in these countries. The opposite may explain weaker investment in Spain. Clearly, the observation that the common factor plays an important role, at least for some countries, is fully in line with our earlier finding that this factor belongs to the cointegration relationship. It supports (again) our choice for the CCEP estimator.

Correlation in panel (b) is 0.34. The model again seems to have the main drivers of R&D investment right for the US, France and Italy. It also explains quite well the change in business R&D investment over time in countries like Austria and Norway. Finland is again by far the largest outlier. On the basis of (changes in) economic and policy related variables it is impossible to explain the strong actual rise in $BERD$ since 1981 in this country. Dropping Finland, correlation in panel (b) rises to 0.50.

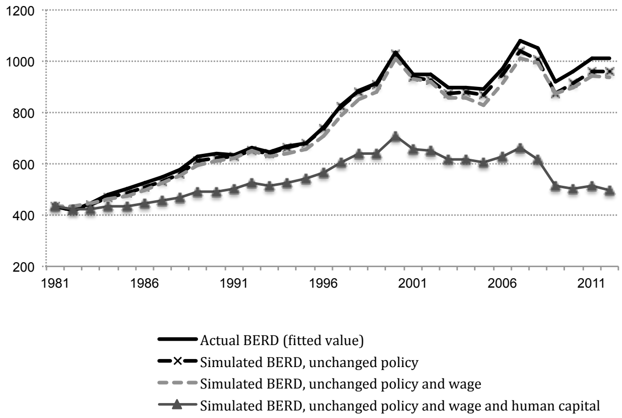
**Counterfactual analysis**

Figure 2.2 reveals the estimated size of the estimated effects on business R&D expenditures of changes in public innovation policy, wage pressure and human capital since 1981 in the US, an average of five EU countries and the Nordic countries in our sample. Each graph compares the model's fitted value for these countries with (i) the simulated value if all policy variables (spending, taxes) had remained at their 1981 level, (ii) the simulated value if all policy variables and wage pressure had remained at their 1981 level, and (iii) the simulated value if all policy variables, wage pressure and human capital had remained at their 1981 level. Individual country graphs are available upon request.

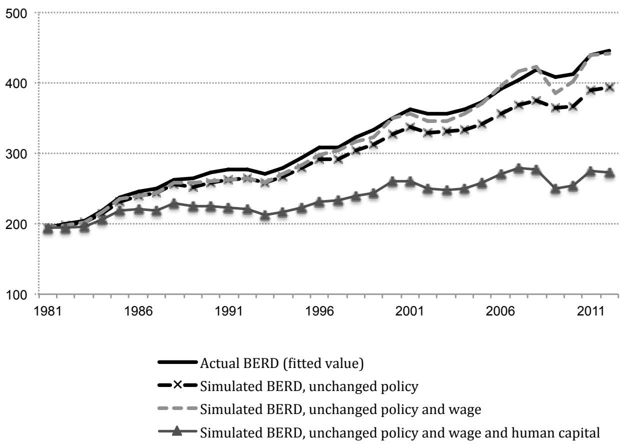
All three graphs underscore the importance of public policy, wage pressure and human capital. As indicated by the lower line in Figure 2.1a, in the US business R&D investment in 2012 would have been only a little bit higher than in 1981 if these variables had remained unchanged. The core EU5 countries would have realized only about 1/3 of the actual increase in $BERD$ if policy variables, wage pressure and human capital had remained at their 1981 level. The Nordic countries only about 50%. In this sense, Figure 2.2 is fully consistent with our earlier findings in Figure 2.1. The observed policy and other variables were very important for the evolution of business R&D investment in most countries. It seems again, though, that in comparative perspective the Nordic countries also benefited strongly from the evolution of the unobserved common factor. In the US its impact was minimal, especially so when we consider the most recent years.

**Figure 2.2:** Counterfactual analysis: fitted and simulated model (Table 2.2, specification 6)

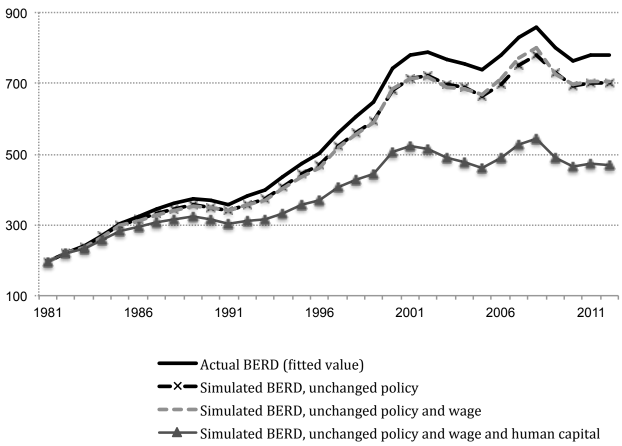
(a) United States




(b) Core-EU5 (Austria, Belgium, France, Italy, Netherlands)




(c) Nordic-4



As to the relative contribution of the set of policy variables, the wage gap, and high skilled human capital for the evolution of $BERD$, Figure 2.2 leaves no doubt that the latter was the most important. In the US the increase of human capital contributed to more than 75% of the total increase in $BERD$. In the core EU that was almost 70%, in the Nordic countries about 50%.

Public innovation policy comes second in line, especially in the core EU countries. In these countries, changes in policy accounted for a little more than 20% of the observed increase in $BERD$ since 1981. In the Nordic countries the contribution of policy changes was about 13%, in the US about 9%. Finally, changes in the wage gap may have contributed the least to change in business R&D investment. This conclusion holds in particular for the US and the Nordic countries where fairly limited changes in wage pressure, on average, had rather neutral effects. Changes in the wage gap did matter, however, in the core EU5. The focus on wage moderation in countries like the Netherlands, Austria and Italy in particular had an important negative impact on $BERD$ over time. Figure 2.2 shows that, for the evolution of $BERD$, the stimulating effect of public policy in the core EU5 countries was entirely neutralized by the negative effects of wage moderation.

### 2.4.3 Robustness test: alternative specification of the wage indicator

To construct our wage indicator, $\ln WAGE$, in Section 2.3.1, we used data on the share of private capital ($\alpha$), public capital ($\beta$) and labour ($1 - \alpha - \beta$) in total income. Estimation of a basic production function for the set of countries in our empirical analysis gave us the required information. However, to show that our results are not sensitive to the exact choice of the income shares, we also constructed an alternative wage indicator based on different (but evenly realistic) output elasticities. More specifically, we set $\alpha$ and $\beta$ equal to respectively 0.30 and 0.10, which is in line with the results reported by Bom and Ligthart (2014), and the resulting labour share to 0.6. Using these elasticities, we recalculated $\ln WAGE$ and re-estimated all related specifications with the CCEP estimator. Results can be found in Appendix 2.B. For all specifications, results are similar to the ones in Table 2.2 and the same conclusions apply. As an additional robustness check we took into account the empirical observation that bargained wages tend to be lower the higher the unemployment rate (see e.g. Blanchflower and Oswald, 1994; Nickell, Nunziata, Ochel, and Quintini, 2003). This may somewhat bias our wage gap indicator. As a second robustness test, we controlled for this by following Arpaia and Pichelmann (2007) and added the unemployment rate to our wage indicator. Again, results are very similar to the ones reported in Table 2.2[12].

[12] Results using this alternative wage indicator are not reported here, but are available upon request.

### 2.4.4 Direction of causation

The empirical results in Table 2.2 give proof of a long-run relationship between $\ln BERD_{it}$ and its determinants. To provide evidence that the long-run coefficients in Table 2.2 can be interpreted as empirical causal effects, we apply a test for the direction of caution based on the approach of Eberhardt and Teal (2013) which builds on the discussion in Canning and Pedroni (2008). From the Granger Representation Theorem (Engle and Granger, 1987) we know that if there exists a cointegration relationship between the variables in the model, these series can be represented in the form of a dynamic error correction model.

Equations (2.14)-(2.15) formalize this relationship for our empirical model. For notational covenience, this is done under the assumption of 1 ($r = 1$) common factor, $f_t$, and of 1 variable included in $X_{it}$.

$$\Delta \ln BERD_{it} = \kappa_{1i} + \alpha_1 \widehat{\varepsilon}_{i,t-1} + \rho_{1i}\Delta f_t + \sum_{j=1}^{J} \phi_{11j} \Delta \ln BERD_{i,t-j} + \sum_{j=1}^{J} \phi_{12j} \Delta X_{i,t-j} + \nu_{1it}, \tag{2.14}$$

$$\Delta X_{it} = \kappa_{2i} + \alpha_2 \widehat{\varepsilon}_{i,t-1} + \rho_{2i}\Delta f_t + \sum_{j=1}^{J} \phi_{21j} \Delta \ln BERD_{i,t-j} + \sum_{j=1}^{J} \phi_{22j} \Delta X_{i,t-j} + \nu_{2it}. \tag{2.15}$$

where $\widehat{\varepsilon}_{i,t-1}$ represents the 'disequilibrium term'. The cointegration test results from Table 2.2 show there is cointegration between $(y_{it}, X_{it}, f_t)$. This implies that the 'disequilibrium term' is constructed as $\widehat{\varepsilon}_{it} = \ln BERD_{it} - \gamma_i - X_{it}\beta - \lambda_i f_t$ and that $f_t$ is included in equations (2.14)-(2.15). As a proxy for $f_t$ and for $\widehat{\varepsilon}_{it}$, we use the results of the PANIC cointegration testing procedure which provides us respectively with $\widehat{f}_t^{pc}$ and $\widehat{\epsilon}_{it}^{pc}$. Equations (2.14)-(2.15) further include lagged differences of the observable variables in the cointegrating relationship.

For a long-run relationship to exist between $\ln BERD_{it}$, $X_{it}$ and $f_t$, $\alpha_1$ or $\alpha_2$ must be nonzero . If $\alpha_1 \neq 0$ then $X_{it}$ has a causal impact on $\ln BERD_{it}$; if $\alpha_2 \neq 0$ then $\ln BERD_{it}$ has a causal impact on $X_{it}$. If both $\alpha_1$ and $\alpha_2$ are non-zero, $X_{it}$ and $\ln BERD_{it}$ determine each other jointly. In the above example there are only two equations, as we have two variables in the cointegration relationship. In our empirical analysis we will have $k + 1$ equations, with $k$ being the number of variables in $X_{it}$. Empirical estimates for $\alpha_1$, $\alpha_2$,...,$\alpha_{k+1}$ are investigated using standard t-ratios, given that all variables in the ECM regression are stationary[13].

[13] The disequilibrium term $\widehat{\varepsilon}_{it}$ constructed from specifications (1), (2), (3) and (5) is not stationary at the 5% significance level but still stationary at the 10% level for specifications (2) and (5). This implies that for the 'direction of causation' test based on specification (1) and (3) we should employ simulated critical values. However, in our analysis we still use standard t-ratios with the reason being that the p-values of stationarity of the disequilibrium term are very close to 10 % and that we are mainly interested in the specifications that include our wage measure.

Results are presented in Table 2.3 for two lags ($J = 2$), but the same conclusions can be drawns for one lag ($J = 1$). Due to the limited time series dimension of our data, we do not consider extra lags. In Table 2.3, the first row of each specification refers to the estimation of $\widehat{\alpha}_1$, while for all other rows, $\widehat{\alpha}_2$ is estimated with the dependent variable the variable mentioned in the column 'Variable'. Table 2.3 shows that for each specification that we have estimated, $X_{it}$ has an impact on $\ln BERD_{it}$. This can be seen from the estimation of equation (2.14) in row 1 for each specification in Table 2.3. To be sure that the estimated impact is causal, equation (2.15) is estimated for each element in $X_{it}$ as a dependent variable. If the error correction term of these equations is zero, then the corresponding x-variable has a causal impact on $\ln BERD_{it}$. The results in Table 2.3 show that all results can be interpreted as empirical causal effects as no error correction term is significant when estimating equation (2.15).

As an additional check we allow the short term coefficients ($\phi_{11j}$, $\phi_{12j}$, $\phi_{21j}$ and $\phi_{22j}$) and the error correction terms ($\alpha_1$ and $\alpha_2$) in equations (2.14) and (2.15) to vary across countries. Results for the 'direction of causation' test when allowing for this heterogeneity can be found in Table 2.4, where the mean group results are reported. When allowing for short-term heterogeneity across countries, conclusions on the direction of causation are somewhat different. First, there is clear evidence that $\ln HERD_{it}$ and $\ln BERD_{it}$ determine each other jointly. This implies that the coefficient on $\ln HERD_{it}$ in our specifications should be interpreted as a correlation and not as a causal effect. Evidence of reverse causality is also present for $\ln VA_{it}$ as is shown by the test results of specification (3), (5),(7) and (8). For $PMR_{it}$, the test results of specification (10) indicate a possible problem of reverser causality, although only at the 10 % significance level. Finally, it is also important to note that only in specification (7) there is some indication that the coefficients on $WAGE_{it}$ could not be interpreted as causal. However, this is only the case at the 10% level of significance. Moreover, all other specifications show that the estimated effect of $WAGE_{it}$ is causal.

**Table 2.3:** Test for direction of causation

| Variable | $\widehat{\alpha}$ | std | Verdict | Variable | $\widehat{\alpha}$ | std | Verdict | Variable | $\widehat{\alpha}$ | std | Verdict |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Specification** (1) | | | | **Specification**(2) | | | | **Specification** (3) | | | |
| $\ln BERD_{it}$ | $-0.182^{***}$ | (0.041) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.196^{***}$ | (0.049) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.229^{***}$ | (0.053) | $x \rightarrow y$ |
| $\ln VA_{it}$ | 0.001 | (0.023) | | $\ln VA_{it}$ | -0.003 | (0.025) | | $\ln VA_{it}$ | -0.011 | (0.028) | |
| $\ln BINDEX_{it}$ | 0.036 | (0.037) | | $\ln BINDEX_{it}$ | 0.042 | (0.041) | | $\ln BINDEX_{it}$ | 0.34 | (0.045) | |
| $\ln SUBS_{it}$ | -0.179 | (0.125) | | $\ln SUBS_{it}$ | -0.169 | (0.137) | | $\ln SUBS_{it}$ | -0.194 | (0.152) | |
| $\ln GOVERD_{it}$ | 0.052 | (0.062) | | $\ln GOVERD_{it}$ | $0.042^{*}$ | (0.068) | | $\ln GOVERD_{it}$ | 0.060 | (0.076) | |
| $\ln HERD_{it}$ | $0.050^{*}$ | (0.237) | | $\ln HERD_{it}$ | 0.039 | (0.047) | | $\ln HERD_{it}$ | 0.054 | (0.052) | |
| | | | | $OPEN_{it}$ | 0.010 | (0.039) | | $HCAP_{it}$ | 0.097 | (0.167) | |
| **Specification** (4) | | | | **Specification** (5) | | | | **Specification** (6) | | | |
| $\ln BERD_{it}$ | $-0.188^{***}$ | (0.048) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.171^{**}$ | (0.078) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.237^{***}$ | (0.095) | $x \rightarrow y$ |
| $\ln VA_{it}$ | 0.001 | (0.025) | | $\ln VA_{it}$ | 0.001 | (0.039) | | $\ln VA_{it}$ | -0.011 | (0.042) | |
| $\ln BINDEX_{it}$ | 0.034 | (0.041) | | $\ln BINDEX_{it}$ | 0.017 | (0.064) | | $\ln BINDEX_{it}$ | 0.027 | (0.069) | |
| $\ln SUBS_{it}$ | -0.182 | (0.137) | | $\ln GOVERD_{it}$ | 0.048 | (0.109) | | $\ln SUBS_{it}$ | -0.116 | (0.239) | |
| $\ln GOVERD_{it}$ | 0.053 | (0.069) | | $\ln HERD_{it}$ | 0.040 | (0.074) | | $\ln GOVERD_{it}$ | 0.081 | (0.118) | |
| $\ln HERD_{it}$ | 0.046 | (0.046) | | $HCAP_{it}$ | 0.254 | (0.231) | | $\ln HERD_{it}$ | 0.031 | (0.082) | |
| $\ln WAGE_{it}$ | -0.002 | (0.023) | | $\ln Wage_{it}$ | 0.013 | (0.037) | | $HCAP_{it}$ | 0.202 | (0.262) | |
| | | | | $\ln SUBS_{it} * low$ | -0.020 | (0.083) | | $OPEN_{it}$ | 0.032 | (0.068) | |
| | | | | $\ln SUBS_{it} * medium$ | -0.102 | (0.166) | | $\ln WAGE_{it}$ | 0.009 | (0.039) | |
| | | | | $\ln SUBS_{it} * high$ | -0.106 | (0.132) | | $\ln WAGE_{it} * OPEN_{it}$ | -0.026 | (0.078) | |
| **Specification** (7) | | | | **Specification** (8) | | | | **Specification** (9) | | | |
| $\ln BERD_{it}$ | $-0.227^{***}$ | (0.081) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.176^{**}$ | (0.076) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.263^{***}$ | (0.091) | $x \rightarrow y$ |
| $\ln VA_{it}$ | -0.021 | (0.042) | | $\ln VA_{it}$ | -0.001 | (0.038) | | $\ln VA_{it}$ | -0.020 | (0.045) | |
| $\ln BINDEX_{it}$ | 0.020 | (0.067) | | $\ln BINDEX_{it}$ | 0.016 | (0.062) | | $\ln BINDEX_{it}$ | 0.034 | (0.078) | |
| $\ln SUBS_{it}$ | -0.131 | (0.231) | | $\ln SUBS_{it}$ | -0.049 | (0.216) | | $\ln SUBS_{it}$ | -0.096 | (0.264) | |
| $\ln GOVERD_{it}$ | 0.078 | (0.115) | | $\ln GOVERD_{it}$ | 0.064 | (0.106) | | $\ln GOVERD_{it}$ | 0.089 | (0.131) | |
| $\ln HERD_{it}$ | 0.052 | (0.078) | | $\ln HERD_{it}$ | 0.066 | (0.072) | | $\ln HERD_{it}$ | 0.062 | (0.088) | |
| $HCAP_{it}$ | 0.080 | (0.253) | | $HCAP_{it}$ | 0.185 | (0.286) | | $HCAP_{it}$ | 0.134 | (0.286) | |
| $\ln WAGE_{it} * epl_{low}$ | -0.004 | (0.016) | | $\ln WAGE_{it} * anglo$ | -0.009 | (0.015) | | $\ln WAGE_{it}$ | 0.022 | (0.043) | |
| $\ln WAGE_{it} * epl_{middle}$ | 0.019 | (0.023) | | $\ln WAGE_{it} * euro$ | 0.028 | (0.019) | | $PMR_{it}$ | 0.212 | (0.143) | |
| $\ln WAGE_{it} * epl_{high}$ | 0.009 | (0.029) | | $\ln WAGE_{it} * nordic$ | -0.002 | (0.028) | | $PMR_{it}^2$ | 1.214 | (0.757) | |
| **Specification** (10) | | | | | | | | | | | |
| $\ln BERD_{it}$ | $-0.252^{***}$ | (0.002) | $x \rightarrow y$ | | | | | | | | |
| $\ln VA_{it}$ | -0.006 | (0.046) | | | | | | | | | |
| $\ln BINDEX_{it}$ | 0.022 | (0.077) | | | | | | | | | |
| $\ln SUBS_{it}$ | -0.049 | (0.265) | | | | | | | | | |
| $\ln GOVERD_{it}$ | 0.102 | (0.131) | | | | | | | | | |
| $\ln HERD_{it}$ | 0.047 | (0.089) | | | | | | | | | |
| $HCAP_{it}$ | 0.233 | (0.287) | | | | | | | | | |
| $\ln WAGE_{it}$ | 0.009 | (0.043) | | | | | | | | | |
| $PMR_{it}$ | 0.223 | (0.147) | | | | | | | | | |
| $\ln WAGE_{it} * PMR_{it}$ | -0.147 | (0.145) | | | | | | | | | |

Notes: The first row for each specification presents the results for $\widehat{\alpha}_1$ (see eq. (2.14)). For all other rows 'Variable' refers to the ECM or dynamic regression with 'Variable' on the left hand side. In the first column we report the $\widehat{\alpha}_2$ coefficient as is described in eq. (2.15). The second and third column respectively denote the standard deviation of $\widehat{\alpha}$ and the final conclusion. For the first row, '$x \rightarrow y$' means that $X_{it}$ has an impact on $\ln BERD_{it}$. For the rows where the column 'Verdict' is empty, this implies that the corresponding x-variable has a causal impact on $\ln BERD_{it}$. The rows where the 'Verdict' column indicates '$\longleftrightarrow$' point to reverse causality between the corresponding x-variable and $\ln BERD_{it}$ and results for this explanatory variable should thus be interpreted carefully. $^{*}$, $^{**}$ and $^{***}$ indicate significance at the 10%, 5% and 1% level respectively.

**Table 2.4:** Test for direction of causation: heterogeneous short-term effects

| Variable | $\widehat{\alpha}$ | std | Verdict | Variable | $\widehat{\alpha}$ | std | Verdict | Variable | $\widehat{\alpha}$ | std | Verdict |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Specification** (1) | | | | **Specification** (2) | | | | **Specification** (3) | | | |
| $\ln BERD_{it}$ | $-0.180^{***}$ | (0.036) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.169^{***}$ | (0.045) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.220^{***}$ | (0.064) | $x \rightarrow y$ |
| $\ln VA_{it}$ | 0.011 | (0.024) | | $\ln VA_{it}$ | 0.017 | (0.027) | | $\ln VA_{it}$ | $0.078^{**}$ | (0.029) | $\longleftrightarrow$ |
| $\ln BINDEX_{it}$ | 0.055 | (0.041) | | $\ln BINDEX_{it}$ | 0.095 | (0.056) | | $\ln BINDEX_{it}$ | $0.134^{**}$ | (0.061) | $\longleftrightarrow$ |
| $\ln SUBS_{it}$ | $-0.241^{**}$ | (0.111) | $\longleftrightarrow$ | $\ln SUBS_{it}$ | -0.327 | (0.197) | | $\ln SUBS_{it}$ | -0.251 | (0.196) | |
| $\ln GOVERD_{it}$ | 0.060 | (0.080) | | $\ln GOVERD_{it}$ | 0.057 | (0.078) | | $\ln GOVERD_{it}$ | 0.052 | (0.089) | |
| $\ln HERD_{it}$ | $0.149^{*}$ | (0.078) | $\longleftrightarrow$ | $\ln HERD_{it}$ | 0.143 | (0.085) | | $\ln HERD_{it}$ | 0.145 | (0.091) | |
| | | | | $OPEN_{it}$ | 0.046 | (0.043) | | $HCAP_{it}$ | 0.157 | (0.236) | |
| **Specification** (4) | | | | **Specification** (5) | | | | **Specification** (6) | | | |
| $\ln BERD_{it}$ | $-0.211^{***}$ | (0.033) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.173^{*}$ | (0.095) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.230^{*}$ | (0.128) | $x \rightarrow y$ |
| $\ln VA_{it}$ | 0.035 | (0.032) | | $\ln VA_{it}$ | $0.069^{*}$ | (0.038) | $\longleftrightarrow$ | $\ln VA_{it}$ | 0.087 | (0.056) | |
| $\ln BINDEX_{it}$ | 0.069 | (0.046) | | $\ln BINDEX_{it}$ | 0.070 | (0.223) | | $\ln BINDEX_{it}$ | $0.215^{**}$ | (0.086) | $\longleftrightarrow$ |
| $\ln SUBS_{it}$ | -0.162 | (0.111) | | $\ln SUBS_{it}$ | -0.189 | (0.109) | | $\ln SUBS_{it}$ | -0.460 | (0.325) | |
| $\ln GOVERD_{it}$ | 0.046 | (0.082) | | $\ln GOVERD_{it}$ | -0.065 | (0.099) | | $\ln GOVERD_{it}$ | -0.146 | (0.131) | |
| $\ln HERD_{it}$ | $0.134^{*}$ | (0.071) | $\longleftrightarrow$ | $\ln HERD_{it}$ | $0.253^{**}$ | (0.102) | $\longleftrightarrow$ | $\ln HERD_{it}$ | $0.283^{**}$ | (0.127) | $\longleftrightarrow$ |
| $\ln WAGE_{it}$ | -0.016 | (0.027) | | $\ln HCAP_{it}$ | $0.369^{*}$ | (0.18) | $\longleftrightarrow$ | $HCAP_{it}$ | 0.170 | (0.392) | |
| | | | | $\ln WAGE_{it}$ | -0.028 | (0.033) | | $OPEN_{it}$ | 0.112 | (0.100) | |
| | | | | | | | | $\ln WAGE_{it}$ | -0.063 | (0.056) | |
| | | | | | | | | $\ln WAGE_{it} * OPEN_{it}$ | -0.118 | (0.083) | |
| **Specification** (7) | | | | **Specification** (8) | | | | **Specification** (9) | | | |
| $\ln BERD_{it}$ | $-0.220^{*}$ | (0.109) | $x \rightarrow y$ | $\ln BERD_{it}$ | $-0.283^{***}$ | (0.096) | $x \rightarrow y$ | $\ln BERD_{it}$ | $0.655^{***}$ | (0.196) | $x \rightarrow y$ |
| $\ln VA_{it}$ | $0.111^{**}$ | (0.046) | $\longleftrightarrow$ | $\ln VA_{it}$ | -0.001 | (0.038) | $\longleftrightarrow$ | $\ln VA_{it}$ | -0.067 | (0.051) | |
| $\ln BINDEX_{it}$ | 0.134 | (0.079) | | $\ln BINDEX_{it}$ | $0.061^{*}$ | (0.034) | | $\ln BINDEX_{it}$ | -0.015 | (0.165) | |
| $\ln SUBS_{it}$ | -0.131 | (0.231) | | $\ln SUBS_{it}$ | -0.195 | (0.234) | | $\ln SUBS_{it}$ | -0.288 | (0.456) | |
| $\ln GOVERD_{it}$ | 0.0854 | (0.088) | | $\ln GOVERD_{it}$ | -0.084 | (0.092) | | $\ln GOVERD_{it}$ | -0.194 | (0.195) | |
| $\ln HERD_{it}$ | $0.314^{**}$ | (0.108) | $\longleftrightarrow$ | $\ln HERD_{it}$ | $0.224^{**}$ | (0.084) | $\longleftrightarrow$ | $\ln HERD_{it}$ | $0.265^{*}$ | (0.137) | $\longleftrightarrow$ |
| $HCAP_{it}$ | -0.094 | (0.214) | | $HCAP_{it}$ | 0.088 | (0.210) | | $HCAP_{it}$ | 0.641 | (0.631) | |
| $\ln WAGE_{it}$ | $-0.096^{*}$ | (0.047) | $\longleftrightarrow$ | $\ln WAGE_{it}$ | -0.030 | (0.033) | | $\ln WAGE_{it}$ | 0.065 | (0.056) | |
| | | | | | | | | $PMR_{it}$ | -0.168 | (0.871) | |
| | | | | | | | | $PMR^2_{it}$ | 0.401 | (3.941) | |
| **Specification** (10) | | | | | | | | | | | |
| $\ln BERD_{it}$ | $-0.530^{***}$ | (0.178) | $x \rightarrow y$ | | | | | | | | |
| $\ln VA_{it}$ | -0.031 | (0.084) | | | | | | | | | |
| $\ln BINDEX_{it}$ | 0.130 | (0.109) | | | | | | | | | |
| $\ln SUBS_{it}$ | 0.160 | (0.534) | | | | | | | | | |
| $\ln GOVERD_{it}$ | -0.017 | (0.166) | | | | | | | | | |
| $\ln HERD_{it}$ | 0.076 | (0.102) | | | | | | | | | |
| $HCAP_{it}$ | -0.355 | (0.371) | | | | | | | | | |
| $\ln WAGE_{it}$ | -0.010 | (0.070) | | | | | | | | | |
| $PMR_{it}$ | $0.542^{*}$ | (0.253) | $\longleftrightarrow$ | | | | | | | | |
| $\ln WAGE_{it} * PMR_{it}$ | $-0.512^{**}$ | (0.210) | $\longleftrightarrow$ | | | | | | | | |

Notes: The first row for each specification presents the results for $\sum_{i=1}^{N} \widehat{\alpha}_{1i}$ (see eq. (2.14)). For all other rows 'Variable' refers to the ECM or dynamic regression with 'Variable' on the left hand side. In the first column we report the $\sum_{i=1}^{N} \widehat{\alpha}_2$ coefficient as is described in eq. (2.15). The second and third column respectively denote the standard deviation of $\widehat{\alpha}$ and the final conclusion. For the first row, '$x \rightarrow y$' means that $X_{it}$ has an impact on $\ln BERD_{it}$. For the rows where the column 'Verdict' is empty, this implies that the corresponding x-variable has a causal impact on $\ln BERD_{it}$. The rows where the 'Verdict' column indicates '$\longleftrightarrow$' point to reverse causality between the corresponding x-variable and $\ln BERD_{it}$ and results for this explanatory variable should thus be interpreted carefully. *, ** and *** indicate significance at the 10%, 5% and 1% level respectively.

## 2.5 Conclusion

The wedge between private and social returns to the creation of knowledge and technology justifies government involvement in the area of research and development. Nevertheless, in the current environment of restoring sustainability of public finances and search for an increasing efficiency of public policy, the question arises which policy options are most effective in stimulating private R&D investment. This chapter therefore analyses the effects of different policies on aggregate business funded and performed R&D investment in a panel of 14 OECD countries since 1981. Concerning traditional policy options, we find that tax incentives are effective. Public funding (subsidization) of R&D performed by firms can also be effective if subsidies are not too low nor too high. The optimal subsidization rate may be somewhere between 6 and 10%. R&D performed within the government sector and within institutions of higher education is basically neutral with respect to business R&D. We find no evidence for crowding out nor for complementarity, which implies that each euro spent on R&D within the government feeds through one-to-one in aggregate R&D. The higher education sector may, however, indirectly be of great significance. This chapter revealed human capital accumulation at the tertiary level as the most important driver of business funded and performed R&D in the OECD during the last decades.

One of the main contributions of this chapter is its attention to the impact of wage formation on business R&D investment. Conflicting hypotheses have been introduced in the literature, but not yet systematically analysed. One hypothesis is that innovation and investment in R&D benefit from low or moderate wages, since these are important for firm profitability, which is a key condition for investment. Wage restraint is also important to convince firms that rents from innovation will not be appropriated by the unions through higher wages. The opposite hypothesis is that an excessive focus on wage moderation may kill incentives to innovate. Wage moderation may for example increase the survival probability of the least innovative firms and retard the process of creative destruction. Conversely, according to this hypothesis, higher wage pressure may force firms to innovate as a key element in their competitive strategy. Our empirical analysis favours the first hypothesis in fairly closed economies and in economies with flexible labour markets. The Anglo-Saxon countries may be the closest to this type. In highly open economies and economies with rigid labour markets, however, rather the opposite holds and high wage pressure may encourage innovation. Many European countries are more likely to match this type.

Our paper may also contribute to the macro R&D literature methodologically. More than existing studies, we pay particular attention to the time series properties of the data. As most variables in our empirical model are found to be non-stationary, we estimate a cointegrating relationship. Moreover, we also take into account the presence of cross-sectionally correlated error terms, which we find to be induced by an unobserved (non-stationary) common factor that drives private R&D spending. A sensible interpretation is that this common factor reflects the worldwide level of technology and knowledge. To capture this, we adopt the CCEP estimator of Pesaran (2006). We find that the standard fixed effects estimator yields spurious results.

The policy implications of our results include a warning against excessive wage moderation in highly open economies with rigid labour markets. Even though this may promote employment in the short run, it may undermine the economy's innovative capacity and productivity in the long run. The fairly poor growth of business R&D investment in a country like the Netherlands may illustrate this long-run disadvantage. Conversely, however, in our view our findings provide no argument in favour of excessive wage pressure. In rigid labour markets the loss of employment that excessive wages may cause in the short run, may persist in the longer run due to for example hysteresis effects in bad times. If promotion of business investment in R&D is the objective, our paper suggests better alternatives, in particular tax incentives, well-chosen innovation subsidies and the development of high skilled human capital.

# Appendix

## 2.A Fixed effects regression results

**Table 2.A.1:** FE regression results

Dependent variable: $\ln BERD_{it}$
Sample period: 1981-2012, 14 OECD countries

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Coefficient estimates** | | | | | | | | | | |
| **Explanatory variables** | | | | | | | | | | |
| $\ln VA_{it}$ | $1.069^{***}$ | $1.014^{***}$ | $1.080^{***}$ | $1.114^{***}$ | $1.103^{***}$ | $1.030^{***}$ | $1.058^{***}$ | $0.963^{***}$ | $1.120^{***}$ | $1.013^{***}$ |
| | (0.124) | (0.129) | (0.127) | (0.164) | (0.167) | (0.161) | (0.174) | (0.172) | (0.175) | (0.166) |
| $\ln BINDEX_{it}$ | $0.264^{**}$ | $0.275^{***}$ | $0.256^{**}$ | $0.260^{**}$ | 0.129 | $0.189^{*}$ | $0.252^{***}$ | $0.291^{***}$ | 0.150 | 0.127 |
| | (0.104) | (0.104) | (0.106) | (0.105) | (0.111) | (0.102) | (0.107) | (0.105) | (0.108) | (0.105) |
| $\ln SUBS_{it}$ | $0.243^{***}$ | $0.237^{***}$ | $0.240^{***}$ | $0.244^{***}$ | | $0.201^{***}$ | $0.241^{***}$ | $0.240^{***}$ | $0.265^{***}$ | $0.255^{***}$ |
| | (0.023) | (0.023) | (0.024) | (0.023) | | (0.024) | (0.025) | (0.024) | (0.025) | (0.024) |
| $\ln GOVERD_{it}$ | $-0.182^{***}$ | $-0.179^{***}$ | $-0.179^{***}$ | $-0.183^{***}$ | $-0.115^{***}$ | $-0.079^{*}$ | $-0.163^{***}$ | $-0.176^{***}$ | $-0.216^{***}$ | $-0.197^{***}$ |
| | (0.041) | (0.041) | (0.041) | (0.041) | (0.041) | (0.042) | (0.042) | (0.042) | (0.042) | (0.040) |
| $\ln HERD_{it}$ | $0.528^{***}$ | $0.516^{***}$ | $0.544^{***}$ | $0.517^{***}$ | $0.465^{***}$ | $0.541^{***}$ | $0.537^{***}$ | $0.551^{***}$ | $0.434^{***}$ | $0.481^{***}$ |
| | (0.048) | (0.048) | (0.060) | (0.054) | (0.065) | (0.060) | (0.063) | (0.062) | (0.068) | (0.066) |
| $HCAP_{it}$ | | | $-0.003$ | | -0.002 | -0.004 | -0.002 | -0.000 | -0.008 | $-0.012^{*}$ |
| | | | (0.007) | | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) |
| $OPEN_{it}$ | | 0.002 | | | | $0.028^{***}$ | | | | |
| | | (0.001) | | | | (0.004) | | | | |
| $\ln WAGE_{it}$ | | | | 0.076 | 0.186 | $-1.738^{***}$ | | | 0.078 | $1.302^{***}$ |
| | | | | (0.179) | (0.188) | (0.340) | | | (0.179) | (0.282) |
| $PMR_{it}$ | | | | | | | | | 0.123 | $-0.456^{***}$ |
| | | | | | | | | | (0.095) | (0.076) |
| $PMR_{it}^2$ | | | | | | | | | $-0.043^{**}$ | |
| | | | | | | | | | (0.018) | |
| $\ln SUBS_{it} * low$ | | | | | $0.453^{***}$ | | | | | |
| | | | | | (0.049) | | | | | |
| $\ln SUBS_{it} * medium$ | | | | | $0.124^{***}$ | | | | | |
| | | | | | (0.031) | | | | | |
| $\ln SUBS_{it} * high$ | | | | | $0.106^{***}$ | | | | | |
| | | | | | (0.035) | | | | | |
| $\ln WAGE_{it} * OPEN_{it}$ | | | | | | $0.031^{***}$ | | | | |
| | | | | | | (0.005) | | | | |
| $\ln WAGE_{it} * PMR_{it}$ | | | | | | | | | | $-0.446^{***}$ |
| | | | | | | | | | | (0.086) |
| $\ln WAGE_{it} * epl_{low}$ | | | | | | | $-0.689^{*}$ | | | |
| | | | | | | | (0.415) | | | |
| $\ln WAGE_{it} * epl_{middle}$ | | | | | | | 0.129 | | | |
| | | | | | | | (0.228) | | | |
| $\ln WAGE_{it} * epl_{high}$ | | | | | | | 0.124 | | | |
| | | | | | | | (0.124) | | | |
| $\ln WAGE_{it} * anglo$ | | | | | | | | $-0.809^{**}$ | | |
| | | | | | | | | (0.410) | | |
| $\ln WAGE_{it} * euro$ | | | | | | | | $0.456^{**}$ | | |
| | | | | | | | | (0.202) | | |
| $\ln WAGE_{it} * nordic$ | | | | | | | | $-0.460^{*}$ | | |
| | | | | | | | | (0.245) | | |
| **Panic Cointegration test (one common factor)** | | | | | | | | | | |
| ADF-GLS on $\widehat{f}_t^{pc}$ | -2.541 | -2.635 | -2.580 | -2.538 | -2.877 | -2.909 | -2.608 | -2.736 | -2.437 | -2.589 |
| | [0.31] | [0.27] | [0.29] | [0.31] | [0.18] | [0.17] | [0.28] | [0.23] | [0.35] | [0.29] |
| MW on $\widehat{e}_{it}^{pc}$ | -0.619 | -1.325 | -0.534 | -0.492 | -0.489 | -1.469 | -0.383 | 0.654 | 0.366 | $1.366^{*}$ |
| | [0.73] | [0.91] | [0.70] | [0.69] | [0.69] | [0.93] | [0.65] | [0.26] | [0.35] | [0.09] |

Notes: standard errors are in parentheses. $^{*}$, $^{**}$ and $^{***}$ indicate significance at the 10%, 5% and 1% level respectively. For the panel cointegration test results, the unit root test on the common factor $\widehat{F}_t$ is a ADF-GLS test for a model with constant. The corresponding (simulated) p-values are reported in square brackets. The unit root test on the estimated idiosyncratic errors $\widehat{e}_{it}^{pc}$ is a MW test. The corresponding p-values are reported in square brackets

## 2.B CCEP results with alternative wage indicator based on different production function elasticities

**Table 2.B.1:** CCEP regression results for alternative calculation of TFP and the wage gap

Dependent variable: $\ln BERD_{it}$
Sample period: 1981-2012, 14 OECD countries

| | (4') | (5') | (6') | (7') | (8') | (9') | (10') |
|---|---|---|---|---|---|---|---|
| **Coefficient estimates** | | | | | | | |
| **Explanatory variables** | | | | | | | |
| $\ln VA_{it}$ | 0.375 | $0.597^{**}$ | $0.554^{**}$ | 0.395 | $0.655^{***}$ | 0.314 | 0.357 |
| | (0.249) | (0.238) | (0.267) | (0.258) | (0.230) | (0.240) | (0.248) |
| $\ln BINDEX_{it}$ | $-0.171^{**}$ | $-0.160^{*}$ | -0.093 | -0.085 | $-0.188^{**}$ | $-0.217^{***}$ | $-0.146^{*}$ |
| | (0.086) | (0.084) | (0.093) | (0.092) | (0.022) | (0.087) | (0.081) |
| $\ln SUBS_{it}$ | 0.002 | | 0.029 | 0.031 | 0.034 | $0.049^{**}$ | $0.050^{**}$ |
| | (0.023) | | (0.024) | (0.024) | (0.022) | (0.023) | (0.022) |
| $\ln GOVERD_{it}$ | 0.067 | 0.068 | $0.092^{**}$ | $0.143^{***}$ | 0.020 | 0.023 | 0.033 |
| | (0.044) | (0.044) | (0.047) | (0.051) | (0.042) | (0.053) | (0.050) |
| $\ln HERD_{it}$ | 0.100 | -0.046 | 0.047 | 0.039 | 0.077 | -0.015 | 0.007 |
| | (0.068) | (0.064) | (0.071) | (0.071) | (0.066) | (0.065) | (0.066) |
| $HCAP_{it}$ | | $0.092^{***}$ | $0.058^{***}$ | $0.065^{***}$ | $0.093^{***}$ | $0.044^{***}$ | $0.062^{***}$ |
| | | (0.012) | (0.011) | (0.010) | (0.011) | (0.012) | (0.010) |
| $OPEN_{it}$ | | | $0.012^{***}$ | | | | |
| | | | (0.004) | | | | |
| $\ln WAGE_{it}$ | -0.289 | 0.011 | $-1.182^{***}$ | | | -0.206 | 0.269 |
| | (0.195) | (0.186) | (0.413) | | (0.192) | (0.404) | |
| $PMR_{it}$ | | | | | | $0.419^{**}$ | -0.111 |
| | | | | | | (0.198) | (0.135) |
| $PMR_{it}^2$ | | | | | | -0.045 | |
| | | | | | | (0.037) | |
| $\ln SUBS_{it} * low$ | | -0.055 | | | | | |
| | | (0.076) | | | | | |
| $\ln SUBS_{it} * medium$ | | $0.070^{**}$ | | | | | |
| | | (0.035) | | | | | |
| $\ln SUBS_{it} * high$ | | $-0.080^{**}$ | | | | | |
| | | (0.040) | | | | | |
| $\ln WAGE_{it} * OPEN_{it}$ | | | $0.013^{**}$ | | | | |
| | | | (0.005) | | | | |
| $\ln WAGE_{it} * PMR_{it}$ | | | | | | | $-0.308^{**}$ |
| | | | | | | | (0.151) |
| $\ln WAGE_{it} * epl_{low}$ | | | | $-1.127^{***}$ | | | |
| | | | | (0.391) | | | |
| $\ln WAGE_{it} * epl_{middle}$ | | | | 0.042 | | | |
| | | | | (0.432) | | | |
| $\ln WAGE_{it} * epl_{high}$ | | | | -0.126 | | | |
| | | | | (0.239) | | | |
| $\ln WAGE_{it} * anglo$ | | | | | -0.551 | | |
| | | | | | (0.413) | | |
| $\ln WAGE_{it} * euro$ | | | | | $1.215^{***}$ | | |
| | | | | | (0.322) | | |
| $\ln WAGE_{it} * nordic$ | | | | | 0.143 | | |
| | | | | | (0.282) | | |
| **Panic Cointegration test (one common factor)** | | | | | | | |
| ADF-GLS on $\widehat{f}_t^{pc}$ | -0.812 | -1.498 | -2.043 | -1.606 | -2.254 | -0.091 | -0.289 |
| | [0.95] | [0.81] | [0.55] | [0.77] | [0.44] | [0.99] | [0.99] |
| MW on $\widehat{e}_{it}^{pc}$ | $1.949^{**}$ | $1.423^{*}$ | $2.524^{***}$ | $2.635^{***}$ | $1.408^{*}$ | $1.757^{**}$ | $3.125^{***}$ |
| | [0.03] | [0.08] | [0.01] | [0.00] | [0.08] | [0.04] | [0.00] |

Notes: standard errors are in parentheses. $^{*}$, $^{**}$ and $^{***}$ indicate significance at the 10%, 5% and 1% level respectively. For the panel cointegration test results, the unit root test on the common factor $\widehat{F}_t$ is a ADF-GLS test for a model with constant. The corresponding (simulated) p-values are reported in square brackets. The unit root test on the estimated idiosyncratic errors $\widehat{e}_{it}^{pc}$ for different number of common factors r=1,2 is a MW test. The corresponding p-values are reported in square brackets

## 2.C Construction of data and data sources

**Table 2.C.1:** Construction of data and data sources

| Name | Notation | Construction | Data Sources |
|---|---|---|---|
| **Real per capita business sector funded and performed R&D** | $BERD_{it}$ | $\frac{BERDVOL_{it}}{POP1564_{it}}$ | |
| Real business sector funded and performed R&D | $BERDVOL_{it}$ | $\frac{BERDVAL_{it}}{DEFL_{it}}$ | |
| Business sector funded and performed R&D, value | $BERDVAL_{it}$ | Original data | OECD, Main Science and Technology Indicators |
| Working-age population between 15 and 64 years | $POP1564_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| GDP deflator, market prices | $DEFL_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| **Real per capita value added in the business sector** | $VA_{it}$ | $\frac{VAVOL_{it}}{POP1564_{it}}$ | |
| Real value added in the business sector | $VAVOL_{it}$ | $\frac{VAVAL_{it}}{DEFL_{it}}$ | |
| Value added in the business sector, value | $VAVAL_{it}$ | Original data | OECD, Main Science and Technology Indicators |
| **B-index** | $BINDEX_{it}$ | Original data | OECD Science and Technology industry Outlook 2014, based on Warda (2013) |
| **Real per capita government funded expenditure on R&D performed in the business sector** | $SUBS_{it}$ | $\frac{SUBSVOL_{it}}{POP1564_{it}}$ | |
| Real government funded expenditure on R&D in the business sector | $SUBSVOL_{it}$ | $\frac{SUBSVAL_{it}}{DEFL_{it}}$ | |
| Government funded expenditure on R&D in the business sector, value | $SUBSVAL_{it}$ | $PERCGOV_{it} * BERDTOTAL_{it}$ | |
| Business enterprise expenditure on R&D, value | $BERDTOTAL_{it}$ | Original data | OECD, Main Science and Technology Indicators |
| Percentage of $BERDTOTAL_{it}$ financed by the government | $PERCGOV_{it}$ | Original data | OECD, Main Science and Technology Indicators |

*To be continued on the next page*

| Name | Notation | Construction | Data Sources |
|---|---|---|---|
| **Real per capita government intramural expenditure on R&D** | $GOVERD_{it}$ | $\frac{GOVERDVOL_{it}}{POP1564_{it}}$ | |
| Real government intramural expenditure on R&D | $GOVERDVOL_{it}$ | $\frac{GOVERDVAL_{it}}{DEFL_{it}}$ | |
| Government intramural expenditure on R&D, value | $GOVERDVAL_{it}$ | Original data | OECD, Main Science and Technology Indicators |
| **Real per capita expenditure on R&D in the higher education sector** | $HERD_{it}$ | $\frac{HERDVOL_{it}}{POP1564_{it}}$ | |
| Real expenditure on R&D in the higher education sector | $HERDDVOL_{it}$ | $\frac{HERDVAL_{it}}{DEFL_{it}}$ | |
| expenditure on R&D in the higher education sector, value | $HERDVAL_{it}$ | Original data | OECD, Main Science and Technology Indicators |
| **Percentage of population aged 15 and over that has completed tertiary schooling** | $HCAP_{it}$ | Data are available for 1980, 1985,1990,...2010. Data for the intermediate years are calculated by interpolation and data is extrapolated for 2011 and 2012 | Barro and Lee (2013) |
| **Degree of openness in the economy** | $OPEN_{it}$ | $\frac{IMPORTS_{it}+EXPORTS_{it}}{GDPVAL_{it}} * 100$ | |
| Imports of goods and services, value, national accounts basis | $IMPORTS_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| Exports of goods and services, value, national accounts basis | $EXPORTS_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| Gross domestic product, value, market prices | $GDPVAL_{it}$ | Original data | OECD, Economic Outlok, No 95, May 2014 |

*To be continued on the next page*

| Name | Notation | Construction | Data Sources |
|---|---|---|---|
| **Wage pressure indicator** | $\ln WAGE_{it}$ | $\ln W_{it} - \ln A_{it}$ | |
| Real compensation of employees per hour | $W_{it}$ | $\frac{\frac{Wval_{it}}{DEFL_{it}}}{L_{it}}$ | |
| Compensation of employees, value | $Wval_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| Total hours worked in the economy | $L_{it}$ | Original data | The Conference Board, Total Economy Database, January 2014 |
| Harrod-neutral technical progress (in logs) | $\ln A_{it}$ | $\frac{1}{1-\alpha-\beta}\left[\ln Y_{it} - \alpha \ln K_{it} - \beta \ln G_{it} - (1-\alpha-\beta)\ln L_{it}\right]$ | For more details, see Section 2.3.1 |
| GDP, volume, market prices | $Y_{it}$ | Original data | OECD, Economic Outlook, No 95, May 2014 |
| Private, non-residential net capital stock | $K_{it}$ | See Everaert, Heylen, and Schoonackers (2015) | Everaert, Heylen, and Schoonackers (2015) |
| Real government net capital stock | $G_{it}$ | See Everaert, Heylen, and Schoonackers (2015) | Everaert, Heylen, and Schoonackers (2015) |
| **Product market regulation index** | $PMR_{it}$ | Data are available for 1998, 2003, 2008 and 2013. Data for the intermediate years are calculated by interpolation. Data for the years before 1998 are retropolated using growth rates of PMR data for seven network industries. This data is also taken from Koske, Warner, Biteti, and Barbier (2014) | Koske, Warner, Biteti, and Barbier (2014) |
| **Low average subsidization rate** | *low* | a dummy variable equal to one for the countries for which on average $\frac{SUBSVAL_{it}}{BERDTOTAL_{it}} \leq 4\%$ | based on Guellec and Van Pottelsberghe (2003) |
| **Medium average subsidization rate** | *medium* | a dummy variable equal to one for the countries for which on average $4\% \leq \frac{SUBSVAL_{it}}{BERDTOTAL_{it}} \leq 11\%$ | based on Guellec and Van Pottelsberghe (2003) |
| **High average subsidization rate** | *high* | a dummy variable equal to one for the countries for which on average $\frac{SUBSVAL_{it}}{BERDTOTAL_{it}} > 11\%$ | based on Guellec and Van Pottelsberghe (2003) |

*To be continued on the next page*

| Name | Notation | Construction | Data Sources |
| --- | --- | --- | --- |
| **Low employment protection legislation** | $epl_{low}$ | a dummy variable equal to one<br>for the countries for which on average $EPL_{it} \leq 1.10$. | |
| **Medium employment protection legislation** | $epl_{middle}$ | a dummy variable equal to one<br>for the countries for which on average $1.10 \leq EPL_{it} \leq 2.07$ | |
| **High employment protection legislation** | $epl_{high}$ | a dummy variable equal to one<br>for the countries for which on average $EPL_{it} > 2.07$ | |
| Employment protection legislation index | $EPL_{it}$ | Average of the index for legislation<br>on temporary contracts and on regular<br>contracts. Annual time series data for 1985-2013.<br>Data before 1985 is retropolated based on<br>the data from Berger and Heylen (2011) | OECD, Employment Outlook, 2013 |
| **Anglo-Saxon countries** | $anglo$ | a dummy variable equal to one<br>for the Anglo-Saxon countries in our sample<br>i.e. Australia, Canada, UK and US | |
| **Core European countries** | $euro$ | a dummy variable equal to one<br>for the core European countries in our sample<br>i.e. Austria, Belgium, France, Netherlands, Italy and Spain | |
| **Nordic countries** | $nordic$ | a dummy variable equal to one<br>for the Nordic countries in our sample<br>i.e. Denmark, Finland, Norway and Sweden | |

# Chapter 3

# Is the excess sensitivity time-varying? A Bayesian model selection approach for the US[1]

This chapter investigates the degree of time-variation in the excess sensitivity of aggregate consumption growth to anticipated aggregate disposable income growth using quarterly US data over the period 1954-2014 in an empirical framework containing the possibility of stickiness in aggregate consumption growth and taking into account measurement error and time aggregation. We use a Bayesian model selection approach to deal with the non-regular test for the null hypothesis of no time-variation in the excess sensitivity parameter. Anticipated income growth is calculated by incorporating an instrumental variables estimation approach in our MCMC algorithm. The results of estimating our extended empirical specification show that the excess sensitivity parameter is stable at around 0.23.

## 3.1 Introduction

Traditional permanent income and life cycle models of consumption predict that aggregate consumption should follow a random walk (see Hall, 1978). Empirical studies however have revealed that aggregate consumption growth is excessively sensitive to anticipated disposable income growth (see e.g., Campbell and Mankiw, 1989, 1990, 1991). The most common interpretations given to this observation are the occurrence of liquidity constraints (see e.g., Flavin, 1985; Deaton, 1991; Ludvigson, 1999) and the prevalence of precautionary and buffer stock savings motives (see e.g., Carroll, 1992; Ludvigson and Michaelides, 2001) which increase the weight given by consumers to current income in their consumption decisions. In a number of empirical studies, the assumption that the ES parameter is constant has been relaxed in favor of time-varying specifications (see e.g.,

[1]This chapter is joint work with Gerdie Everaert and Lorenzo Pozzi.

Campbell and Mankiw, 1991; McKiernan, 1996; Bacchetta and Gerlach, 1997; Girardin, Sarno, and Taylor, 2000; Peersman and Pozzi, 2007). Some of these studies report that ES has become less important during the last decades in the US (see e.g., Bacchetta and Gerlach, 1997) and in other developed economies (see e.g., Girardin, Sarno, and Taylor, 2000; Blundell-Wignall, Browne, and Cavaglia, 1991). This has been attributed to financial liberalization and the development of financial markets. These structural developments are thought to have improved the possibilities of consumers to smooth consumption over time and across states of the world, i.e., by curbing the importance of credit constraints and precautionary saving motives in consumer decisions these developments have, over time, reduced the ES parameter.

A number of recent papers argue that the measured degree of ES of aggregate consumption growth becomes less important once other forms of aggregate consumption predictability are taken into account (see e.g., Basu and Kimball, 2002; Sommer, 2007; Kiley, 2010; Carroll, Slacalek, and Sommer, 2011). Sommer (2007) and Carroll, Slacalek, and Sommer (2011) in particular show that the degree of ES measured in quarterly US data falls considerably in a model that contains a mechanism - i.e., habit formation, rational inattention or imperfect information - that generates dependency of aggregate consumption growth to its own past (i.e., 'stickiness'). Sommer (2007) further argues that it is necessary to adequately deal with both measurement error and time aggregation to obtain valid estimates of the ES parameter.

Up until now a framework containing the possibility of stickiness in aggregate consumption growth and containing an adequate treatment of measurement error and time aggregation has only served as a benchmark for testing for ES under the assumption that the degree of ES is constant. This chapter contributes to the literature by investigating *time-varying* ES in this extended empirical framework. We allow the ES parameter to vary over time according to a standard unobserved random walk process. The chapter further contributes to the literature by suggesting an appropriate methodological approach that allows to test whether the time-variation is statistically significant and that can adequately deal with all the complications that arise when estimating time-varying ES in our extended empirical set-up.

First, a key question is whether time-variation in the ES parameter is statistically relevant. This is a non-regular testing problem as the null hypothesis that the variance of the innovations to the time-varying ES parameter is zero lies on the boundary of the parameter space. This hypothesis has not yet been tested explicitly. In this chapter, we use the Bayesian model selection approach recently suggested by Frühwirth-Schnatter and Wagner (2010) to test for time variation in the ES parameter. Their approach implies splitting the time-varying parameter in a constant part and a time-varying part and introducing a stochastic binary model indicator which is one if the time-varying part should be included in the model and zero otherwise. Using Markov Chain Monte Carlo (MCMC) methods, these stochastic binary indicators can then be sampled jointly with the other model parameters. Moreover, the standard inverse Gamma prior for the variance parameters is replaced by a Gaussian prior centered at zero for the standard deviation. The reason for this is that when using an inverse Gamma prior for the variance parameters, the choice of the shape and scale hyperparameters that define this distribution have a strong influence on the posterior when the true value of the variance is close to zero. More specifically, as the inverse Gamma does not have probability mass at zero, using it as a prior distribution tends to push the posterior density away from zero. This is of particular importance when estimating the variance of the innovations to the time-varying ES parameter as we want to decide whether time-variation is relevant or not. An interesting implication of estimating the standard deviation instead of the variance of the the innovations to the time-varying parameters is that the sign of the standard deviation is not identified. This offers an extra piece of information as it implies the posterior distribution to become bimodal when there is time variation, while being unimodal at zero when there is no time variation.

Second, as anticipated income growth is not observed, the ES parameter is estimated from the relation between consumption growth and ex-post observed income growth using an instrumental variables (IV) method. Time-varying ES parameter models with endogenous regressors have been estimated by, among others, Bacchetta and Gerlach (1997) and Peersman and Pozzi (2007) using approximate methods. In a recent paper, Kim and Kim (2011) show that the control function approach to IV estimation can be used to construct an exact state space representation which can then be estimated using Maximum Likelihood (ML). Building on their paper, we incorporate a control function type approach in our MCMC algorithm to deal with endogeneity. The advantage of our Gibbs sampling approach is that it is computationally much more easy to implement and, as such, does not suffer from the ML estimator's numerical optimization problems reported by Kim and Kim (2011). Moreover, as our Bayesian IV approach relies on sampling the posterior distribution rather than using asymptotic approximations, it allows for exact inference even when instruments are weak.

Third, stickiness in consumption growth on the one hand and time aggregation and measurement error in the log level of consumption on the other hand imply that consumption growth follows an AR(1) process with MA(3) errors. To obtain valid estimates of the ES to income growth parameter, these ARMA terms need to be taken into account. We therefore include lagged consumption growth in the model and follow Chib and Greenberg (1994) who developed exact methods to analyze models with MA errors using MCMC sampling. The recursive transformations suggested in their paper allow to diagonalize the covariance matrix of the error terms such that the conditional (on the MA coefficients) distributions are easily obtained and sampled from, while the MA coefficients can be sampled suing a Metropolis-Hastings step within the Gibbs sampler.

Fourth, in the aggregate consumption growth equation we include an intercept that is allowed to be time-varying. As such we capture and control for unspecified and/or hard-to-estimate components of consumption growth. Our framework allows to test if the time-variaton in the intercept is relevant and thus provides information whether other time-varying variables are influencing aggregate consumption growth.

The estimation results show that in a basic model, including only anticipated income growth, the ES of US consumption growth to anticipated income growth has decreased over time, starting from around 0.4 in the early 1950s and ending close to 0.2 in 2014. This confirms the result in Bacchetta and Gerlach (1997) that ES drops gradually over time. However, when estimating our extended empirical specification, modeling stickiness in consumption growth along with time aggregation and measurement errors, the excess sensitivity parameter turns out to be stable at around 0.23 over the entire sample period. This implies that the time-variation of the ES parameter in the basic model is due to a specification error. In line with Carroll, Slacalek, and Sommer (2011), the coefficient on lagged consumption growth is found to be around 0.58 showing that there is a notable amount of stickiness in aggregate consumption growth.

The remainder of this chapter is organized as follows. In Section 3.2 we present a benchmark theoretical model for consumption to which we add anticipated income growth to allow for time-varying excess sensitivity. Section 3.3 outlines our empirical specification and estimation methodology. Section 3.4 presents the estimation results for the US over the period 1954-2014. Section 3.5 concludes.

## 3.2 Theoretical framework

In this section we first derive a benchmark model for aggregate consumption growth with stickiness modeled through habit formation in consumer preferences[2] and MA(3) errors to capture the effects of time aggregation and measurement errors. Following, among others, Bacchetta and Gerlach (1997) and Carroll, Slacalek, and Sommer (2011) we next add anticipated income growth to the consumption growth equation to allow for time-varying ES of consumption to income.

### 3.2.1 A benchmark theoretical model with habit formation

Suppose a representative consumer maximizes the following stream of discounted utilities

$$\max E_t \sum_{j=0}^{T} \rho^j U\left(\overline{C}_{t+j}; X_{t+j}\right), \tag{3.1}$$

[2]Alternative mechanisms by which stickiness can be incorporated into consumption growth are rational inattention (see e.g., Reis, 2006; Carroll, Slacalek, and Sommer, 2011) and imperfect information (see e.g., Pischke, 1995).

subject to the budget constraint

$$A_t = R\left[A_{t-1} + Y_t^L - C_t^*\right], \tag{3.2}$$

where $E_t$ denotes the consumer's expectation conditional on period $t$ information, $\rho$ is the discount factor, $\overline{C}_t$ is the level of period $t$ 'effective' consumption, $X_t$ is a variable or a combination of variables that shifts marginal utility at time $t$[3], $A_t$ is the consumer's stock of financial wealth, $R$ is the gross real interest rate (or interest factor), $Y_t^L$ denotes period $t$ labor income or earnings and $C_t^*$ is the representative agent's consumption level in period $t$. Effective consumption is assumed to be

$$\overline{C}_t = C_t^* - \gamma C_{t-1}^*, \tag{3.3}$$

such that utility depends on the level of consumption $C_t^*$ relative to last period's consumption level $C_{t-1}^*$, with the parameter $\gamma$ (where $0 \leq \gamma \leq 1$ ) capturing the strength of habits. When $\gamma = 0$ habits are irrelevant and the consumer derives utility only from the level of consumption. When $\gamma = 1$ habits are most important and the consumer derives utility only from the change in consumption. When $0 < \gamma < 1$ the consumer derives utility both from the level of consumption and from the change in consumption. Hayashi (1985) and Dynan (2000) show that, provided the interest rate is constant and $T$ is large, the first-order condition under time-nonseparable preferences can be written as

$$E_{t-1}\left[R\rho \frac{U'(\overline{C}_t; X_t)}{U'(\overline{C}_{t-1}; X_{t-1})}\right] = 1, \tag{3.4}$$

with $U'(\overline{C}_t; X_t) = \frac{\partial U(\overline{C}_t; X_t)}{\partial \overline{C}_t}$.

Assuming that the utility function is of the CRRA type, i.e., $U(\overline{C}_t; X_t) = \frac{\overline{C}_t^{1-\psi}}{1-\psi} X_t$ with $\psi > 0$, so that $U'(\overline{C}_t; X_t) = \overline{C}_t^{-\psi} X_t$ and using this into equation (3.4) gives

$$E_{t-1}\left[R\rho \left(\frac{\overline{C}_t}{\overline{C}_{t-1}}\right)^{-\psi} \frac{X_t}{X_{t-1}}\right] = E_{t-1}\left[Z_t\right] = 1, \tag{3.5}$$

where $Z_t \equiv R\rho \left(\frac{\overline{C}_t}{\overline{C}_{t-1}}\right)^{-\psi} \frac{X_t}{X_{t-1}}$. Assuming that $\Delta \ln \overline{C}_t$ and $\Delta \ln X_t$ are jointly conditionally normally distributed implies that $\ln Z_t = \ln(R\rho) - \psi \Delta \ln \overline{C}_t + \Delta \ln X_t$ is conditionally Gaussian as well. From the lognormal property we can therefore write

$$E_{t-1}\left[Z_t\right] = \exp\left[E_{t-1}(\ln Z_t) + \frac{1}{2} V_{t-1}(\ln Z_t)\right]. \tag{3.6}$$

[3]Examples are hours worked (see e.g., Kiley, 2010) and/or government consumption (see e.g., Evans and Karras, 1998).

We then substitute equation (3.6) into equation (3.5) and take logs of the resulting equality to obtain (after some rearrangement of terms)

$$E_{t-1}\left(\Delta \ln \overline{C}_t\right) = \frac{1}{2\psi}\sigma^2_{\ln Z,t} + \frac{1}{\psi}\ln(R\rho) + \frac{1}{\psi}\mu_{\Delta \ln X,t}, \tag{3.7}$$

where $\sigma^2_{\ln Z,t} \equiv V_{t-1}[\ln Z_t] = V_{t-1}[\Delta \ln X_t] - 2\psi cov_{t-1}[\Delta \ln X_t, \Delta \ln \overline{C}_t] + \psi^2 V_{t-1}[\Delta \ln \overline{C}_t]$ and where $\mu_{\Delta \ln X,t} = E_{t-1}\left(\Delta \ln X_t\right)$. This can also be written as

$$\Delta \ln \overline{C}_t = \frac{1}{2\psi}\sigma^2_{\ln Z,t} + \frac{1}{\psi}\ln(R\rho) + \frac{1}{\psi}\mu_{\Delta \ln X,t} + \epsilon_t, \tag{3.8}$$

where $\epsilon_t = \left[\Delta \ln \overline{C}_t - E_{t-1}\left(\Delta \ln \overline{C}_t\right)\right]$.

After collecting the first three terms of equation (3.8) into a time-varying variable $\beta_{0t}$ and using the approximation $\Delta \ln \overline{C}_t = \Delta \ln(C^*_t - \gamma C^*_{t-1}) \approx \Delta \ln C^*_t - \gamma \Delta \ln C^*_{t-1}$ as suggested by Muellbauer (1988) and Dynan (2000), we obtain

$$\Delta \ln C^*_t = \beta_{0t} + \gamma \Delta \ln C^*_{t-1} + \epsilon_t, \tag{3.9}$$

where $\beta_{0t} = \frac{1}{2\psi}\sigma^2_{\ln Z,t} + \frac{1}{\psi}\ln(R\rho) + \frac{1}{\psi}\mu_{\Delta \ln X,t}$. As such, $\beta_{0t}$ is a catch-all term that allows to capture and control for unspecified (i.e., the conditional mean and variance of $\Delta \ln X_t$) and/or hard-to-estimate (i.e., the conditional variance $V_{t-1}[\Delta \ln \overline{C}_t]$ in $\sigma^2_{\ln Z,t}$) components of aggregate consumption growth.[4]

### 3.2.2 Time aggregation and measurement error

Assuming that consumption decisions are made more frequently than the intervals at which consumption is measured causes time aggregation. Sommer (2007) shows that time aggregation in combination with the presence of habits induces an MA(2) structure in the error term $\epsilon_t$ of true aggregate consumption growth $\Delta \ln C^*_t$, where 'true' refers to consumption in the absence of measurement error and other transitory components. This implies that equation (3.9) should be written as

$$\Delta \ln C^*_t = \beta_{0t} + \gamma \Delta \ln C^*_{t-1} + \theta^{\xi}(L)\,\xi_t, \tag{3.10}$$

with $\xi_t$ an *i.i.d.* error term and $\theta^{\xi}(L) = 1 + \theta^{\xi}_1 L + \theta^{\xi}_2 L^2$ an MA(2) lag polynomial with parameters being complicated functions of $\gamma$.[5]

[4]Note that while the model is derived under a constant interest factor $R$, the presence of $\beta_{0t}$ in the model implicitly also allows to control for a time-varying interest rate in the estimation.

[5]Note that the proof in Sommer (2007) is based on a model with a constant mean in aggregate consumption growth whereas we have the time-varying variable $\beta_{0t}$ in the model. We can however rewrite equation (3.9) as $(\Delta \ln C^*_t - \mu_t) = \gamma(\Delta \ln C^*_{t-1} - \mu_{t-1}) + \varepsilon_t$ with $\mu_t = \beta_{0t} + \gamma\mu_{t-1}$ so that his proof can equally be applied to our model.

Sommer (2007) further notes that aggregate consumption data measured at the quarterly level are often plagued by measurement error and other sources of transitory consumption fluctuations. He argues that measurement error is best modeled as an MA(1) structure in the log-level of consumption. This implies that measured aggregate consumption growth $\Delta \ln C_t$ should be modeled as the sum of of true aggregate consumption growth $\Delta \ln C_t^*$ given by equation (3.10) and an MA(2) error term

$$\Delta \ln C_t = \Delta \ln C_t^* + \theta^{\zeta}(L) \varsigma_t, \tag{3.11}$$

where $\varsigma_t$ an *i.i.d.* error term and $\theta^{\zeta}(L) = 1 + \theta_1^{\zeta} L + \theta_2^{\zeta} L^2$ an MA(2) lag polynomial. Note that this specification encompasses the simpler classical case where measurement error is assumed to be a white noise error term in the log-level of consumption. This implies an MA(1) error term in equation (3.11), with $\theta_1^{\zeta} = -1$.

Combining equations (3.10) and (3.11) to obtain an expression containing only measured consumption growth $\Delta \ln C_t$ gives

$$\begin{aligned} \Delta \ln C_t &= \beta_{0t} + \gamma \Delta \ln C_{t-1} + \theta^{\zeta}(L)(\varsigma_t - \varsigma_{t-1}) + \theta^{\xi}(L) \xi_t, \\ &= \beta_{0t} + \gamma \Delta \ln C_{t-1} + \theta(L) \varepsilon_t, \end{aligned} \tag{3.12}$$

with $\varepsilon_t$ an *i.i.d.* error term and $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3$ an MA(3) lag polynomial.[6]

### 3.2.3 Time-varying excess sensitivity

Empirical studies have demonstrated that aggregate consumption growth is excessively sensitive to anticipated disposable income growth (see e.g., Campbell and Mankiw, 1989, 1990, 1991). We follow the standard approach to test for this type of ES by adding *anticipated* income growth to the consumption growth model. In line with, among others, Bacchetta and Gerlach (1997) we allow the ES parameter to vary over time. More specifically, we extend our benchmark in equation (3.12) to

$$\Delta \ln C_t = \beta_{0t} + \beta_{1t} E_{t-1}(\Delta \ln Y_t) + \gamma \Delta \ln C_{t-1} + \theta(L) \varepsilon_t, \tag{3.13}$$

where $\Delta \ln Y_t$ is aggregate income growth and $\beta_{1t}$ is the time-varying ES parameter. This approach differs from the method followed by among others Campbell and Mankiw (1990) and Kiley (2010) who test for ES by writing down aggregate consumption growth as the sum or (weighted) average between consumption growth of optimizing permanent income consumers and consumption growth of current income ('rule-of-thumb') consumers.

We will use the model in equations (3.13) to test for time-varying ES of aggregate consumption

[6]Note that $\theta(L) \varepsilon_t$ is the sum of the two independent MA processes $\theta^{\zeta}(L)(\varsigma_t - \varsigma_{t-1})$ and $\theta^{\xi}(L) \xi_t$, the first being of order order 3 and the second of order 2. From Hamilton (1994) we can write the sum of two independent MA processes as an MA process of which the order equals that of the highest order process in the sum.

growth with respect to income growth against the benchmark model in equation (3.12). This deviates from the past literature in a number of ways. First, ES is usually tested against a framework where aggregate consumption growth is either white noise (i.e., the standard random walk model) or an MA(1) process if time aggregation and classical measurement error are taken into account (see e.g., Bacchetta and Gerlach (1997)). The results of Sommer (2007) and Carroll, Slacalek, and Sommer (2011) show however that allowing for stickiness (i.e., the dependence of aggregate consumption growth on its own lag) is important when testing for the ES of consumption to income. In our model this is incorporated by introducing a habit formation mechanism. Second, as noted by Sommer (2007), allowing for classical measurement error may not be sufficient such that a more general framework with MA($q$) errors is called for. The relevant order $q$ will be determined empirically. Third, the time-varying variable $\beta_{0t}$ controls for all potentially omitted variables that may affect aggregate consumption growth (i.e., marginal utility shifters such as hours worked and government consumption, the conditional variance of consumption growth which reflects a potential precautionary savings motive, the interest rate that captures potential intertemporal substitution effects).

## 3.3 Empirical methodology

In this section we outline our empirical specification and econometric methodology to estimate the model for aggregate consumption growth outlined in Section 3.2.

### 3.3.1 Empirical specification

We use equation (3.13) to test for time-varying ES of aggregate consumption growth with respect to income growth against the benchmark model in equation (3.12). The empirical implementation of equation (3.13) requires a number of further assumptions. These are outlined below.

#### Time-varying parameters

The parameters $\beta_{0t}$ and $\beta_{1t}$ in equation (3.13) are allowed to change over time according to a random walk process

$$\beta_{i,t+1} = \beta_{it} + \eta_{it}, \qquad \eta_{it} \sim i.i.d.\mathcal{N}(0, \sigma^2_{\eta_i}), \tag{3.14}$$

with $i = 0, 1$. his allows for a very flexible evolution over time.

**Anticipated income growth and IV**

Anticipated income growth $E_{t-1}(\Delta \ln Y_t)$ is not observed, but can be estimated by assuming that observed income growth $\Delta \ln Y_t$ is linearly related to a set of forecasting variables $Z_t$ known to the consumer at time $t-1$

$$\Delta \ln Y_t = Z_t \delta + \nu_t, \tag{3.15}$$

such that $Z_t$ is uncorrelated with $\varepsilon_t$ in equation (3.13) and where $\nu_t$ an i.i.d. error term unpredictable at time $t$, i.e. $E_{t-1}\nu_t = 0$. Taking $E_{t-1}$ of equation (3.15)

$$E_{t-1}(\Delta \ln Y_t) = Z_t \delta + E_{t-1}\nu_t = Z_t \delta, \tag{3.16}$$

and substituting this in (3.13) yields

$$\Delta \ln C_t = \beta_{0t} + \beta_{1t} Z_t \delta + \gamma \Delta \ln C_{t-1} + \theta(L)\varepsilon_t. \tag{3.17}$$

Equation (3.17) is an IV-type of regression model with instruments $Z_t$ and $\delta$ estimated using the first stage regression model (3.15). Because of common shocks to income and consumption, equations (3.15) and (3.17) are seemingly-unrelated regressions with cross-equation parameter restrictions. The correlation structure in the error terms $\nu_t$ and $\varepsilon_t$ can be expressed as

$$\Sigma_{\nu,\varepsilon} = \begin{bmatrix} \sigma_\nu^2 & \rho\sigma_\nu\sigma_\varepsilon \\ \rho\sigma_\nu\sigma_\varepsilon & \sigma_\varepsilon^2 \end{bmatrix}, \tag{3.18}$$

where $\rho$ is the correlation between $\nu_t$ and $\varepsilon_t$. Using a Cholesky factorization of $\Sigma_{\nu,\varepsilon}$ we can write

$$\begin{bmatrix} \nu_t \\ \varepsilon_t \end{bmatrix} = \begin{bmatrix} \sigma_\nu & 0 \\ \rho\sigma_\varepsilon & \sigma_\varepsilon\sqrt{1-\rho^2} \end{bmatrix} \begin{bmatrix} \mu_{1t} \\ \mu_{2t} \end{bmatrix}, \tag{3.19}$$

with $\mu_{1t}$ and $\mu_{2t}$ being *i.i.d.* error terms with unit variance. Replacing $\varepsilon_t$ in eq. (3.17) by

$$\varepsilon_t = \frac{\rho\sigma_\varepsilon}{\sigma_\nu}\nu_t + \sigma_\varepsilon\sqrt{1-\rho^2}\mu_{2t}, \tag{3.20}$$

yields

$$\Delta \ln C_t = \beta_{0t} + \beta_{1t} Z_t \delta + \gamma \Delta \ln C_{t-1} + \rho\nu_t^* + \theta(L)\mu_t, \tag{3.21}$$

with $\nu_t^* = \sigma_\varepsilon \theta(L)\nu_t/\sigma_\nu$ and $\mu_t = \sigma_\varepsilon\sqrt{1-\rho^2}\mu_{2t}$ an *i.i.d.* error not correlated with any other error in the model. Equation (3.21) is a control function type of IV regression model similar to the one outlined by Kim and Kim (2011) to deal with endogeneity in a time-varying parameter model.[7] However, in stead of using their joint or two-step ML procedure to estimate the non-linear model implied by equations (3.15) and (3.21), we use the Gibbs sampler as outlined in Subsection 3.3.3 below. The advantage of our modeling and sampling approach is that when estimating equation (3.21) we explicitly take into account that the error terms $\nu_t$ and $\varepsilon_t$ may be correlated and that $\delta$ is estimated in a first step, such that $Z_t\widehat{\delta}$ is a generated regressor. Moreover, as our Bayesian approach relies on sampling the posterior distribution rather than using asymptotic approximations, it allows for exact inference even when the instruments $Z_t$ are weak.

### 3.3.2 Stochastic model specification search

A key question in the above model is whether the ES parameter $\beta_{1t}$ is time-varying or constant. Although $\beta_{1t}$ can be filtered using the Kalman filter and the variance of the innovations $\sigma^2_{\eta_1}$ can be estimated using ML, testing whether the time-variation is statistically significant implies testing $\sigma^2_{\eta_1} = 0$ against $\sigma^2_{\eta_1} > 0$, which is a non-regular testing problem as the null hypothesis lies on the boundary of the parameter space. In a recent article, Frühwirth-Schnatter and Wagner (2010) show how to extend Bayesian model selection for observed variables in standard regression models to unobserved components in state space models. Their approach relies on a non-centered parameterization of the state space model in which (i) binary stochastic indicators for each of the model components are sampled together with the parameters and (ii) the standard inverse Gamma prior for the variances of innovations to the components is replaced by a Gaussian prior centered at zero for the square root of these variances.

#### Non-centered parameterization

Frühwirth-Schnatter and Wagner (2010) argue that a first piece of information on the hypothesis whether the variance of innovations to a state variable is zero or not can be obtained by considering a non-centered parameterization. This implies rearranging the data generating process for the time-varying parameters $\beta_{it}$ in equation (3.14) to

$$\beta_{it} = \beta_{i0} + \sigma_{\eta_i}\beta^*_{it}, \tag{3.22}$$

$$\text{with} \qquad \beta^*_{i,t+1} = \beta^*_{it} + \eta^*_{it}, \qquad \beta^*_{i0} = 0, \qquad \eta^*_{it} \sim i.i.d.\mathcal{N}(0,1), \tag{3.23}$$

[7] One apparent difference is that our specification includes anticipated income growth, which is a predetermined regressor calculated using instrumental variables, while the specification of Kim and Kim (2011) includes an endogenous regressor. Next to the error terms from the first step auxiliary regression, the control function equation in Kim and Kim (2011) therefore includes the endogenous regressor instead of $Z_t\delta$ as in our equation (3.21).

for $i = 0, 1$ and where $\beta_{i0}$ is the initial value of $\beta_{it}$ when this coefficient is time-varying ($\sigma_{\eta_i} > 0$) while being the constant value of $\beta_{it}$ when there is no time variation ($\sigma_{\eta_i} = 0$). A crucial aspect of the non-centered parameterization is that it is not identified as the signs of $\sigma_{\eta_i}$ and $\beta^*_{it}$ can be changed by multiplying both with -1 without changing their product in equation (3.22). As a result of the non-identification, the likelihood function is symmetric around 0 along the $\sigma_{\eta_i}$ dimension. When $\beta_{it}$ is time-varying ($\sigma^2_{\eta_i} > 0$) the likelihood function is bimodal with modes $-\sigma_{\eta_i}$ and $\sigma_{\eta_i}$. For $\sigma^2_{\eta_i} = 0$ the likelihood function is unimodal around zero. As such, allowing for non-identification of $\sigma_{\eta_i}$ provides useful information on whether $\sigma^2_{\eta_i} > 0$.

#### Stochastic model specification

A second advantage of the non-centered parameterization in equation (3.22) is that when $\sigma^2_{\eta_i} = 0$ the transformed component $\beta^*_{it}$ (in contrast to $\beta_{it}$) degenerates to zero with the time-invariant parameter now represented by $\beta_{i0}$. As such, the question whether the ES parameter is time-varying or not can be expressed as a variable selection problem in equation (3.22). To this aim Frühwirth-Schnatter and Wagner (2010) introduce the stochastic model specification

$$\beta_{it} = \beta_{i0} + \iota_i \sigma_{\eta_i} \beta^*_{it}, \tag{3.24}$$

where $\iota_i$ is a binary indicator which is either 0 or 1. If $\iota_i = 0$, the component $\beta^*_{it}$ drops from the model such that $\beta_{i0}$ represents the constant intercept or slope parameter. If $\iota_i = 1$ then $\beta^*_{it}$ is included in the model and $\sigma_{\eta_i}$ is estimated from the data. In this case $\beta_{i0}$ is the initial value of $\beta_{it}$.

#### Gaussian priors centered at zero for $\sigma_{\eta_i}$

Our Bayesian estimation approach requires choosing prior distributions for the model parameters. When using the standard inverse Gamma prior distribution for the variance parameters, the choice of the shape and scale hyperparameters that define this distribution have a strong influence on the posterior when the true value of the variance is close to zero. More specifically, as the inverse Gamma does not have probability mass at zero, using it as a prior distribution tends to push the posterior density away from zero. This is of particular importance when estimating the variances $\sigma^2_{\eta_i}$ of the innovations to the time-varying parameters $\beta_{it}$ as for these components we want to decide whether they are relevant or not. As $\sigma^2_{\eta_i}$ is a regression coefficient in equation (3.24) a further important advantage of the non-centered parameterization is that it allows us to replace the standard inverse Gamma prior on the variance parameter $\sigma^2_{\eta_i}$ by a Gaussian prior centered at zero on $\sigma_{\eta_i}$. Centering the prior distribution at zero makes sense as for both $\sigma^2_{\eta_i} = 0$ and $\sigma^2_{\eta_i} > 0$, $\sigma_{\eta_i}$ is symmetric around zero. Frühwirth-Schnatter and Wagner (2010) show that the posterior density of $\sigma_{\eta_i}$ is much less sensitive to the hyperparameters of the Gaussian distribution and is not pushed away from zero when $\sigma^2_{\eta_i} = 0$. As such, we choose a Gaussian prior distribution centered at zero $\mathcal{N}(0, V_0)$ for $\sigma_{\eta_0}$ and $\sigma_{\eta_1}$, which are the standard deviations of the innovations to the time-varying parameters.

**Other priors**

For the variances of the error terms $\sigma^2_\mu$ and $\sigma^2_\nu$, which are always included in the model, we choose the standard inverse Gamma prior distribution $IG(c_0, C_0)$. For each of the model parameters $\beta_{00}$, $\beta_{10}$, $\gamma$, $\rho$, $\theta$ and $\delta$ we assume a normal prior distribution $\mathcal{N}(b_0, V_0)$. Details on the chosen hyperparameters $(b_0, V_0)$ for the prior $\mathcal{N}$ distributions and $(c_0, C_0)$ for the $IG$ distributions are presented in Section 3.4.2 below. For the binary indicators $\iota_0$ and $\iota_1$ we choose a uniform prior distribution over all combinations of the indicators such that each model has the same prior probability and each model component has a 1/2 prior probability of being included in the model, i.e. $p(\iota_0 = 1|\iota_1) = p(\iota_1 = 1|\iota_0) = 0.5$.

### 3.3.3 Gibbs sampler

Using equation (3.24), the model in equation (3.21) can be rewritten as

$$\Delta \ln C_t = (\beta_{00} + \iota_0 \sigma_{\eta_0} \beta^*_{0t}) + (\beta_{10} + \iota_1 \sigma_{\eta_1} \beta^*_{1t})\, Z_t \delta + \gamma \Delta \ln C_{t-1} + \rho \nu^*_t + \theta\,(L)\, \mu_t. \tag{3.25}$$

Taken together, equations (3.15) and (3.25) can be considered as the observation equations of a state space (SS) model, with the unobserved states $\beta^*_{0t}$ and $\beta^*_{1t}$ evolving according to the state equations in (3.23). In a standard linear Gaussian SS model, the Kalman filter can be used to filter the unobserved states from the data and to construct the likelihood function such that the unknown parameters can be estimated using Maximum Likelihood. However, the stochastic model specification search outlined in subsection 3.3.2 implies a non-regular estimation problem for which the standard approach via the Kalman filter and maximum likelihood is not feasible. Instead we use the Gibbs sampler which is a Markov chain Monte Carlo (MCMC) method to simulate draws from the intractable joint and marginal posterior distributions of the unknown parameters and the unobserved states using only tractable conditional distributions. Intuitively, this amounts to reducing the complex non-linear model into a sequence of blocks for subsets of parameters/states that are tractable conditional on the other blocks in the sequence.

For notational convenience, define the time-varying parameter vector $\beta^*_t = (\beta^*_{0t}, \beta^*_{1t})$, the unknown parameter vectors $\phi_1 = \left(\delta, \sigma^2_\nu\right)$, $\phi_2 = \left(\beta_{00}, \beta_{10}, \sigma_{\eta_0}, \sigma_{\eta_1}, \gamma, \rho, \sigma^2_\mu\right)$ and $\phi = (\phi_1, \phi_2, \theta)$ and the model indicator $\mathcal{M} = (\iota_0, \iota_1)$ . Let $D_t = (\Delta \ln C_t, \Delta \ln Y_t, Z_t)$ be the data vector. Stacking observations over time, we denote $D = \{D_t\}^T_{t=1}$ and similarly for $\beta^*$. The posterior density of interest is then given by $f(\phi, \beta^*, \mathcal{M}|D)$. Building on Frühwirth-Schnatter and Wagner (2010) for the stochastic model specification part and on Chib and Greenberg (1994) for the MA part, our MCMC scheme is as follows:

1. Sample the first step parameters $\phi_1$ from $f(\phi_1|D)$ using the regression model in equation (3.15) and calculate $Z_t\delta$ and $\nu_t^*$.

2. Sample the MA coefficients $\theta$ from $f(\theta|\phi_1, \phi_2, \beta^*, \mathcal{M}, D)$ conditional on the parameters $\phi_2$, the time-varying parameters $\beta^*$, the binary indicators in $\mathcal{M}$ and $Z_t\delta$ and $\nu_t^*$ calculated in the first block.

3. Sample the binary indicators $\mathcal{M}$ and the second step parameters $\phi_2$ using the non-centered parameterization in equation (3.25) conditional on the MA coefficients $\theta$, the time-varying parameters $\beta^*$ and $Z_t\delta$ and $\nu_t^*$ calculated in the first block.

   (a) Sample the binary indicators $\mathcal{M}$ from $f(\mathcal{M}|\phi_1, \theta, \beta^*, D)$ marginalizing over the parameters $\phi_2$ for which variable selection is carried out.

   (b) Sample the unrestricted parameters in $\phi_2$ from $f(\phi_2|\phi_1, \theta, \beta^*, \mathcal{M}, D)$ while setting the restricted parameters $\sigma_{\eta_i}$ (for which the corresponding component $\beta_{it}^*$ is not included in the model $\mathcal{M}$) equal to 0.

4. Sample the unrestricted (i.e. for which $\iota_i = 1$) time varying parameters in $\beta^*$ from $f(\beta^*|\phi, \mathcal{M}, D)$ again using the non-centered parameterization in equation (3.25) conditional on the second step parameters $\phi_2$, the binary indicators $\mathcal{M}$ and $Z_t\delta$ and $\nu_t^*$ calculated in the first block. The restricted time varying parameters (for which $\iota_i = 0$) in $\beta_{it}^*$ are sampled directly from their prior distribution using equation (3.23).[8]

5. Perform a random sign switch for $\sigma_{\eta_i}$ and $\{\beta_{it}^*\}_{t=1}^T$, i.e., $\sigma_{\eta_i}$ and $\{\beta_{it}^*\}_{t=1}^T$ are left unchanged with probability 0.5 while with the same probability they are replaced by $-\sigma_{\eta_i}$ and $\{-\beta_{it}^*\}_{t=1}^T$.

Given an arbitrary set of starting values, sampling from these blocks is iterated $J$ times and, after a sufficiently large number of burn-in draws $B$, the sequence of draws $(B+1, ..., J)$ approximates a sample from the virtual posterior distribution $f(\phi, \beta^*, \mathcal{M}|D)$. Details on the exact implementation of each of the blocks can be found in 3.A. The results reported below are based on 10,000 Gibbs sampler iterations, with the first 5,000 draws discarded as a burn-in sequence.

[8] Even when $\iota_i = 0$ a sample for $\beta_{it}^*$ is required as this will be used to calculate the marginal likelihood of a model with a time-varying $\beta_{it}^*$ in block 3(a).

## 3.4 Empirical results

### 3.4.1 Data

To estimate our empirical model, we use quarterly data for the United States over the period 1954:q1-2014:q3. The effective sample size is 237, since 4 observations are lost as a result of lagging. Where necessary, data are seasonally adjusted. For $C_t$ we use real per capita expenditures on nondurables and services (excluding clothing and footwear). For $Y_t$ real per capita personal disposable income is used. Both are deflated by the deflator of nondurables and services (excluding clothing and footwear) with base year 2009=100, for which also quarterly data is available. With respect to estimating anticipated income growth, $Z_t$ contains a number of instruments suggested by Campbell and Mankiw (1990), i.e., lagged disposable income growth, lagged consumption growth, lagged changes in the short-term nominal interest rate and a lagged error correction term, i.e. log consumption minus log disposable income (see also Campbell, 1987). As Campbell and Mankiw (1990) further argue that changes in stock prices help to forecast changes in income, we also use lagged changes in the S&P 500 index as an additional instrument. Following Fuhrer (2000) and Kiley (2010), we further include lags of the inflation rate, calculated as the log change in the CPI index. Finally, in line with Sommer (2007) we also use lags of the Index of Consumer sentiment and of the change in unemployment rate. For consumption and income growth 4 lags are used while for all other instruments we consider 2 lags.

Data for expenditures on nondurables and services (excluding clothing and footwear), for nominal personal disposable income and for the corresponding deflator are taken from the National Product and Income Accounts (NIPA). Population data are taken from the OECD quarterly national accounts. For the short-term nominal interest rate, we use the three-month T-bill rate with data taken from the Board of Governors. Data for the S&P 500 index comes from Sommer (2007) and is updated with data from Thomson Reuters Datastream. Finally, for the CPI-index and the unemployment rate, data are taken from the Bureau of Labor Statistics while for consumer sentiment the index constructed by the University of Michigan is used.

### 3.4.2 Prior choice

Summary information on the prior distributions for the unknown parameters is reported in Table 3.1. For the variances $\sigma_\mu^2$ and $\sigma_\nu^2$ of the error terms in the consumption and income growth equations we use an inverse gamma prior distribution $IG(c_0, C_0)$ where the shape $c_0 = \nu_0 T$ and scale $C_0 = c_0\sigma_0^2$ parameters are calculated from the prior belief $\sigma_0^2$ and the prior strength $\nu_0$, which is expressed as a fraction of the sample size $T$.[9] Our prior belief for $\sigma_\mu$ is 0.5, implying that 95% of the quarterly consumption growth shocks lie between -1% and 1%, while our prior belief for $\sigma_\nu$ of 0.75 implies that the 95% of the quarterly income growth shocks lie between -1.5% and +1.5%. The smaller value for $\sigma_\mu$ reflects the idea that income is more volatile than consumption. In both cases, the prior is fairly loose with strength set equal to 0.1.

For the remaining parameters, Gaussian prior distributions $\mathcal{N}(b_0, V_0)$ are used. First, consider the time-varying ES parameter, $\beta_{1t}$. For $\beta_{10}$, the prior is given by $\beta_{10} \sim \mathcal{N}(0.4, 0.2^2)$ which reflects our belief that if there is no time variation in $\beta_{1t}$ (i.e., $\sigma_{\eta_1} = 0$) then the ES parameter ranges from roughly 0 to 0.8. This encompasses all values found in the literature. Campbell and Mankiw (1990) for example report values of 0.5 up to 0.7 for the U.S. Controlling for habits, Kiley (2010) and Sommer (2007) find lower values of about 0.3 and 0.15 respectively. For the standard deviation $\sigma_{\eta_1}$ of the innovations to the time-varying part in $\beta_{1t}$ a Gaussian prior centered at zero $\mathcal{N}(0, 0.2^2)$ is chosen. Note that the prior standard deviation $\sqrt{V_0} = 0.2$ implies a very loose prior as it allows that 95% of the standard deviations of the quarterly innovations to the ES parameter lie between $-0.39$ and 0.39.

For the time-varying intercept, $\beta_{0t}$, the prior distribution for the time-invariant part is fairly uninformative and centered at zero, $\beta_{00} \sim \mathcal{N}(0, 1)$. The prior belief $\sigma_{\eta_0} \sim \mathcal{N}(0, 0.2^2)$ about the degree of time-variation in $\beta_{0t}$ is also centered at zero with the same prior standard deviation as the innovations to the ES parameter.

According to Carroll, Slacalek, and Sommer (2011), the strength of habits in aggregate consumption growth for the U.S. varies between 0.5 and 0.7. These results are confirmed by, amongst others, Fuhrer (2000) and Sommer (2007) who both find a stickiness parameter around 0.7. Therefore our prior for $\gamma$ is $\mathcal{N}(0.6, 0.15^2)$ such that the 95% prior interval ranges from roughly 0.3 to 0.9.

For the degree of correlation $\rho$ between $\nu_t$ and $\varepsilon_t$, an uninformative prior is chosen, i.e., $\rho \sim \mathcal{N}(0, 0.4^2)$. A loose prior centered at zero is also used for the $MA$ parameters $\theta$ and for the parameters $\delta$ on the instrumental variables used to proxy $E_{t-1}(\Delta \ln Y_t)$.

[9] Since this prior is conjugate, $\nu_0 T$ can be interpreted as the number of fictitious observations used to construct the prior belief $\sigma_0^2$.

**Table 3.1:** Prior distributions of model parameters

| **Inverse Gamma priors:** $IG(c_0, C_0) = IG(\nu_0 T, \nu_0 T \sigma_0^2)$ | | | | Percentiles | |
|---|---|---|---|---|---|
| | | $\sigma_0$ | $\nu_0$ | 2.5% | 97.5% |
| error term consumption equation | $\sigma_\mu$ | 0.50 | 0.10 | 0.42 | 0.62 |
| error term income equation | $\sigma_\nu$ | 0.75 | 0.10 | 0.63 | 0.94 |
| **Gaussian priors:** $\mathcal{N}(b_0, V_0)$ | | | | Percentiles | |
| *Non-centered components* | | $b_0$ | $\sqrt{V_0}$ | 2.5% | 97.5% |
| std. of time-varying intercept | $\sigma_{\eta_0}$ | 0.00 | 0.20 | −0.78 | 0.78 |
| std. of time-varying ES parameter | $\sigma_{\eta_1}$ | 0.00 | 0.20 | −0.39 | 0.39 |
| *Model parameters* | | | | | |
| constant value intercept | $\beta_{00}$ | 0.00 | 1.00 | −1.96 | 1.96 |
| constant value ES parameter | $\beta_{10}$ | 0.40 | 0.20 | 0.01 | 0.79 |
| consumption habits parameter | $\gamma$ | 0.60 | 0.15 | 0.31 | 0.89 |
| degree of correlation between $\nu_t$ and $\varepsilon_t$ | $\rho$ | 0.00 | 0.40 | −0.78 | 0.78 |
| $MA$ parameters | $\theta$ | 0.00 | 0.50 | −0.98 | 0.98 |
| parameters first stage income equation | $\delta$ | 0.00 | 0.50 | −0.98 | 0.98 |

Notes: We set IG priors on the variance parameters $\sigma^2$ but in the top panel of this table we report details on the implied prior distribution for the standard deviations $\sigma$ as these are easier to interpret. Likewise, in the bottom panel of the table we report $\sqrt{V_0}$ instead of $V_0$.

### 3.4.3 Estimation results

We successively estimate 4 empirical models with increasing complexity. The fourth and last model coincides with the empirical specification presented in Section 3. This approach facilitates the investigation of the impact of the features incorporated into the model on the obtained estimates for excess sensitivity and its variation over time. It also allows us to compare our findings to those obtained in the literature. Hence, for each of the models, the importance of time variation in the ES parameter is discussed as is the robustness of the results under different instrument sets $Z_t$. We end this section with the presentation of the results for the parsimonious model selected by the stochastic model specification search.

#### Instrument sets

As anticipated income growth $E_{t-1}(\Delta \ln Y_t)$ is not observed, a set of instrumental variables $Z_t$ is used to estimate it. As Campbell and Mankiw (1990) and Kiley (2010), amongst others, show that the choice of instruments can be critically important, inference on the significance of time variation will be reported under 3 different instrument sets. A first instrument set, $Z^1$, is based upon Campbell and Mankiw (1990) and includes lags 1-4 of disposable income growth and consumption growth, a lagged error correction term and lags 1-2 of the change in the short term interest rate and the stock prices. In instrument set $Z^2$ we add the first and second lag of the inflation rate to the instruments contained in $Z^1$ (see Fuhrer, 2000; Kiley, 2010). Following Sommer (2007), in instrument set $Z^3$ we further add lags 1-2 of the Consumer Sentiment Index and of the change in the unemployment rate. Concerning the choice of lags, note that in general the presence of autocorrelation of the MA form in the error term $\mu_t$ necessitates the instruments to be appropriately lagged, i.e., depending on the order of the MA component in $\mu_t$. However, as our empirical approach explicitly takes into account and controls for the MA terms, we do not face this issue.

In column 2 of Table 3.2 we report the average explanatory power ($R^2$) of the different instrument sets in explaining $\Delta \ln Y_t$. For all instrument sets we find an average $R^2$ over all iterations of about 30%, which is very reasonable.

### Model 1 (M1): no habits, no time-varying intercept, no MA in the error terms

We start by testing for time variation in the ES parameter using a basic model in which there is no time-variation in the intercept ($\sigma_{\eta_0} = 0$), no dependency of aggregate consumptions growth on its own past, and no MA structure in the error term. Based on equation (3.21), the empirical specification for aggregate consumption growth then becomes

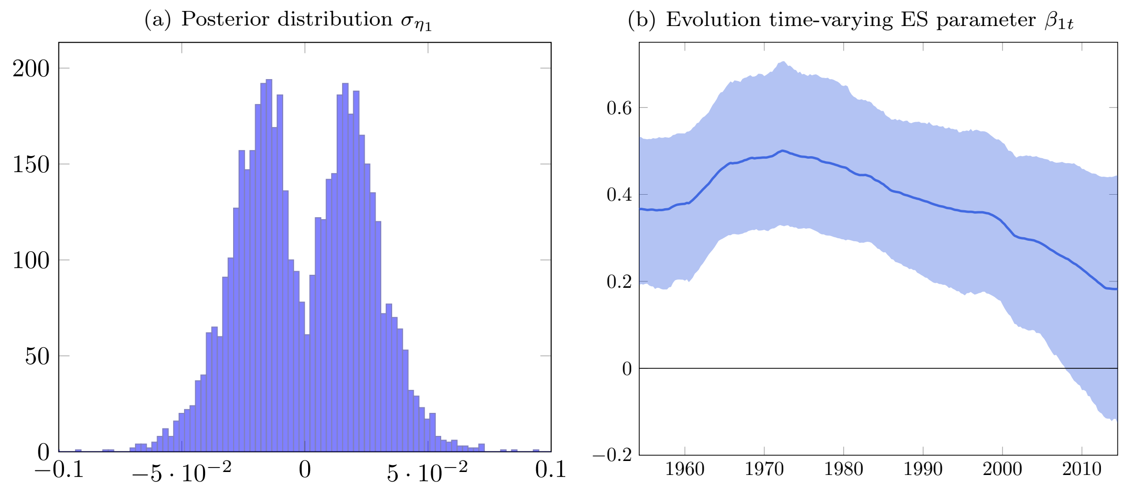
$$\Delta \ln C_t = \beta_{00} + \beta_{1t} Z_t \delta + \rho \nu_t^* + \mu_t.$$

where the data generating process for $\beta_{1t}$ is represented by equations (3.23) and (3.24).

We first estimate this model with the binary indicator $\iota_1$ set to 1 to generate a posterior distribution for the standard deviation ($\sigma_{\eta_1}$) of the innovations to the ES parameter. If this distribution is bimodal, with low or no probability mass at zero, this can be taken as a first indication of a time-varying ES. Figure 3.1 presents the resulting posterior distribution as well as the mean of the posterior distribution of the time-varying ES parameter and its 90 % highest posterior density (HPD) interval. When looking at panel (a), we find clear-cut bimodality in the posterior distribution of the standard deviation of the innovations to the ES parameter, pointing to a significant amount of time-variation. Panel (b) further shows the resulting time-variation in ES, which starts at a value close to 0.4 in 1954 and increases to around 0.5 in the early 1970's after which it keeps on decreasing until it is lower than 0.2 in 2014.

As a more formal test for time variation, we next sample the stochastic binary indicator $\iota_1$ together with the other parameters of the model. Table 3.2 reports the posterior probabilities that the binary indicators $\iota_i$ attached to the time-varying parameters $\beta_{it}$ equal one for each of the four different models that we estimate and for the three instrument sets discussed above. The posterior probabilities for the binary indicators are calculated as the average selection frequencies over all iterations of the Gibbs sampler. In the baseline scenario, we assign a 0.5 prior probability

**Figure 3.1:** Stochastic model selection and time-varying parameters (binary indicators set to 1) in M1




Note: Figures are presented for the results using instrument set $Z^3$ but are similar when using instrument sets $Z^1$ and $Z^2$

to each of the binary indicators being one. Results for this baseline scenario are presented in the upper part of Table 3.2. As a sensitivity control, we re-estimate the different models with the prior inclusion probability set to 0.1 and 0.9 respectively. The resulting posterior probabilities are reported in the middle and lower part of Table 3.2.

For M1, the results in the baseline scenario ($p(\iota_i = 1) = 0.5$) show that when using instrument sets $Z^2$ and $Z^3$ the inclusion probability of a time-varying ES parameter varies around 0.35. For instrument set $Z^1$ it is somewhat lower. Only when increasing the prior inclusion probability to 0.9, there is some sign of time-variation. All in all the results indicate that, despite the clear bimodal posterior distribution of $\sigma_{\eta_1}$, there is no real evidence in favor of time-varying excess sensitivity.

### Model 2 (M2): no habits, no TV intercept, MA(2) error terms

In the absence of habits, time aggregation and measurement error induce an MA(2) structure in the growth rate of consumption. This leads to the following empirical specification for aggregate consumption growth

$$\Delta \ln C_t = \beta_{00} + \beta_{1t} Z_t \delta + \rho \nu_t^* + \theta(L)\mu_t.$$

with $\theta(L) = 1 + \theta_1 L + \theta_2 L^2$ an MA(2) lag polynomial.

As we did when discussing M1, we report results for two steps. First, Figure 3.2 shows the posterior distribution for the standard deviation $\sigma_{\eta_1}$ and plots the time-varying ES-parameter. Second, the individual posterior probability for the binary indicator $\iota_1$ is reported in Table 3.2.

**Table 3.2:** Posterior inclusion probabilities for the binary indicators over different models and instrument sets

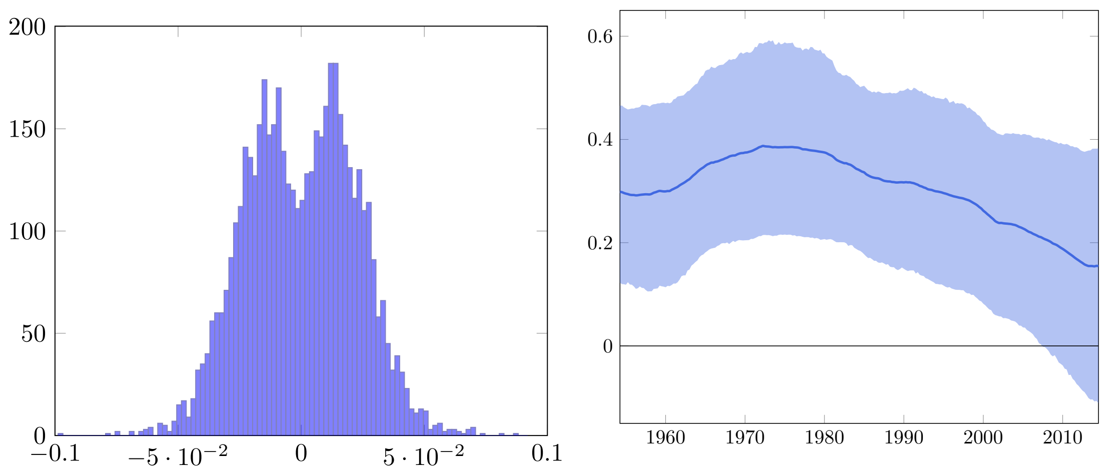
| Prior | Instrument set | | Posterior | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | M1 | M2 | M3 | | M4 | | |
| | $Z$ | $R^2$ | $\iota_1$ | $\iota_1$ | $\iota_0$ | $\iota_1$ | $\iota_0$ | $\iota_1$ | |
| $p(\iota_i = 1) = 0.5$ | $Z^1$ | 0.30 | 0.24 | 0.19 | 0.38 | 0.18 | 0.06 | 0.07 | |
| | $Z^2$ | 0.33 | 0.36 | 0.23 | 0.41 | 0.20 | 0.06 | 0.07 | |
| | $Z^3$ | 0.33 | 0.35 | 0.22 | 0.41 | 0.20 | 0.06 | 0.07 | |
| $p(\iota_i = 1) = 0.1$ | $Z^1$ | 0.30 | 0.05 | 0.03 | 0.08 | 0.03 | 0.01 | 0.01 | |
| | $Z^2$ | 0.33 | 0.09 | 0.04 | 0.08 | 0.04 | 0.01 | 0.01 | |
| | $Z^3$ | 0.33 | 0.09 | 0.04 | 0.10 | 0.04 | 0.01 | 0.01 | |
| $p(\iota_i = 1) = 0.9$ | $Z^1$ | 0.30 | 0.69 | 0.63 | 0.82 | 0.58 | 0.36 | 0.40 | |
| | $Z^2$ | 0.33 | 0.79 | 0.70 | 0.83 | 0.61 | 0.36 | 0.40 | |
| | $Z^3$ | 0.33 | 0.80 | 0.68 | 0.83 | 0.59 | 0.36 | 0.40 | |
| | Model specification | | | | | | | | |
| | Habits | | No | No | No | | Yes | | |
| | TV intercept | | No | No | Yes | | Yes | | |
| | MA error terms | | No | MA(2) | MA(2) | | MA(3) | | |

Notes: The instrument set $Z^1$ includes lags 1-4 of disposable income growth and consumption growth, a lagged error correction term and lags 1-2 of the change in stock prices and the short term interest rate. Instrument set $Z^2$ adds the first and second lag of the inflation rate. Instrument set $Z^3$ further includes lags 1-2 of the Consumer Sentiment Index and of the change in the unemployment rate.

Panel (a) of Figure 3.2 suggests that there is some bimodality in the posterior distribution for $\sigma_{\eta_1}$ but compared to M1 it is less clear. Looking at the posterior inclusion probability for the time-varying part of the ES parameter in Table 3.2 shows that in the baseline scenario there is no significant time-variation as for all instrument sets the probabilities vary around 0.2. For the two other scenarios ($p(\iota_i = 1) = 0.1$ and $p(\iota_i = 1) = 0.9$) posterior probabilities are also lower than the corresponding ones for M1.

**Figure 3.2:** Stochastic model selection and time-varying parameters (binary indicators set to 1) in M2

(a) Posterior distribution $\sigma_{\eta_1}$ (b) Evolution time-varying ES parameter $\beta_{1t}$




Note: Figures are presented for the results using instrument set $Z^3$ but are similar when using instrument sets $Z^1$ and $Z^2$

Further, to underline the importance of controlling for the MA process in the error terms, we report the posterior distribution of the different MA coefficients $\theta$ in Table 3.3. For M2, the 95% HPD interval of $\theta_1$ varies between -0.01 and 0.34. While there is some probability mass at zero, it is very limited. For $\theta_2$ the 95% posterior interval ranges between 0.03 and 0.34 with a mean of 0.18 which shows us that controlling for the MA terms is necessary.

A similar model to M2 was also estimated by McKiernan (1996). Opposed to our analysis, their results indicate that the relationship between consumption and income significantly changes over the period 1959-1994 as a likelihood ratio test rejected the null hypothesis of a fixed parameter model against the alternative stochastic parameter model. However, they also find no considerable drop over time in the excess sensitivity parameter.

**Table 3.3:** Posterior distribution for the MA parameters over different models

| MA parameter | Posterior distribution | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | M2 | | | M3 | | | M4 | | |
| | 2.5% | mean | 97.5% | 2.5% | mean | 97.5% | 2.5% | mean | 97.5% |
| $\theta_1$ | -0.01 | 0.17 | 0.34 | -0.02 | 0.15 | 0.32 | -0.47 | -0.29 | -0.11 |
| $\theta_2$ | 0.03 | 0.18 | 0.32 | 0.01 | 0.15 | 0.30 | -0.11 | 0.06 | 0.22 |
| $\theta_3$ | | | | | | | -0.08 | 0.06 | 0.20 |

Note: Results are presented using instrument set $Z^3$ and assuming $p(\iota_i = 1) = 0.5$ but are similar when using other instrument sets and prior inclusion probabilities

### Model 3 (M3): no habits, time-varying intercept, MA(2) error terms

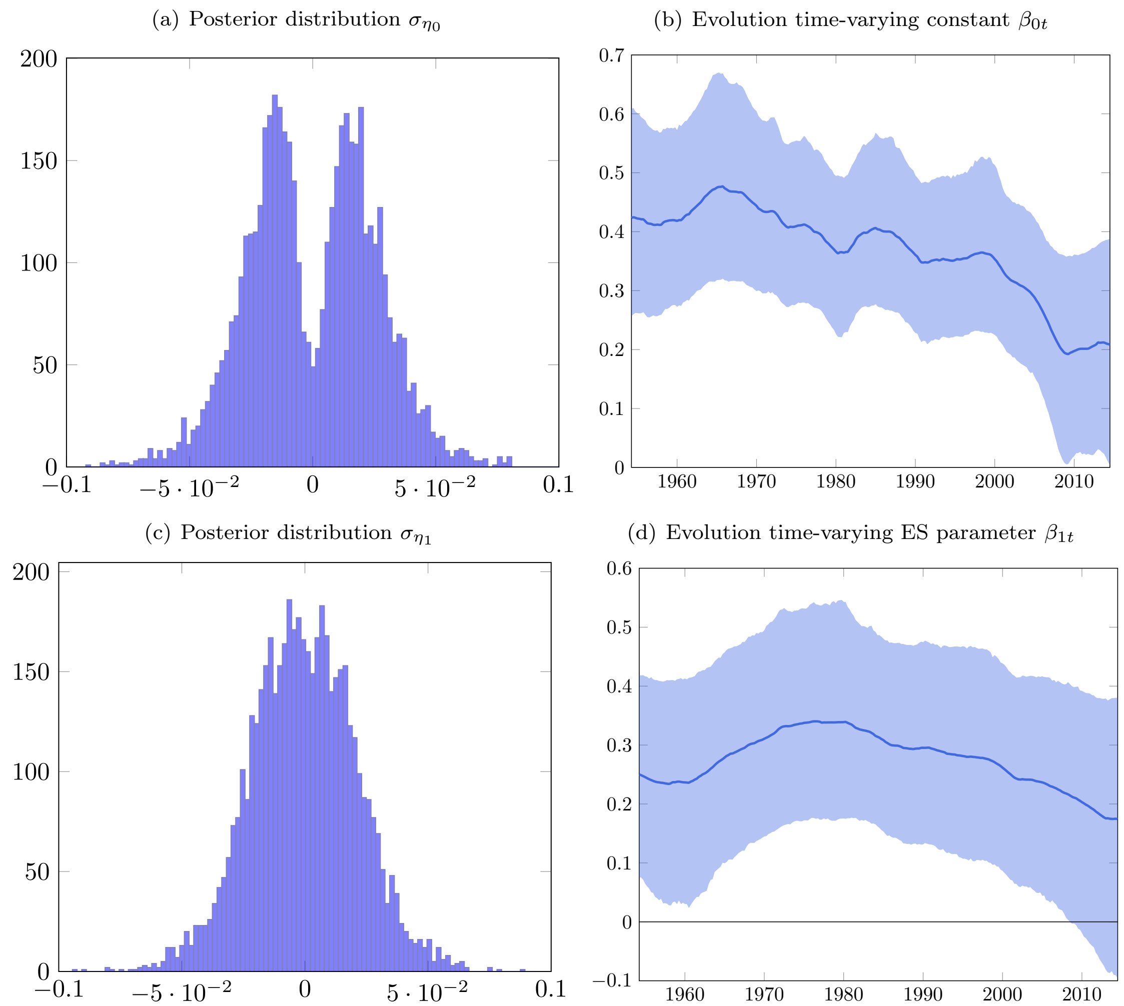
Models M1 and M2 are rather restrictive as they do not allow other variables, besides expected income growth, to have an impact on aggregate consumption growth. In M3 we allow for a time-varying constant $\beta_{0t}$ that controls for potentially omitted variables that may affect aggregate consumption growth. The empirical specification for $\Delta \ln C_t$ then becomes

$$\Delta \ln C_t = \beta_{0t} + \beta_{1t} Z_t \delta + \rho \nu_t^* + \theta(L)\mu_t,$$

with $\theta(L) = 1 + \theta_1 L + \theta_2 L^2$ an MA(2) lag polynomial and where equations (3.23) and (3.24) represent the processes for the time-varying variables $\beta_{0t}$ and $\beta_{1t}$.

As we now allow for a time-varying intercept, Figure 3.3 and Table 3.2 also provide information on whether the time-variation in the intercept is statistically significant. When analyzing the posterior distribution of $\sigma_{\eta_0}$, we notice that Figure 3.3 panel (a) provides evidence of a bimodal distribution with low probability mass at zero, pointing to significant time-variation in the intercept. When analyzing the posterior distribution of $\sigma_{\eta_1}$, Figure 3 panel (c) suggests that there is no

**Figure 3.3:** Stochastic model selection and time-varying parameters (binary indicators set to 1) in M3




Note: Figures are presented for the results using instrument set $Z^3$ but are similar when using instrument sets $Z^1$ and $Z^2$

bimodality in the posterior distribution of $\sigma_{\eta_1}$ and thus no time variation in ES. This is confirmed in Table 3.2 as in the baseline scenario the posterior probability of $\iota_1$ equal to 1 varies around 0.20 for all instrument sets. Even when increasing the prior inclusion probability up to 0.9, the posterior does not exceed 0.61. The model selection thus cearly rejects time variation in the ES parameter. For the intercept on the contrary, results are mixed. While Figure 3.3 panel (a) points to a time-varying intercept, results on the posterior inclusion probability give no clear evidence for time-variation in the intercept. Related to the importance of taking into account the MA process in the error terms, Table 3.3 shows similar posterior distributions for the MA coefficients in M3 as those reported for M2.

In a comparable framework, Bacchetta and Gerlach (1997) find that the ES of consumption to income fell gradually from about 0.75 in the early 1970s to about 0.4 in the early 1990s. This contrasts a lot with our results as is shown by Figure 3.3 panel (d). Bacchetta and Gerlach (1997) however did not test if the founded time-variation was statistically relevant

**Model 4 (M4): habits, time-varying intercept, MA(3) error terms**

Finally, in M4 we allow for habits in aggregate consumption growth and estimate the empirical specification presented in Section 3, i.e., equation (3.21)

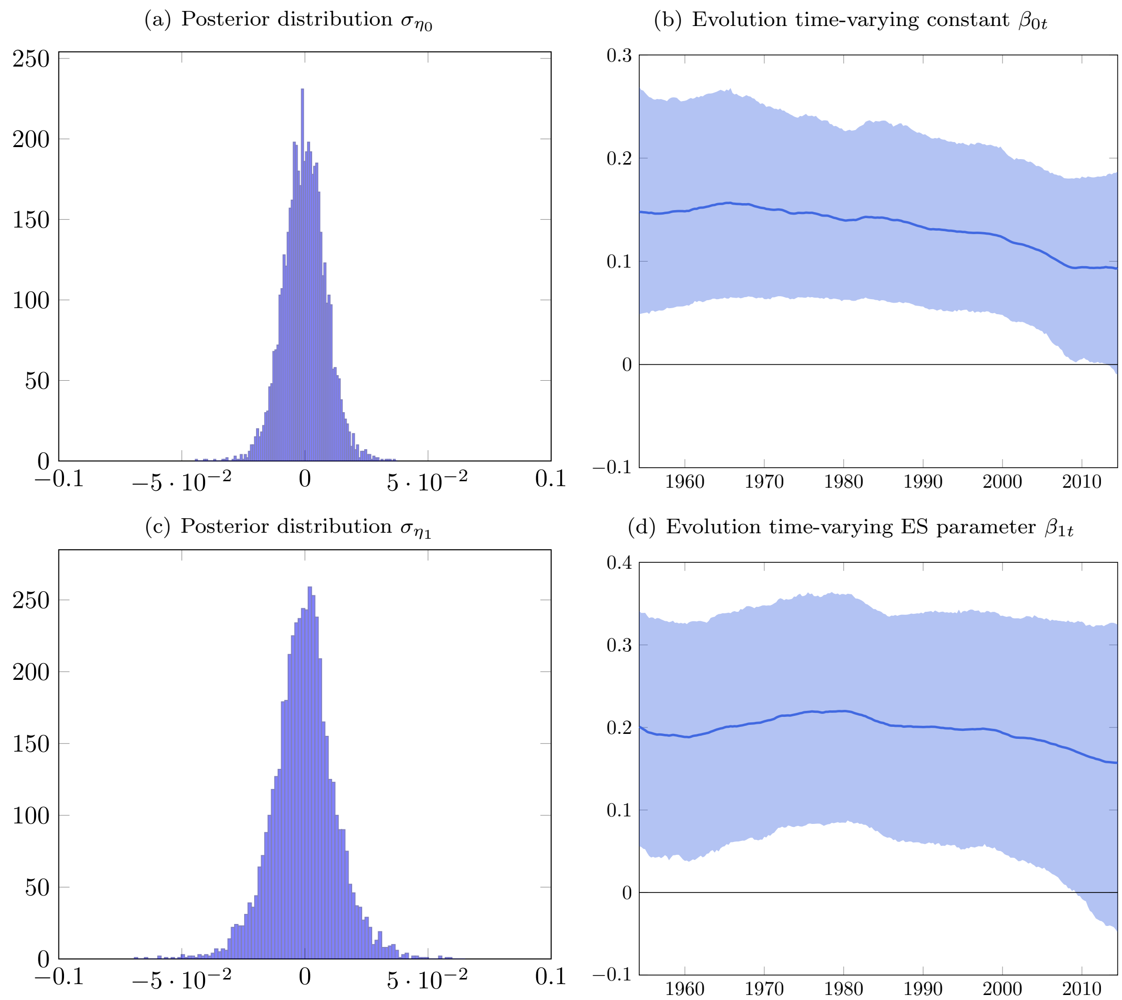
$$\Delta \ln C_t = \beta_{0t} + \beta_{1t} Z_t \delta + \gamma \Delta \ln C_{t-1} + \rho \nu_t^* + \theta(L)\mu_t.$$

with $\theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \theta_3 L^3$ an MA(3) lag polynomial as is explained in Section 3.2.2 and where the data generating processes for $\beta_{0t}$ and $\beta_{1t}$ are shown by equations (3.23) and (3.24).

For model M4 panels (a) and (c) of Figure 3.4 clearly show that the posterior distributions of $\sigma_{\eta_0}$ and $\sigma_{\eta_1}$ are unimodal at zero. This suggests that these components are stable over time. Next, when sampling the stochastic binary indicators together with the other parameters, the results reported in Table 3.2 support these findings. The posterior probabilities for the binary indicators being one for the time-varying parts in the intercept and in the ES parameter are both about 0.07 over the different instrument sets. Even when increasing the prior inclusion probability up to 0.9, the posterior probabilities are not bigger than 0.4. The model selection thus strongly rejects time variation in the intercept and in the ES of private consumption growth to expected disposable income growth. The unambiguous rejection of a time-varying intercept suggests that the omission of time-varying variables like hours worked and government consumption in our empirical specification is not a major source of concern. While, as M3 shows, there is still some indication of time-variation in the intercept when lagged consumption growth is not included in the model, once we control for stickiness in aggregate consumption growth this is no longer the case. This confirms the results of Sommer (2007) and Carroll, Slacalek, and Sommer (2011) who argue that allowing for consumption growth to depend on its own lag is important when testing for the ES of consumption to income. Further, when analyzing the MA structure of the residuals, we notice that only the first MA term is relevant as the 95 % HPD for $\theta_1$ varies between -0.47 and -0.11 with a mean of -0.29 while the posterior distributions of $\theta_2$ and $\theta_3$ have considerable probability mass at zero.

Finally, as can be seen from Table 3.1, the prior beliefs about the degree of time variation in $\beta_{0t}$ and $\beta_{1t}$ are both centered at zero with a prior standard deviation of 0.2. To check robustness, Table 3.4 shows results for the posterior inclusion probabilities for the time-varying parts over alternative values for $\sqrt{V_0}$ for M4 in the baseline scenario ($\iota_i = 0.5$). The first row shows the results for $\sqrt{V_0} = 0.2$. The second row presents results for the case where $\sqrt{V_0}$=0.05. This corresponds to a relatively strong prior that allows for little time variation. The third row shows results for

**Figure 3.4:** Stochastic model selection and time-varying parameters (binary indicators set to 1) in M4




Note: Figures are presented for the results using instrument set $Z^3$ but are similar when using instrument sets $Z^1$ and $Z^2$

a diffuse prior distribution that allows for a large variance on the time-varying component. We can conclude that over all three prior specifications, we find no evidence of time variation in both the intercept and the ES parameter. Compared to the baseline scenario, the posterior inclusion probabilities fall well below 5 % when more diffuse priors are used. When the prior distribution allows for little time variation, the inclusion probabilities increase but still remain low.[10]

[10]The increase in the posterior probability may appear counter intuitive, but is due to the fact that by restricting the amount of time variation, the competing models (a model with and one without time variation) become similar in their marginal likelihoods and thus the posterior probability shrinks towards the prior probability.

**Table 3.4:** Posterior inclusion probabilities for the binary indicators over different priors on the degree of time-variation in M4

| prior | posterior | |
|---|---|---|
| $\sqrt{V_0}$ | $\iota_0$ | $\iota_1$ |
| 0.2 | 0.11 | 0.12 |
| 0.05 | 0.19 | 0.21 |
| 1.00 | 0.01 | 0.02 |

Note: Results are presented using instrument set $Z^3$ but are similar when using instrument set $Z^1$ and $Z^2$.

### A parsimonious model

When allowing for stickiness in aggregate consumption growth, the time variation in both the intercept and the ES parameter is found to be irrelevant using the model selection criteria. We therefore restricted these parameters to be time-invariant in the parsimonious model. Next, the estimates of the MA terms reported in Table 3.3 show that, for M3, only the first MA term is relevant. As such, we allow for only one MA term. This leads to the following specification for aggregate consumption growth

$$\Delta \ln C_t = \beta_{00} + \beta_{10} Z_t \delta + \gamma \Delta \ln C_{t-1} + \rho \nu_t^* + \theta(L)\mu_t$$

with $\theta(L) = 1 + \theta_1 L$ an MA(1) lag polynomial.

Descriptive statistics on the posterior distributions of the parsimonious model's parameters are given in Table 3.5. The results show that for the ES parameter the 95% HPD interval varies between 0.11 and 0.35 with a mean value of 0.23. The stickiness in consumption growth parameter ranges between 0.49 and 0.68 with a mean of 0.58. Both these results are similar to findings of Carroll, Slacalek, and Sommer (2011) and Kiley (2010)[11] and show that even if there is no significant amount of time variation, the ES of private consumption to disposable income remains a factor contributing to the predictability of aggregate consumption growth. With respect to the presence of autocorrelation of the MA form in the error term, the posterior distribution points to a negative MA coefficient. The results also indicate that it is important to control for common shocks to income and consumption as the 95% HPD interval of $\rho$ ranges between 0.18 and 0.44.

[11] More specifically, for the US Carroll, Slacalek, and Sommer (2011) find an ES parameter of 0.27 and a sticky consumption growth coefficient of 0.55 when using an instrumental variable approach. Kiley (2010) reports an ES parameter of 0.3 and a coefficient on lagged consumption growht of 0.65 when using their preferred instrument set (which includes lagged levels of inflation).

**Table 3.5:** Posterior distributions of model parameters (parsimonious model)

| | | | Percentiles | |
|---|---|---|---|---|
| | | mean | 2.5% | 97.5% |
| error term consumption equation | $\sigma_\mu$ | 0.39 | 0.36 | 0.43 |
| error term income equation | $\sigma_\nu$ | 0.78 | 0.72 | 0.84 |
| | | | Percentiles | |
| *Model parameters* | | mean | 2.5% | 97.5% |
| constant value of intercept | $\beta_{00}$ | 0.10 | 0.04 | 0.17 |
| constant value of ES parameter | $\beta_{10}$ | 0.23 | 0.11 | 0.35 |
| consumption stickiness | $\gamma$ | 0.58 | 0.49 | 0.68 |
| degree of correlation between $\nu_t$ and $\epsilon_t$ | $\rho$ | 0.30 | 0.18 | 0.44 |
| MA(1) parameter | $\theta_1$ | $-0.33$ | $-0.49$ | $-0.16$ |

Note: Results are presented using instrument set $Z^3$ but are similar when using instrument set $Z^1$ and $Z^2$.

## 3.5 Conclusion

Up until now a framework containing the possibility of stickiness in aggregate consumption growth and containing an adequate treatment of measurement error and time aggregation has only served as a benchmark for testing for ES under the assumption that the degree of ES is constant. This chapter contributes to the literature by investigating *time-varying* ES in this extended empirical framework using a Gibbs sampling approach. We allow the ES parameter to vary over time according to a standard unobserved random walk process. We further test whether the time variation is statistically relevant using the Bayesian model selection approach recently suggested by Frühwirth-Schnatter and Wagner (2010). Their approach implies splitting the time-varying parameter in a constant part and a time-varying part and introducing a stochastic binary model indicator which is one if the time-varying part should be included in the model and zero otherwise. To control for endogeneity in our framework, we further incorporate a control function type approach in our MCMC algorithm. The advantage of our Gibbs sampling approach is that it is computationally much more easy to implement and, as such, does not suffer from the ML estimator's numerical optimization problems reported by Kim and Kim (2011). Moreover, as our

Bayesian IV approach relies on sampling the posterior distribution rather than using asymptotic approximations, it allows for exact inference even when instruments are weak.

The estimation results show that in a basic model, including only anticipated income growth, the ES of US consumption growth to anticipated income growth has decreased over time, starting from around 0.4 in the early 1950s and ending close to 0.2 in 2014. This confirms the result in Bacchetta and Gerlach (1997) that ES drops gradually over time. However, when estimating our extended empirical specification, modeling stickiness in consumption growth along with time aggregation and measurement errors, the excess sensitivity parameter turns out to be stable at around 0.23 over the entire sample period. This implies that the time variation of the ES parameter in the basic model is due to a specification error. In line with Carroll, Slacalek, and Sommer (2011), the coefficient on lagged consumption growth is found to be around 0.58 showing that there is a notable amount of stickiness in aggregate consumption growth.

# Appendix

## 3.A Gibbs sampling algorithm

In this appendix we provide details on the Gibbs sampling algorithm used in Subsection 3.3.3 to jointly sample the binary indicators $\mathcal{M}$, the parameters $\phi$ and the time-varying parameters $\beta^*$.

### Blocks 1-3: Sampling the binary indicators $\mathcal{M}$ and parameters $\phi$

For notational convenience, let us define a general regression model

$$y_t = x_t^{\mathcal{M}} b^{\mathcal{M}} + \theta(L) e_t, \qquad e_t \sim \mathcal{N}\left(0, \sigma_e^2\right), \tag{3.26}$$

where $y_t$ is a scalar dependent variable, $x_t$ an unrestricted predictor vector that contains variables that are relevant for explaining $y_t$, $b$ is the corresponding parameter vector, $\theta(L)$ is a lag polynomial of order $q$ and $e_t$ is a white noise error with variance $\sigma_e^2$. The restricted predictor matrix $x_t^{\mathcal{M}}$ and restricted parameter vector $b^{\mathcal{M}}$ exclude those elements in $x_t$ and $b$ for which the corresponding binary indicator in $\mathcal{M}$ is 0. Further let $y = [y_1, \ldots, y_T]'$, $x = [x_1', \ldots, x_T']'$ and $\Phi$ be a subset of $\phi$ including all unknown parameters in equation (3.26), with restricted versions $x^{\mathcal{M}}$ and $\Phi^{\mathcal{M}}$.

The MA($q$) errors in equation (3.26) imply a model which is non-linear in the parameters. As suggested by Ullah, Vinod, and Singh (1986) and Chib and Greenberg (1994), conditional on $\theta$ a linear model can be obtained from a recursive transformation of the data. For $t = 1, \ldots T$ let

$$\widetilde{y}_t = y_t - \sum_{i=1}^{q} \theta_i \widetilde{y}_{t-i}, \qquad \text{with} \quad \widetilde{y}_t = 0 \quad \text{for } t \leq 0, \tag{3.27}$$

$$\widetilde{x}_t = x_t - \sum_{i=1}^{q} \theta_i \widetilde{x}_{t-i}, \qquad \text{with} \quad \widetilde{x}_t = 0 \quad \text{for } t \leq 0, \tag{3.28}$$

and further for $j = 1, \ldots, q$

$$\omega_{jt} = -\sum_{i=1}^{q} \theta_i \omega_{j,t-i} + \theta_{t+j-1}, \qquad \text{with} \quad \omega_{jt} = 0 \quad \text{for } t \leq 0, \tag{3.29}$$

where $\theta_s = 0$ for $s > q$. Equation (3.26) can then be transformed as

$$\begin{aligned}\widetilde{y}_t &= \widetilde{x}_t^{\mathcal{M}} b^{\mathcal{M}} + \omega_t \lambda + e_t, \\ &= \widetilde{w}_t^{\mathcal{M}} \Phi^{\mathcal{M}} + e_t, \end{aligned} \tag{3.30}$$

with $\omega_t = (\omega_{1t}, \ldots, \omega_{qt})$, $\widetilde{w}_t = (\widetilde{x}_t, \omega_t)$ and $\Phi^{\mathcal{M}} = \left(b^{\mathcal{M}\prime}, \lambda'\right)'$ and where $\lambda = (e_0, \ldots, e_{-q+1})'$ are initial conditions that can be estimated as unknown parameters. Conditional on $\theta$, equation (3.30) is a standard linear regression with observed variables $\widetilde{y}_t$ and $\widetilde{w}_t^{\mathcal{M}}$ and *i.i.d.* errors $e_t$. Under the normal-inverse gamma conjugate prior

$$p\left(\Phi^{\mathcal{M}}\right) = \mathcal{N}\left(a_0^{\mathcal{M}}, A_0^{\mathcal{M}} \sigma_e^2\right), \qquad p\left(\sigma_e^2\right) = \mathcal{IG}\left(c_0, C_0\right), \tag{3.31}$$

the conditional posterior distributions of $\Phi^{\mathcal{M}}$ and $\sigma_e^2$ are

$$p\left(\Phi^{\mathcal{M}} | y, x, \theta, \sigma_e^2, \mathcal{M}\right) = \mathcal{N}\left(a_T^{\mathcal{M}}, A_T^{\mathcal{M}} \sigma_e^2\right), \qquad p\left(\sigma_e^2 | y, x, \theta, \mathcal{M}\right) = \mathcal{IG}\left(c_T, C_T^{\mathcal{M}}\right), \tag{3.32}$$

with the posterior moments $a_T^{\mathcal{M}}$, $A_T^{\mathcal{M}}$, $c_T$ and $C_T^{\mathcal{M}}$ given by

$$a_T^{\mathcal{M}} = A_T^{\mathcal{M}} \left(\left(\widetilde{w}^{\mathcal{M}}\right)' \widetilde{y} + \left(A_0^{\mathcal{M}}\right)^{-1} a_0^{\mathcal{M}}\right), \tag{3.33}$$

$$A_T^{\mathcal{M}} = \left(\left(\widetilde{w}^{\mathcal{M}}\right)' \widetilde{w}^{\mathcal{M}} + \left(A_0^{\mathcal{M}}\right)^{-1}\right)^{-1}, \tag{3.34}$$

$$c_T = c_0 + T/2\ , \tag{3.35}$$

$$C_T^{\mathcal{M}} = C_0 + 0.5\left(\widetilde{y}'\widetilde{y} + \left(a_0^{\mathcal{M}}\right)' \left(A_0^{\mathcal{M}}\right)^{-1} a_0^{\mathcal{M}} - \left(a_T^{\mathcal{M}}\right)' \left(A_T^{\mathcal{M}}\right)^{-1} a_T^{\mathcal{M}}\right). \tag{3.36}$$

**Block 1: Sampling the first step parameters $\phi_1$ and calculating $Z_t\delta$ and $\nu_t^*$**

Equation (3.15) can be written in the general notation of equation (3.26) as: $y_t = \Delta \ln Y_t$, $x_t = Z_t$, $b = \delta$ and $\theta(L) = 1$ such that $\theta(L)e_t = \nu_t$ and $\sigma_e^2 = \sigma_\nu^2$. Sampling $\delta$ and $\sigma_\nu^2$ can then be done from their posterior distributions in equation (3.32). Using the sampled $\delta$ and $\sigma_\nu^2$, calculate $E_{t-1}\left(\Delta \ln Y_t\right) = Z_t\delta$ and $\nu_t^* = \sigma_\varepsilon \theta\left(L\right)\left(\Delta \ln Y_t - Z_t\delta\right)/\sigma_\nu$ conditional on $\theta$ and $\sigma_\varepsilon^2$ with the latter calculated from $\phi_2$ as $\sigma_\varepsilon^2 = \sigma_\mu^2/(1-\rho^2)$.

**Block 2: Sampling the MA coefficients $\theta$**

Conditional on the parameters $\phi_1$ and $\phi_2$, on the time-varying coefficients $\beta^*$ and on the binary indicators $\mathcal{M}$, equation (3.17) can be written in the general notation of equation (3.26) as:

$y_t = \Delta \ln C_t$, $x_t = (1,\ Z_t\delta,\ \beta^*_{0t},\ \beta^*_{1t}Z_t\delta,\ \Delta \ln C_{t-1})$, $b = (\beta_{00},\ \beta_{01},\ \sigma_{\eta_0},\ \sigma_{\eta_1},\ \gamma)$ and $e_t = \varepsilon_t$, such that $\sigma^2_e = \sigma^2_\varepsilon$ with the latter calculated conditional on $\phi_2$ as $\sigma^2_\varepsilon = \sigma^2_\mu / (1-\rho^2)$. The values of the binary indicators in $\mathcal{M}$ then imply the restricted $x^{\mathcal{M}}_t$ and $b^{\mathcal{M}}$.

Under the normal conjugate prior $p(\theta) = \mathcal{N}\left(a^\theta_0, A^\theta_0\sigma^2_e\right)$, the exact conditional distribution of $\theta$ is given by[12]

$$p\left(\theta|\Phi, \sigma^2_e, \mathcal{M}, y, x\right) \propto \prod_{t=1}^{T} \exp\left(-\frac{e_t(\theta)^2}{2\sigma^2_e}\right) \times \exp\left(-\frac{1}{2}\left(\theta - a^\theta_0\right)' \left(A^\theta_0\sigma^2_e\right)^{-1}\left(\theta - a^\theta_0\right)\right), \qquad (3.37)$$

where $e_t(\theta) = \widetilde{y}_t(\theta) - \widetilde{w}^{\mathcal{M}}_t(\theta)\,\Phi^{\mathcal{M}}$ is calculated from the transformed model in equation (3.30) further conditioning on the initial conditions $\lambda$ to obtain $\Phi^{\mathcal{M}} = \left(b^{\mathcal{M}'}, \lambda'\right)'$.

Direct sampling of $\theta$ using equation (3.37) is not possible, though, as $e_t(\theta)$ is a non-linear function of $\theta$. To solve this issue, Chib and Greenberg (1994) propose to linearize $e_t(\theta)$ around $\theta^*$ using a first-order Taylor expansion

$$e_t(\theta) \approx e_t(\theta^*) - \Psi_t(\theta - \theta^*), \qquad (3.38)$$

where $\Psi_t = (\Psi_{1t}, \ldots, \Psi_{qt})$ is a $1 \times q$ vector including the first-order derivatives of $e_t(\theta)$ evaluated at $\theta^*$ obtained using the following recursion

$$\Psi_{it} = -e_{t-i}(\theta^*) - \sum_{j=1}^{q} \theta^*_j \Psi_{i,t-j}, \qquad (3.39)$$

where $\Psi_{it} = 0$ for $t \leq 0$. An adequate approximation can be obtained by choosing $\theta^*$ to be the non-linear least squares estimate of $\theta$ conditional on the other parameters in the model, which can be obtained as

$$\theta^* = \underset{\theta}{\operatorname{argmin}} \sum_{t=1}^{T} \left(e_t(\theta)\right)^2, \qquad (3.40)$$

For given values of $\theta^*$, equation (3.38) can then be rewritten as an approximate linear regression model

$$e_t(\theta^*) + \Psi_t\theta^* \approx \Psi_t\theta + e_t(\theta), \qquad (3.41)$$

with dependent variable $e_t(\theta^*) + \Psi_t\theta^*$ and explanatory variables $\Psi_t$. As such a normal approxi-

[12] Note that the expression in Chib and Greenberg (1994) also includes a term ($p_2(\theta)$ in their notation) which evaluates the initial conditions ($\alpha_0$ in their notation) which are drawn (using a value for $\theta$) as initial values in a state space representation. As is apparent from equation (3.30), in a pure MA model (see also Chib and Greenberg, 1994, eq. (15)), the initial conditions are easily estimated together with $\beta$. As such, they are conditioned on in equation (3.37).

mation to the exact conditional distribution of $\theta$ is given by

$$q\left(\theta|\theta^{*}, \Phi, \sigma_e^2, \mathcal{M}, y, x\right) \sim \mathcal{N}\left(a_T^{\theta}, A_T^{\theta}\sigma_e^2\right), \tag{3.42}$$

with

$$a_T^{\theta} = A_T^{\theta}\left(\Psi'\Xi + \left(A_0^{\theta}\right)^{-1} a_0^{\theta}\right), \qquad A_T^{\theta} = \left(\Psi'\Psi + \left(A_0^{\theta}\right)^{-1}\right)^{-1}, \tag{3.43}$$

and where $\Xi$ is a $T \times 1$ vector with $t$th element $(e_t(\theta^{*}) + \Psi_t\theta^{*})$ and $\Psi$ is a $T \times q$ matrix with $t$th row $\Psi_t$.

We can now sample $\theta$ using a Metropolis-Hastings (MH) algorithm. Suppose $\theta^{(i)}$ is the current draw in the Markov chain. To obtain the next draw $\theta^{(i+1)}$, first draw a candidate $\theta^{c}$ from the proposal distribution in equation (3.42). The MH step then implies a further randomization which amounts to accepting the candidate draw $\theta^{c}$ with probability

$$\alpha\left(\theta^{(i)}, \theta^{c}\right) = \min\left\{\frac{p\left(\theta^{c}|\Phi, \sigma_e^2, \mathcal{M}, y, x\right)}{p\left(\theta^{(i)}|\Phi, \sigma_e^2, \mathcal{M}, y, x\right)} \frac{q\left(\theta^{(i)}|\theta^{*}, \Phi, \sigma_e^2, \mathcal{M}, y, x\right)}{q\left(\theta^{c}|\theta^{*}, \Phi, \sigma_e^2, \mathcal{M}, y, x\right)}, 1\right\}. \tag{3.44}$$

If $\theta^{c}$ is accepted, $\theta^{(i+1)}$ is set equal to $\theta^{c}$ while if $\theta^{c}$ is rejected, $\theta^{(i+1)}$ is set equal to $\theta^{(i)}$.

#### Block 3: Sampling the binary indicators $\mathcal{M}$ and the second step parameters $\phi_2$

Conditional on the time-varying coefficients $\beta_t^{*}$ and on the first step results $Z_t\delta$ and $\nu_t^{*}$, equation (3.25) can be written in the general notation of equation (3.26) as: $y_t = \Delta \ln C_t$, $x_t = (1,\, Z_t\delta,\, \beta_{0t}^{*},\, \beta_{1t}^{*} Z_t\delta,\, \Delta \ln C_{t-1},\, \nu_t^{*})$, $b = (\beta_{00},\, \beta_{01},\, \sigma_{\eta_0},\, \sigma_{\eta_1},\, \gamma,\, \rho)$ and $e_t = \mu_t$, such that $\sigma_e^2 = \sigma_\mu^2$. Further conditioning on the $MA$ parameters $\theta$, the unrestricted transformed variables $\widetilde{y}_t$ and $\widetilde{w}_t$ in equation (3.30) are obtained, with corresponding unrestricted extended parameter vector $\Phi = (b', \lambda')'$. The values of the binary indicators in $\mathcal{M}$ then imply the restricted $\widetilde{w}_t^{\mathcal{M}}$ and $\Phi^{\mathcal{M}}$.

A naive implementation of the Gibbs sampler would be to first sample $\mathcal{M}$ from $f\left(\mathcal{M}|\Phi, \sigma_e^2, \widetilde{y}, \widetilde{w}\right)$ and next $\Phi^{\mathcal{M}}$ and $\sigma_e^2$ from $f\left(\Phi^{\mathcal{M}}, \sigma_e^2|\mathcal{M}, \widetilde{y}, \widetilde{w}\right)$. However, this approach does not result in an irreducible Markov chain as whenever an indicator in $\mathcal{M}$ equals zero, the corresponding coefficient in $\Phi$ is also zero which implies that the chain has absorbing states. Therefore, as in Frühwirth-Schnatter and Wagner (2010) we marginalize over the parameters $\Phi$ and $\sigma_e^2$ when sampling $\mathcal{M}$ and next draw the parameters $\Phi^{\mathcal{M}}$ and $\sigma_e^2$ conditional on the binary indicators in $\mathcal{M}$.

***Block 3(a): Sampling the binary indicators*** $\mathcal{M}$

The posterior distribution $f(\mathcal{M}|\widetilde{y},\widetilde{w})$ can be obtained using Bayes' Theorem as

$$f(\mathcal{M}|\widetilde{y},\widetilde{w}) \propto f(\widetilde{y}\,|\mathcal{M},\widetilde{w})\,p(\mathcal{M}), \tag{3.45}$$

with $p(\mathcal{M})$ being the prior probability of $\mathcal{M}$ and $f(\widetilde{y}\,|\mathcal{M},\widetilde{w})$ the marginal likelihood of the regression model (3.30) where the effect of the parameters $\Phi$ and $\sigma_e^2$ has been integrated out. Under the normal-inverse gamma conjugate prior in equation (3.31), the closed form solution of the marginal likelihood is given by:

$$f(\widetilde{y}\,|\mathcal{M},\widetilde{w}) \propto \frac{\left|A_T^{\mathcal{M}}\right|^{0.5}}{\left|A_0^{\mathcal{M}}\right|^{0.5}} \frac{\Gamma(c_T)\,C_0^{c_0}}{\Gamma(c_0)\left(C_T^{\mathcal{M}}\right)^{c_T}}, \tag{3.46}$$

with $\Gamma$ being the gamma function and the posterior moments $a_T^{\mathcal{M}}$, $A_T^{\mathcal{M}}$, $c_T$ and $C_T^{\mathcal{M}}$ given in equations (3.33)-(3.36).

Following George and McCulloch (1993) we use a single-move sampler in which the binary indicators $\iota_0$ and $\iota_1$ in $\mathcal{M}$ are sampled recursively from the Bernoulli distribution with probability

$$p(\iota_i = 1\,|\iota_{-i},\widetilde{y},\widetilde{w}) = \frac{f(\iota_i = 1\,|\iota_{-i},\widetilde{y},\widetilde{w})}{f(\iota_i = 0\,|\iota_{-i},\widetilde{y},\widetilde{w}) + f(\iota_i = 1\,|\iota_{-i},\widetilde{y},\widetilde{w})}, \tag{3.47}$$

for $i = 0, 1$. We further randomize over the sequence in which the binary indicators are drawn.

***Block 3(b): Sampling the second step parameters*** $\phi_2$

Given the binary indicators in $\mathcal{M}$, the second step parameters $\phi_2 = (\beta_{00},\, \beta_{01},\, \sigma_{\eta_0},\, \sigma_{\eta_1},\, \gamma,\, \rho,\, \sigma_\mu^2)$ are sampled, together with $\lambda$, by drawing $\Phi^{\mathcal{M}}$ and $\sigma_e^2$ from the general expression in equation (3.32). Note that the unrestricted $\Phi = (\beta_{00},\, \beta_{01},\, \sigma_{\eta_0},\, \sigma_{\eta_1},\, \gamma,\, \rho,\, \lambda)$ is restricted to obtain $\Phi^{\mathcal{M}}$ by excluding $\sigma_{\eta_i}$ when $\iota_i = 0$. In this case $\sigma_{\eta_i}$ is not sampled but set equal to zero.

**Block 4: Sampling the time-varying parameters** $\beta^*$

In this block we use the forward-filtering and backward-sampling approach of Carter and Kohn (1994) and De Jong and Shephard (1995) to sample the time-varying parameters $\beta^*$ conditionally on the coefficients $\phi_2$ and $\lambda$, on the first step results $Z_t\delta$ and $\nu_t^*$ and on the binary indicators $\mathcal{M}$. More specifically, equation (3.25) can be rewritten as:

$$y_t = \iota_0\sigma_{\eta_0}\beta_{0t}^* + \iota_1\sigma_{\eta_1}\beta_{1t}^* x_{1t} + \theta(L)\,\mu_t, \tag{3.48}$$

with $y_t = \Delta\ln C_t - \beta_{00} - \beta_{01}Z_t\delta - \gamma\Delta\ln C_{t-1} - \rho\nu_t^*$ and $x_{1t} = Z_t\delta$.

Again using the recursive transformation suggested by Ullah, Vinod, and Singh (1986) and Chib and Greenberg (1994), the model in equation (3.48) can be transformed to a model with *i.i.d.* error terms as

$$\widetilde{y}_t = \iota_0 \sigma_{\eta_0} \widetilde{\beta}_{0t} + \iota_1 \sigma_{\eta_1} \widetilde{\beta}_{1t} + \omega_t \lambda + \mu_t, \tag{3.49}$$

where $\widetilde{y}_t$ and $\omega_t = (\omega_{1t}, \ldots, \omega_{qt})$ are calculated (conditional on $\theta$) from equations (3.27) and (3.29) and similarly

$$\widetilde{\beta}_{0t} = \beta^*_{0t} - \sum_{i=1}^{q} \theta_i \widetilde{\beta}_{0,t-i}, \qquad \text{with} \quad \widetilde{\beta}_{0t} = 0 \quad \text{for } t \leq 0, \tag{3.50}$$

$$\widetilde{\beta}_{1t} = \beta^*_{1t} x_{1t} - \sum_{i=1}^{q} \theta_i \widetilde{\beta}_{1,t-i}, \qquad \text{with} \quad \widetilde{\beta}_{1t} = 0 \quad \text{for } t \leq 0. \tag{3.51}$$

Substituting equation (3.23) in (3.50)-(3.50) yields

$$\widetilde{\beta}_{0,t+1} = \beta^*_{0t} - \sum_{i=1}^{q} \theta_i \widetilde{\beta}_{0,t+1-i} + \eta^*_{0t}, \tag{3.52}$$

$$\widetilde{\beta}_{1,t+1} = \beta^*_{1t} x_{1,t+1} - \sum_{i=1}^{q} \theta_i \widetilde{\beta}_{1,t+1-i} + x_{1,t+1} \eta^*_{1t}, \tag{3.53}$$

such that the state space representation of the model in equations (3.49), (3.23) and (3.52)-(3.53) is given by

$$\widetilde{y}_t - \omega_t \lambda = \overbrace{\begin{bmatrix} (0 & \sigma_{\eta_0} & 0 & \ldots & 0) & (0 & \sigma_{\eta_1} & 0 & \ldots & 0) \end{bmatrix}}^{\sigma_\eta} \overbrace{\begin{bmatrix} \alpha_{0t} \\ \alpha_{1t} \end{bmatrix}}^{\alpha_t} + \mu_t, \tag{3.54}$$

$$\underbrace{\begin{bmatrix} \alpha_{0,t+1} \\ \alpha_{1,t+1} \end{bmatrix}}_{\alpha_{t+1}} = \underbrace{\begin{bmatrix} T_{0t} & 0 \\ 0 & T_{1t} \end{bmatrix}}_{T_t} \underbrace{\begin{bmatrix} \alpha_{0t} \\ \alpha_{1t} \end{bmatrix}}_{\alpha_t} + \underbrace{\begin{bmatrix} K_{0t} & 0 \\ 0 & K_{1t} \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \eta^*_{0t} \\ \eta^*_{1t} \end{bmatrix}}_{\eta_t}, \tag{3.55}$$

with $\alpha_{i,t+1}$ given by

$$\underbrace{\begin{bmatrix} \beta^*_{i,t+1} \\ \widetilde{\beta}_{i,t+1} \\ \widetilde{\beta}_{it} \\ \vdots \\ \widetilde{\beta}_{i,t-(q-2)} \end{bmatrix}}_{\alpha_{i,t+1}} = \underbrace{\begin{bmatrix} 1 & 0 & \dots & 0 & 0 \\ x_{i,t+1} & -\theta_1 & \dots & -\theta_{q-1} & -\theta_q \\ 0 & 1 & & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix}}_{T_{it}} \underbrace{\begin{bmatrix} \beta^*_{it} \\ \widetilde{\beta}_{it} \\ \vdots \\ \widetilde{\beta}_{i,t-(q-2)} \\ \widetilde{\beta}_{i,t-(q-1)} \end{bmatrix}}_{\alpha_{it}} + \underbrace{\begin{bmatrix} 1 \\ x_{i,t+1} \\ 0 \\ \vdots \\ 0 \end{bmatrix}}_{K_{it}} \begin{bmatrix} \eta^*_{it} \end{bmatrix}, \tag{3.56}$$

for $i = 0, 1$ and where $x_{0t} = 1\ \forall t$. In line with equations (3.23) and (3.50)-(3.51), each of the states is initialized at zero.

Equations (3.54)-(3.55) constitute a standard linear Gaussian state space model, from which the unknown state variables $\alpha_t$ can be filtered using the standard Kalman filter. Sampling $\alpha_t$ from its conditional distribution can then be done using the multimove simulation smoother of Carter and Kohn (1994) and De Jong and Shephard (1995). Using $\beta_{i0}$, $\sigma_{\eta_i}$ and $\beta^*_{it}$, the time-varying coefficients $\beta_{it}$ in equation (3.21) can then easily be reconstructed from equation (3.22). Note that in a restricted model with $\iota_i = 0$, $\sigma_{\eta_i}$ is excluded from $\sigma_\eta$ and $\alpha_{it}$ is dropped from the state vector $\alpha_t$. In this case, no forward-filtering and backward-sampling for $\beta^*_{it}$ is needed as this can be sampled directly from its prior distribution using equation (3.23).

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