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What Drives Output Volatility? The Role of Demographics and Government Size Revisited

Martin Iseringhausen and Hauke Vierke

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What Drives Output Volatility?

The Role of Demographics and Government Size Revisited

Martin Iseringhausen, Hauke Vierke

Abstract

This paper studies the determinants of output volatility in a panel of 22 OECD countries. In contrast to the existing literature, we avoid ad hoc estimates of volatility based on rolling windows, and we account for possible non-stationarity of the data. Specifically, output volatility is estimated by means of an unobserved components model where the volatility series is the outcome of both macroeconomic determinants and a latent integrated process. A Bayesian model selection is performed to test for the presence of the non-stationary component. The results point to demographics and government size as important determinants of macroeconomic (in)stability. In particular, a larger share of prime-age workers is associated with lower output volatility, while higher public expenditure increases volatility.

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1. INTRODUCTION

Since its first documentation by Kim and Nelson (1999) and McConnell and Perez-Quiros (2000), the persistent reduction in United States business cycle volatility during the 1980s has inspired a large body of literature. Stock and Watson (2003) coined the term “Great Moderation” to describe the puzzling fall in volatility. While it was first documented for the United States, Summers (2005) and Del Negro and Otrok (2008) showed that the decline in volatility has been a global phenomenon with important differences across countries regarding its magnitude, timing, and sources. Much work has been done on explaining the time variation in business cycle volatility, mainly through advances in economic policy or changes in structural factors underlying the economy. In particular, several previous cross-country studies that have strived to explain volatility among OECD countries suggest an important role for government size and the demographic composition of the labour force in stabilising the economy.

A seminal contribution on the role of the size of the government sector for output stabilisation was made by Gali (1994), who investigates the effect of income taxation and government purchases on output volatility in a real business cycle (RBC) model with technology-driven shocks. The model predicts a destabilising effect of tax increases as they reduce after-tax productivity and, thus, lower steady-state employment. The resulting higher labour elasticity leads to greater labour supply sensitivity to technology shocks. Higher government purchases have an opposing effect, but the destabilising effect of higher labour taxes dominates for different calibrations. However, when taken to data from 22 OECD countries the estimated effects do not match with the theoretical predictions. Income taxes and government purchases are found to be “automatic stabilisers” in the Keynesian sense. Fatás and Mihov (2001) estimate the effect of government spending on output volatility for 20 OECD countries (1960-1997) and report that regardless of the volatility or government size measure, the effect on output is always stabilising. In a related study, Martinez-Mongay and Sekkat (2005) test whether the negative relation between government size and output volatility depends on the tax mix. Using data for 25 OECD countries (1960-2000), they find that labour and capital taxes have stabilising effects, although the evidence is weak. Pisani-Ferry, Debrun, and Sapir (2008) extend the literature by exploiting the time series dimension of the data and perform a panel regression for 20 OECD countries (1960-2006). They confirm the link between government size and macroeconomic volatility for the beginning of the sample, but show that the relation disappeared during the 1990s. Carmignani, Colombo, and Tirelli (2011) pay special attention to the endogeneity of government size and estimate simultaneous equations. They find that greater volatility causes larger governments. In contrast to previous studies, their estimates imply a destabilising effect of government expenditure on output volatility. Crespo Cuaresma, Reitschuler, and Silgoner (2011) find a dampening and non-linear effect of government size on output volatility for a sample of EU countries, which reverts at very high levels of government expenditure. Posch (2011) derives the effect of different taxes within a stochastic neoclassical growth model and tests the theoretical predictions through a panel regression of 20 OECD countries. Special attention is paid to the nature of the unobserved variance process. Different tax ratios are found to have ambiguous effects: Taxes on labour and corporate income are stabilising, while capital taxes increase volatility. Recently, Collard, Dellas, and Tavlas (2017) study the role of government size in a neoclassical model allowing for various types of shocks. Their results suggest a volatility damping effect of government size following technology, cost-push, preference, and monetary-policy shocks. However, larger governments amplify the impact of expenditure shocks on volatility. They conclude that the relationship is generally ambiguous and likely nonlinear. Overall, the existing literature suggests a dampening effect of government expenditure on output volatility, in line with the notion of automatic stabilisers. However, when some of the channels are investigated individually, the picture is less clear-cut and opposing effects arise.

Next to the role of government size, a recent strand of the literature discusses the role of demographics as an important structural factor that has undergone significant shifts in most advanced economies during the past decades. As the decline in United States’ output volatility coincides with a decrease in the number of young workers relative to prime-age workers, the demographic composition of the labour force arises as a possible explanation for volatility shifts. Our approach is motivated by the theoretical

contribution of Jaimovich, Pruitt, and Siu (2013), who argue that the volatility of hours worked differs across age groups, and that these differences cannot be explained by age-specific labour supply factors alone. Hence, age-specific demand factors must play an important role as well. The main idea is the introduction of capital-experience complementarity to the production function. Older workers are more experienced on the labour market and may have gained firm-specific knowledge that is complementary to physical capital. As a result, firms tend to hoard 'older' labour, while younger workers exhibit greater volatility in hours worked. A technology shock causes a larger reaction in the demand for young workers and a comparably smaller reaction in the demand for old workers, as the older ones are a complement to physical capital, which is more difficult to adjust in the short-term. Jaimovich and Siu (2009) were the first to empirically test this relationship for a small sample of countries. They start from documenting differences in the volatility of employment and hours worked across different age groups. The youngest and oldest among the workforce experience larger employment fluctuations than prime-age workers. To reflect this U-shaped pattern, the authors define a volatile-age share variable, constructed as the ratio of the 15-29 and 60-64 old workers over the entire workforce. Estimating a panel regression for the G7 countries they find a large and significant effect of the age share on output volatility, defined as the rolling standard deviation of the HP-filtered output gap. The estimated effect is large enough to account for up to one-third of the decline in output volatility in the United States. Lugauer (2012) confirms this significant effect of demographics for a large panel of the 50 federal states. Similar results are also found in Lugauer and Redmond (2012) for 51 advanced and developing countries. Janiak and Monteiro (2016) study demographics as a channel through which fiscal policy affects business cycle volatility thus linking the two strands of the literature. Using a heterogeneous agent OLG model they show that total hours worked by the prime-age groups are less elastic with respect to tax changes compared to those supplied by young and old workers. Hence, higher taxes increase the share of hours worked by prime age groups. Given that prime-age hours worked are less volatile, this reduces aggregate volatility.

However, we identify two important shortcomings in both aforementioned strands of the literature. First, the majority of the studies using panel methods do not discuss the time series properties of the included variables, although many are potentially non-stationary. It is well-known that standard regression methods can erroneously indicate a significant link between two variables while in fact they follow independent stochastic trends. Notable exceptions, which pay attention to this spurious regression problem, are Posch (2011), who performs a cointegration analysis and confirms a long-run relation between taxes and volatility, and Kent, Smith, and Holloway (2005), who discuss the limits of a linear time trend or common time effects in order to capture common volatility trends. Jaimovich and Siu (2009) mention that their findings could be spurious because of omitted non-stationary factors, but argue that cross-country differences in volatility and demographics ensure identification.¹ Everaert and Vierke (2016) replicate three studies on the relationship between demographics and business cycle volatility and show that the commonly used time dummies are potentially insufficient to account for non-stationarity.

Second, the latent volatility series is typically estimated via rolling standard deviations. However, applying this simple approach comes at a price. A number of observations is lost due to the rolling window. In addition, rolling window measures generate a high degree of persistence in the dependent variable due to the overlapping samples, so that the error terms of the subsequent regression exhibit serial correlation. Finally, complex dynamics in output volatility are averaged out through this procedure, e.g. sudden rises in volatility will not be properly captured. The problem is partly acknowledged by Jaimovich and Siu (2009) and Lugauer (2012), who obtain an alternative volatility series from the stochastic volatility model of Stock and Watson (2003). However, volatility is explicitly modeled as a non-stationary process, which emphasises the problem of spurious results when regressing the obtained series on a set of non-stationary explanatory variables. Jaimovich and Siu (2009) and Posch (2011) also address the unobservability of output volatility and estimate a GARCH model borrowed from Ramey and Ramey (1995), which relies on common time dummies to capture time variation that is not explained by the covariates. Posch (2011) touches on the limits of this approach in the context of cointegration. Summing up, the

¹This argument is based on the theoretical results obtained by Phillips and Moon (1999). However, while a large number of cross sections can eliminate the problem of spurious results, this only holds in case of cross-sectionally independent error terms.

different approaches appear conflicting, as the same variable is assumed to be stationary in some studies while explicitly modeled as I(1) in others.

In this paper, a novel approach for estimating the determinants of output volatility is proposed.² The contribution is threefold. First, instead of relying on rolling standard deviations, the volatility estimate is obtained from an unobserved components model with a latent volatility process, which is partly driven by macroeconomic covariates. The second key feature is the inclusion of an unobserved I(1) component in the volatility equation to account for possible non-stationary factors driving volatility. Third, a Bayesian variable selection is performed on the non-stationary factor, similar to a cointegration test. The model is estimated for an unbalanced panel of 22 OECD countries with annual data from 1961 to 2014. We merge a recent literature strand on the effect of demographics with the literature on the role of government stabilisation. Specifically, we try to explain output volatility over time and across countries with the demographic composition of the labour force as well as the size of the government, while controlling for the tax composition and openness of the economy. The regression results suggest important effects of demographics and government size.

The remainder of the paper is structured as follows: Section 2 presents the unobserved components model and gives a short introduction to the testing problem involved in this approach. In Section 3 the Gibbs sampling algorithm and the prior distributions are presented. Section 4 discusses the time series properties of the data.³ Estimation results are presented in Section 5 and Section 6 concludes.

2. EMPIRICAL MODEL

2.1. AN UNOBSERVED COMPONENTS MODEL WITH STOCHASTIC VOLATILITY

The empirical model is based on the following output growth decomposition

$$y_{i,t} = \mu_{i,t} + \rho_{1,i}(y_{i,t-1} - \mu_{i,t-1}) + \rho_{2,i}(y_{i,t-2} - \mu_{i,t-2}) + \exp\{h_{i,t}^*\}\varepsilon_{i,t}, \quad \varepsilon_{i,t} \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1), \quad (1)$$

where $y_{i,t}$ is annual output growth in country $i = 1, \dots, N$ at time $t = 1, \dots, T$. $\mu_{i,t}$ is the time-varying mean growth rate and $\exp\{h_{i,t}^*\}$ is the time-varying standard deviation of output shocks. Deviations from the mean growth rate are assumed to be transitory, i.e. the characteristic roots of the AR(2) process lie strictly outside the unit circle. The mean growth rate is assumed to evolve over time according to a random walk:

$$\mu_{i,t} = \mu_{i,t-1} + \eta_{i,t}^\mu, \quad \eta_{i,t}^\mu \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma_{\mu,i}^2). \quad (2)$$

A persistent decline in potential output growth has recently been documented for the United States by Antolin-Diaz, Drechsel, and Petrella (2017) and Berger, Everaert, and Vierke (2016). This is in line with the literature on the U.S. productivity slowdown in the early 1970s. Perron and Wada (2009), Kim, Piger, and Startz (2007), and Morley and Piger (2012) take this slowdown into account by allowing for structural breaks in the growth rate of potential output. The random walk specification can mirror a similar pattern, but allows for more complex dynamics as well. The volatility process $h_{i,t}^*$ is assumed to be driven by a vector of macroeconomic covariates, $x_{i,t}$, where the country-specific slope coefficients are collected in the vector β_i . These covariates, or a subset of them, may exhibit non-stationarity. Thus, the question of cointegration between output volatility and the explanatory variables arises. As shown by Everaert (2011), standard estimators for the long-run relation between I(1) variables yield spurious results when relevant integrated variables are omitted from the model. Moreover, standard cointegration tests suffer from a severe size distortion rejecting the null hypothesis of no cointegration in too many cases. One solution is to model the omitted variables as a random walk component within an unobserved components (UC) framework, so that the long-run relation between the non-cointegrated variables can be estimated consistently via the Kalman filter. Hence, an unobserved non-stationary error component, $h_{i,t}$,

²We use the term *output volatility* and *business cycle volatility* interchangeably in this paper.

³Readers solely interested in the main results and their economic implications may skip Sections 2 - 4.

is introduced to the model. In line with the literature on stochastic volatility, this component is modeled as a driftless random walk:

$$h_{i,t}^* = \beta_i' x_{i,t} + h_{i,t}, \quad (3)$$

$$h_{i,t} = h_{i,t-1} + \eta_{i,t}^h, \quad \text{where } \eta_{i,t}^h \stackrel{i.i.d.}{\sim} \mathcal{N}(0, \sigma_{h,i}^2). \quad (4)$$

Equations (1)-(4) constitute a state space model, where (1) is the observation equation, linking the latent variables to the observed output series, and (2)-(4) are the state equations, describing the dynamics of the latent variables. Given estimates for the model parameters, the latent variables of this state space system can be estimated via the standard Kalman filter. The proposed model, where the unobserved volatility of output shocks arises endogenously and is driven by both observed macroeconomic covariates and a latent non-stationary factor, is highly non-standard in the literature. For this reason, [APPENDIX B](#) presents Monte Carlo evidence showing that our approach allows for consistent estimation of the coefficients in the volatility equation under various scenarios. Specifically, we show that the Everaert (2011) approach works well in a stochastic volatility setting as used in this paper.

2.2. MODEL SELECTION IN THE UNOBSERVED COMPONENTS FRAMEWORK

A key feature of this paper is to test the presence of a non-stationary country-specific error component $h_{i,t}$. This testing problem is equivalent to testing the hypothesis $\sigma_{h,i}^2 = 0$ against $\sigma_{h,i}^2 > 0$. Note that in the first case, $h_{i,t}$ becomes a constant and takes on the role of a country-specific intercept in the volatility equation, i.e. it captures differences over countries that are not explained by the set of covariates and do not change over time. In the latter case, $h_{i,t}$ will capture omitted and/or unobservable non-stationary factors which permanently shift volatility.⁴ The proposed test is non-regular, since the null hypothesis lies at the boundary of the parameter space. In principle, this could be dealt with by a Lagrange multiplier test.⁵ This paper follows a different approach and applies a Bayesian procedure, mainly for two reasons. First, the Bayesian approach allows to make intuitive statements about the inclusion probability of the non-stationary factors. Second, the estimation of the proposed SV model becomes intractable for the classical approach. A Gibbs sampling approach, which relies on splitting the complex nonlinear model into blocks that are linear and Gaussian conditional on one another, makes estimation feasible and leads to a Bayesian testing procedure without many additional modifications.

Specifically, the stochastic model specification search (SMSS), introduced by Frühwirth-Schnatter and Wagner (2010), is applied. This approach explores the so-called non-centred parametrisation of the model. For this reason, Equation (4) is rewritten in the following way:

$$h_{i,t} = h_{i,0} + \sigma_{h,i} \tilde{h}_{i,t}, \quad (5)$$

$$\tilde{h}_{i,t} = \tilde{h}_{i,t-1} + \tilde{\eta}_{i,t}^h, \quad \text{where } \tilde{h}_{i,0} = 0 \text{ and } \tilde{\eta}_{i,t}^h \stackrel{i.i.d.}{\sim} \mathcal{N}(0, 1). \quad (6)$$

The non-centred parametrisation splits the factor, $h_{i,t}$, into a constant part, $h_{i,0}$, and a time-varying part, $\tilde{h}_{i,t}$. Importantly, $\tilde{h}_{i,t}$ is initialised at 0 which leads to $h_{i,0}$ being the initial value of $h_{i,t}$. The standard deviation of the innovations to the random walk component now enters multiplicatively in Equation (5). As such, the model is not identified. To see that, note that the signs of $\sigma_{h,i}$ and $\tilde{h}_{i,t}$ can be interchanged without affecting the sign of their product. While this lack of identification does not pose a problem, it holds in fact valuable information about the presence of a time-varying component. If the posterior distribution of $\sigma_{h,i}$ is unimodal, the model favours a constant country-specific volatility factor. If the distribution is bimodal around zero, a time-varying factor is favoured. The non-centred parametrisation leads to a more formal test for time variation without much further modification. Frühwirth-Schnatter

⁴*Ex ante*, no correlation structure is imposed on the factors across countries. As explained in [APPENDIX A](#), all country-specific factors are filtered and sampled separately. This approach keeps the size of the covariance matrices manageable, but still allows for *ex post* correlation among the country-specific factors.

⁵See Morley, Panovska, and Sinclair (2017) for an evaluation of the LM test for the presence of a non-stationary component and a discussion of its small sample properties.

and Wagner (2010) introduce a binary indicator to select the most parsimonious specification. Here, the indicator is labelled δ_i , which takes on the value $\delta_i = 1$ for a model with a time-varying volatility factor in country i and $\delta_i = 0$ if the country factor is constant over time. Hence, the final volatility equation is given by

$$h_{i,t}^* = \beta_i' x_{i,t} + h_{i,0} + \delta_i \sigma_{h,i} \tilde{h}_{i,t}. \quad (7)$$

All country-specific indicators are collected in the vector $\mathcal{M} = (\delta_1, \delta_2, \dots, \delta_N)$, where every possible combination of the binary indicators constitutes one specific model. We impose a uniform prior on the model probabilities, so that each model has the same prior probability. The models are then sampled according to their Bayesian model probability.⁶ The SMSS in combination with the non-centred parametrisation holds important advantages: It avoids inverse-Gamma prior distributions, which can lead to a substantial bias for the variance of the non-stationary factor when the true value is close to zero. Instead, the square root of the variance of the non-stationary component now enters as a regression coefficient in Equation (5), for which a normal prior distribution can be used. This prior does not impose the same bias as the inverse-Gamma distribution. Moreover, the SMSS relies on binary model indicators that can easily be sampled within the Gibbs sampling procedure along with the remaining model parameters. These indicators can be used to test for non-stationary factors in the volatility equation and hence provide information about the presence of cointegration.

3. BAYESIAN ESTIMATION

3.1. GIBBS SAMPLING

This paper relies on Markov Chain Monte Carlo (MCMC) methods for estimation. The proposed model is highly nonlinear because of the stochastic volatility components, which enter exponentially into Equation (1). Thus, the standard application of the Kalman filter in combination with maximum likelihood (ML) is not feasible. Instead, a Gibbs Sampling procedure is applied. Specifically, the complex model is split into blocks of parameters and components that are linear conditional on the other blocks. To linearise the nonlinear volatility process, we follow Kim, Shephard, and Chib (1998) and take the logarithm of the square of the process. The resulting linear model, which has non-Gaussian error terms, is then approximated by an offset mixture model. This section only holds a brief description. A detailed explanation of the algorithm is given in APPENDIX A. For notational convenience, the country-specific components are collected in the vectors $\mu_t = (\mu_{1,t}, \dots, \mu_{N,t})$ and $\tilde{h}_t = (\tilde{h}_{1,t}, \dots, \tilde{h}_{N,t})$. Observations are stacked over time, i.e. $x = \{x_t\}_{t=1}^T$, $y = \{y_t\}_{t=1}^T$, $\mu = \{\mu_t\}_{t=1}^T$ and $\tilde{h} = \{\tilde{h}_t\}_{t=1}^T$. Country-specific parameters are collected in the vectors $h_0 = (h_{1,0}, \dots, h_{N,0})$, $\sigma_h = (\sigma_{h,1}, \dots, \sigma_{h,N})$, and $\beta = (\beta_1, \dots, \beta_N)$. Moreover, denote $\rho_i = (\rho_{1,i}, \rho_{2,i})'$ and $\rho = (\rho_1, \dots, \rho_N)$. All parameters are collected in $\psi = (\beta, \rho, h_0, \sigma_h, \sigma_\mu)$. The posterior density of interest is then given by $f(\tilde{h}, \mu, \psi, \mathcal{M} | y, x)$. In short, the algorithm consists of the following Gibbs sampling steps:

1. Sample the binary indicators \mathcal{M} from $f(\mathcal{M} | \tilde{h}, \mu, y, x)$ marginalizing over the parameters ψ and sample the unrestricted parameters in ψ from $f(\psi | \tilde{h}, \mu, \mathcal{M}, y, x)$, while setting $\sigma_{h,i}$ equal to zero for countries where $\delta_i = 0$.
2. Sample the latent components \tilde{h} from $f(\tilde{h} | \mu, \psi, \mathcal{M}, y, x)$ and μ from $f(\mu | \tilde{h}, \psi, \mathcal{M}, y, x)$.
3. Perform a random sign switch for σ_h and \tilde{h} with probability 0.5.

By sampling repeatedly from these blocks, we obtain parameter draws from the joint posterior distribution. We iterate the Gibbs steps 10,000 times and drop the first 3,000 as a ‘‘burn in’’ period. For the first

⁶Details on how to estimate the indicators are given in APPENDIX A.

1,500 of these “burn in” iterations, we restrict the binary indicators to be one, after which they are sampled according to the SMSS. This ensures convergence to the ergodic distribution. The results presented in Section 5 are thus based on the remaining 7,000 iterations.

3.2. PRIOR CHOICE

This paper follows a Bayesian approach and therefore the choice of prior distributions deserves some explanation. Prior distributions for all parameters are given in Table 1.

Table 1: Prior distributions

Name	Description	Density	Specification	
$\beta_{i,k}$	Slope coefficients	$\mathcal{N}(a_0, A_0)$	$\frac{a_0}{0.0}$	$\frac{\sqrt{A_0}}{10.0}$
$h_{i,0}$	Constant country-specific volatility	$\mathcal{N}(a_0, A_0)$	0.0	1.0
$\sigma_{h,i}$	Std. of latent I(1) component	$\mathcal{N}(a_0, A_0)$	0.0	1.0
$\rho_{1,i}$	AR(1) coefficient output gap	$\mathcal{N}(a_0, A_0)$	0.6	0.05
$\rho_{2,i}$	AR(2) coefficient output gap	$\mathcal{N}(a_0, A_0)$	-0.2	0.05
$\sigma_{\mu,i}^2$	Variance of growth trend shocks	$IG(v_0T, v_0T\sigma_0^2)$	$\frac{\text{Belief } \sigma_0^2}{0.1}$	$\frac{\text{Strength } \nu_0}{T \times 0.1}$
$p(\delta_i = 1)$	Inclusion probability of country-specific latent I(1) component	Bern(p)	$\frac{\text{Success rate } p}{0.5}$	

The main parameters of interest are the β coefficients, which represent the effect of the explanatory variables on output volatility. For these parameters a diffuse prior is chosen: The prior is normal with zero mean and large standard deviation. Because of the non-centred parametrisation, normal priors can also be applied to the constant volatility part, $h_{0,i}$, and the standard deviation of the country-specific time-varying volatility, $\sigma_{h,i}$. For both parameters the prior distributions are relatively uninformative with zero mean and unit standard deviation. The normal priors on the autoregressive coefficients ρ imply a low degree of persistence, which is in line with fitting a simple univariate AR model with constant volatility to annual output growth. For the standard deviation of the time-varying output growth rate, the prior distribution is the usual inverse-Gamma distribution $IG(c_0, C_0)$ where the shape c_0 and scale C_0 are expressed in terms of a *prior belief* σ_0^2 and a *prior strength* v_0 . Specifically, we set $c_0 = v_0T$ and $C_0 = s_0\sigma_0^2$, so that the strength can be expressed as a fraction of the sample size. Our belief implies that roughly 95% of shocks to the mean growth rate at annual frequency lie between +/- 0.62%-points. The strength of this belief is relatively weak, as it implies a number of “fictitious” observations equal to 10% of the sample size. Finally, the prior probability for time variation in country-specific output volatility, which is needed for the SMSS procedure, is given by a Bernoulli distribution with $p = 0.5$, which assigns equal weight to the null and alternative hypothesis, respectively.

4. DATA AND TIME SERIES PROPERTIES

This paper studies output volatility dynamics in an unbalanced panel of 22 OECD countries for the years 1961 to 2014.⁷ The choice of a dataset at annual frequency is determined by the data availability of most exogenous variables, which are not available at higher frequency. Output growth is measured by the year-over-year (yoy) growth rate of real GDP. The explanatory variables include 6 indicators for fiscal policy, demographics, and openness. In line with recent studies on the effects of demographics on volatility, we

⁷The countries considered are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

use as a measure the share of the working age population aged 15-29 and 60-64. Empirical estimates by Jaimovich and Siu (2009) suggest a positive effect of the share variable. Regarding the impact of fiscal policy on output volatility, we consider both the revenue and expenditure side. On the expenditure side, we measure the size of the government by the government's final consumption expenditure expressed as a share of GDP. However, as first noted by Rodrik (1998) and then discussed by Fatás and Mihov (2001) and others, the effect of government size might suffer from a simultaneity bias. More open economies might experience greater volatility because of their exposure to international business cycle shocks. If governments can indeed reduce volatility, they will likely be bigger in more open economies, which would induce a downward bias of the estimated effect of government size. Hence, we include trade openness, defined as the sum of exports and imports as a share of GDP, into our regression analysis. Despite the argument of Rodrik (1998), the sign of the effect of openness is not clear-cut, as higher openness can also represent a form of risk diversification that can counteract shocks at the national level. On the revenue side, we measure the tax mix by three different tax variables: Consumption, capital, and labour tax ratios. We combine tax data from two different sources, McDaniel (2007) and Posch (2011), to achieve a larger sample. Specifically, Posch (2011) measures average taxes following Mendoza, Razin, and Tesar (1994) using OECD data. This data set covers 22 countries, but is only available from 1970 onwards. The data provided by McDaniel (2007), however, are based on national accounts and thus start as early as 1950. Unfortunately, the sample covers only 15 out of the 22 countries. Thus, we merge the two sources and extend the data from Posch (2011) with the earlier data from McDaniel (2007) for these 15 countries.⁸ For the recent years since 2008 we compute average effective tax rates ourselves following Mendoza, Razin, and Tesar (1994). This leaves us with an unbalanced panel consisting of 22 countries and a total of 1138 observations. Theoretically, Posch (2011) derives marginal tax effects in a stochastic neoclassical growth model and finds that effects are ambiguous. Labour taxes have negative effects on output volatility in the model, while consumption taxes are volatility neutral. Capital taxes are a form of income taxation but also on investment and wealth. Thus, they have no clear-cut theoretical effect. Further details on variable construction and sources are given in Table A-4 of APPENDIX C.

Table 2: Country-specific and panel unit root tests

Variable	constant		constant & time trend	
	ADF: #($p_i < 5\%$)	Panel MW	ADF: #($p_i < 5\%$)	Panel MW
<i>y</i>	21	339.85 [0.00]	22	398.33 [0.00]
<i>age</i>	1	33.31 [0.88]	2	126.21 [0.00]
<i>openness</i>	2	23.76 [0.00]	1	67.25 [0.00]
<i>govsize</i>	1	61.35 [0.04]	1	43.78 [0.54]
<i>captax</i>	1	53.58 [0.15]	0	38.91 [0.69]
<i>contax</i>	2	63.83 [0.03]	0	42.76 [0.52]
<i>labtax</i>	5	71.32 [0.01]	1	36.52 [0.78]

Note: Optimal lag length was determined by Schwarz criterion with maximum number set to 4.

Before taking the model to the data, the time series properties of the variables are discussed. As argued in the motivation of this paper, some of the explanatory variables may exhibit non-stationarity so that correlations with output volatility are potentially spurious. Table 2 reports the results of country-specific Augmented Dickey and Fuller (1979) (ADF) and Maddala and Wu (1999) (MW) panel unit root tests. In case of the ADF test, the number of cross sections with an individual p-value lower than 5% is reported. For the MW test, the Fisher test statistic is given along with the corresponding p-value in brackets. Columns 2-3 refer to tests with a country-specific constant, while in columns 4-5 a linear trend is added. For the sake of completeness we also test output growth for which the null of a unit root can be rejected using panel tests and in virtually all countries when tested separately.

⁸See McDaniel (2007) for more details on the comparison with the Mendoza, Razin, and Tesar (1994) methodology.

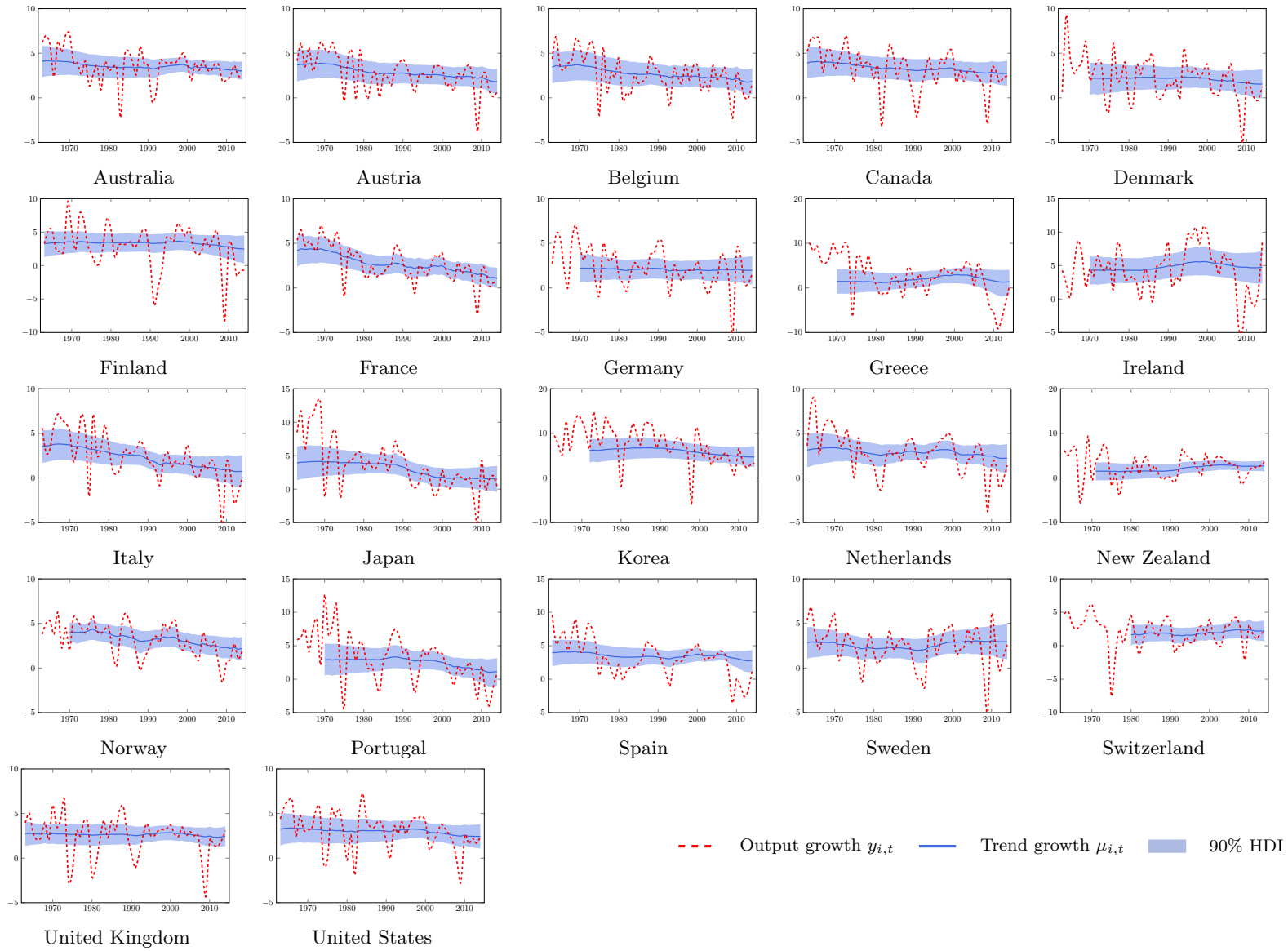


Figure 1: Mean estimate of trend growth rate

Looking at the individual ADF statistics of the explanatory variables suggests that the majority are in fact unit root processes, i.e. the null of a single unit root cannot be rejected in most countries. Results from the MW panel unit root test are less clear-cut. For a model with only country-specific intercepts, the data series for demographics and capital taxes are found to have unit roots. If a linear trend is added to the testing equation, unit roots cannot be rejected for government size, capital, consumption and labour taxes. Taking together the evidence from country-wise and panel unit root tests, it appears important to account for the time series properties of the data when estimating the model in order to avoid spurious results.

5. ESTIMATION RESULTS

Before turning to the estimated effects of the macroeconomic covariates in detail, we first present results on the time-varying and latent output components: The unobserved trend growth rate and the unobserved overall volatility series. The empirical model arises from the decomposition of annual output growth into a (stochastic) trend and innovation term. The estimated country-specific trend components from the baseline model are given in Figure 1. This model includes the full set of explanatory variables. Moreover, all binary indicators are sampled according to the SMSS procedure. Over all countries, the trend rate captures low-frequency movements, so that observed annual growth is mainly driven by the transitory component. The shorter series for some countries are due to limited data availability of the covariates.

One key feature of the approach presented in this paper is the inclusion of a latent non-stationary volatility component, which is selected according to Bayesian model probabilities. As a preliminary test, prior to the stochastic model specification search, one can investigate the importance of this component by looking at the posterior distributions of the country-specific standard deviations of the stochastic components. In Figure 2 and 3 the empirical distributions of $\sigma_{h,i}$ are plotted for both a model without any covariates and the full set of covariates. As such, Figure 2 gives preliminary evidence on the degree of time variation in output volatility when volatility is purely stochastic, i.e. all $\beta_{i,k}$ are set to zero. Comparing Figures 2 and 3 shows how much of the time variation can be accounted for by the explanatory variables. Most of the distributions in Figure 2 are bimodal, giving support for a model with time-varying volatility in the majority of the 22 countries. However, once the explanatory variables are added, there is less evidence for the presence of the latent component. The distribution switches to a unimodal distribution in most countries. As the graphical evidence is mixed for some countries, e.g. Finland or Korea, the binary indicators and their respective inclusion probabilities can give quantitative evidence for the presence of a non-stationary component. Table 3 gives the posterior probability for the country-specific indicators, δ_i , being equal to one, according to the SMSS. Columns 2 and 6 refer to a model without covariates, i.e. time variation can only arise due to the unobserved component.⁹ To make the effect of the number of covariates more visible, columns 3 and 7 report results for a model where demographics is the only explanatory variable as in Jaimovich and Siu (2009). Columns 4 and 8 refer to the full model, i.e. all 6 covariates are included. As expected, the inclusion probabilities for a model without covariates are relatively high in the majority of countries.

Surprisingly, the United States' value of 0.13 is relatively low. We attribute this to our rather small annual dataset. Using quarterly data Berger, Everaert, and Vierke (2016) find much stronger evidence for time variation in the volatility of U.S. output growth shocks. This is also confirmed by our Monte Carlo study in APPENDIX B which suggests that indicator values can be low in small samples even under the presence of the non-stationary component. Unfortunately, since some of the covariates are only available on an annual basis, increasing the frequency of our observations proves difficult. However, results are generally in line with previous findings from the literature that permanent volatility changes occurred in many countries within the postwar period. For the *demographic* model, 7 out of the 22 countries show an important non-stationary component. This confirms the findings of Everaert and Vierke (2016) from panel regressions where demographics is the only explanatory variable.

⁹Two year dummies are included in all models to account for a large outlier in annual growth rates, the Great Recession in 2008/2009.

Figure 2: **Posterior standard deviation of I(1) component, excl. covariates**

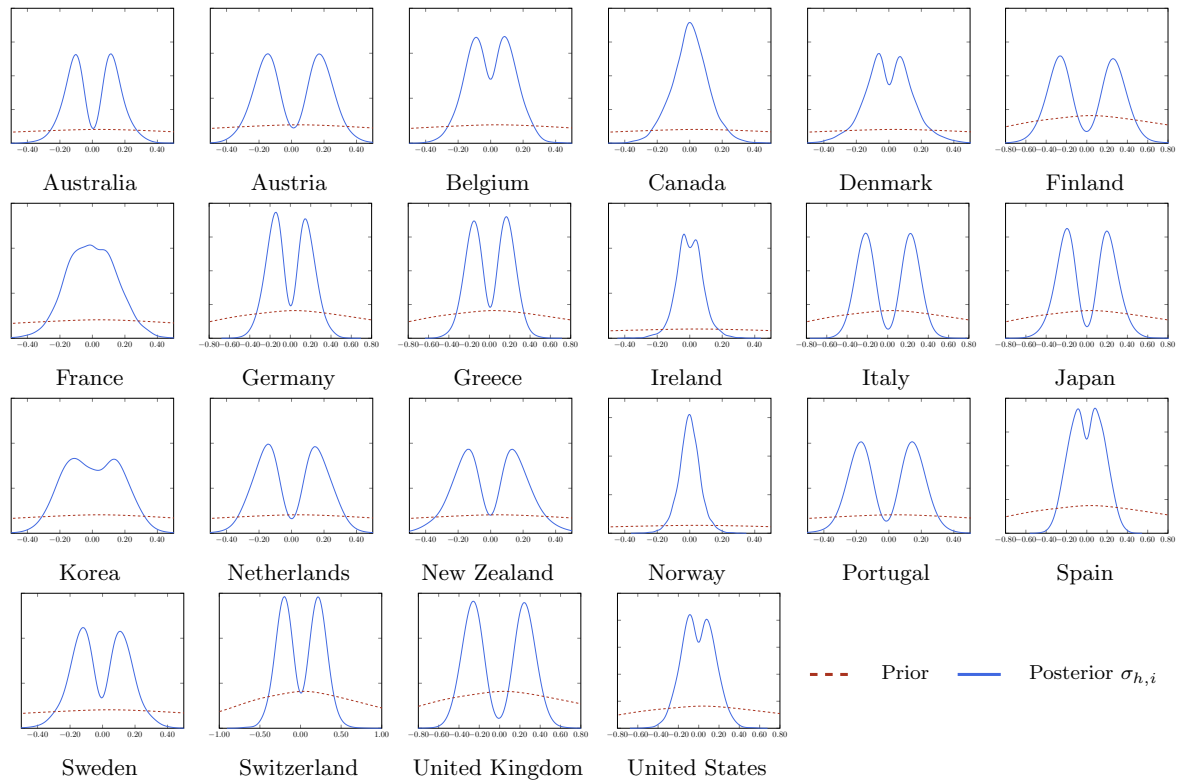
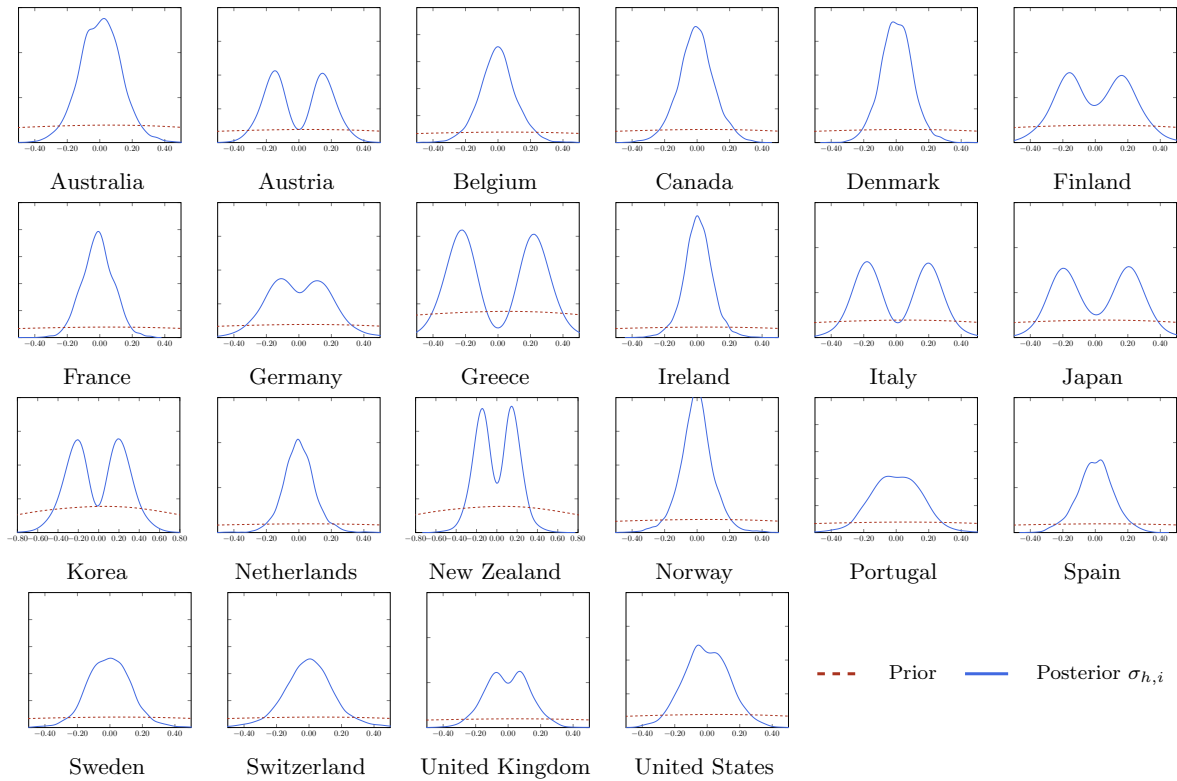


Figure 3: **Posterior standard deviation of I(1) component, baseline model**



Note: In order to obtain the full empirical distributions of the parameters, the binary indicators on the I(1) components are restricted to be $\delta_i = 1$.

The authors cannot reject the null of no cointegration between output volatility and demographics within the G7 countries when using the original sample of Jaimovich and Siu (2009). However, the inclusion probabilities drop further in almost all countries for the full model specification. From the 5 countries left with inclusion probabilities larger 0.5, only Greece is characterised by a maximum inclusion probability. This is a first key result: A larger vector of covariates that includes demographics, openness, and various fiscal indicators does not produce a non-stationary error component in the majority of countries, i.e. results are not spurious.

Table 3: **Posterior inclusion probabilities of unobserved I(1) component**

Country	Probability $\delta_i = 1$			Country	Probability $\delta_i = 1$		
	Excl. x	Age	Full model		Excl. x	Age	Full model
Australia	0.90	0.84	0.54	Japan	1.00	0.61	0.53
Austria	0.61	0.31	0.34	Korea	0.11	0.28	0.59
Belgium	0.13	0.07	0.08	Netherlands	0.68	0.27	0.06
Canada	0.08	0.06	0.08	New Zealand	1.00	0.99	0.26
Denmark	0.12	0.14	0.07	Norway	0.06	0.06	0.07
Finland	0.81	0.22	0.21	Portugal	0.96	0.91	0.07
France	0.12	0.06	0.07	Spain	0.15	0.25	0.10
Germany	0.53	0.11	0.15	Sweden	0.62	0.18	0.07
Greece	0.80	0.83	1.00	Switzerland	0.78	0.35	0.11
Ireland	0.07	0.05	0.06	United Kingdom	0.98	0.82	0.10
Italy	1.00	0.97	0.57	United States	0.13	0.09	0.08

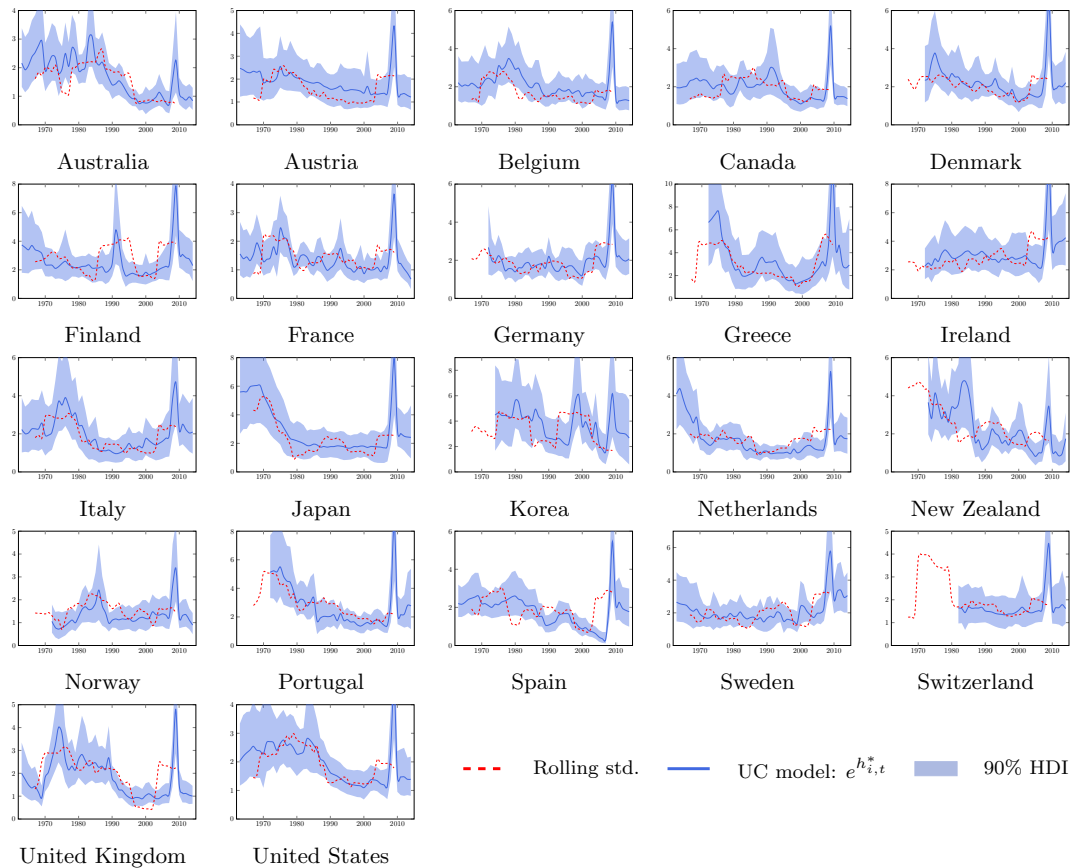
Age: Only *age* variable is included.

Bold numbers indicate probabilities > 0.5 .

The estimated overall volatilities, given by the sum of the explained and unexplained component, are plotted in Figure 4. There is clear evidence of a substantial decline in output volatility in the second half of the sample in the United Kingdom or the United States. Many other countries experience a similar decline, but the steepness and timing of the decline are quite different. This leads to the conclusion that the Great Moderation has been an international phenomenon, but with important differences across countries. However, output volatility has reached unprecedented heights during the Great Recession of the years 2008/2009 which is clearly visible in all countries.

In the most recent years volatility dropped again to the pre-crisis level in many countries indicating that the Great Recession only poses a temporary interruption of the Great Moderation rather than the endpoint of a period of tranquil business cycles. Since the volatility measure in this paper differs from the ones commonly used in the literature, we compare the instantaneous measure obtained from our UC model with the standard deviation of output growth from a centred 9-year rolling window. For many countries, differences between the two series appear rather small. For the United States, for example, the rolling window-based standard deviation evolves quite closely to our instantaneous stochastic volatility series. However, the estimated slope coefficients can be quite different. Moreover, there exist important differences between the two volatility measures for other countries, such as Australia, Greece, Korea and New Zealand. Additionally, centred window measures inhibit future realised volatility by construction. As a consequence the centred window “predates” the Great Recession and is not able to capture its suddenness and severity. The instantaneous volatility measure is robust to this problem.

Figure 4: Mean estimate of overall volatility (full model)



Output volatility: The impact of demographics and fiscal policy

We now turn to the estimated effects of the explanatory variables. Since the common approach in the literature is to pool observations cross-sectionally, i.e. to restrict the coefficients in β to be identical across countries (e.g. Jaimovich and Siu, 2009; Posch, 2011), we show results for both a homogeneous specification and one allowing for heterogeneous effects across countries. It should be noted that if both the dependent and independent variable are integrated and the true population parameters are indeed heterogeneous, both coefficients do in general not measure the same average effect. The homogeneous model yields an estimator which is a weighted average of the individual coefficients where the weights depend on the variation in the regressors. This estimator provides an estimate of the long-run average effect. On the other hand, the mean group estimator which is an unweighted average yields an estimate of the average long-run effect (see Coakley, Fuertes, and Smith, 2001, for a more detailed discussion).

Table 4 presents results of the model when the full set of explanatory variables is included. While the left side shows results for a homogeneous specification, the right side presents the heterogeneous (our baseline) model. In the case of heterogeneous coefficients we report the mean-group estimates, i.e. the arithmetic average of the country-specific slope coefficients. In both cases, we include time effects to control for one major shock across countries, the Great Recession of the years 2008/2009.¹⁰ As has been shown before by our stochastic model selection procedure, we are at least for a subset of countries still dealing with the possibility of omitted I(1) variables when considering the model which includes the full set of explanatory variables. Our model explicitly accounts for the unexplained non-stationarity in the variance equation. As a consequence, standard inference on the coefficients remains valid.¹¹

¹⁰We also estimated the model with a full set of time dummies. In case of the homogeneous specification results remain qualitatively unchanged. When allowing for slope heterogeneity including a full set of dummies creates a heavily overparametrised model such that a meaningful signal can no longer be extracted from the data.

¹¹However, the usual standard errors reported for the pooled estimator are inappropriate when parameters are in fact heteroge-

For both the homogeneous as well as the heterogeneous specification, we report a positive and highly significant effect of demographics. Generally, the null hypothesis of a zero effect of demographics on volatility can be clearly rejected. The estimated median effect of 2.9 indicates that increasing the share of the working age population aged 15-29 and 60-64 by one percentage point is expected to increase the standard deviation of output growth on average by 2.9%. This value is broadly in line with the finding in Jaimovich and Siu (2009) when an instantaneous volatility measure instead of a rolling window is used.

For economic openness, we find a small positive effect on output volatility when pooling observations. This is at odds with results reported in Haddad, Lim, Pancaro, and Saborowski (2013), who argue that trade openness reduces output growth volatility for well-diversified economies. They find a significant negative effect implying that trade openness as a form of risk diversification played an important role for the decrease in output volatility. However, theoretical results on the effect of openness are not clear-cut.

Table 4: Posterior distributions of regression coefficients

Variable	Homogeneous (pooled) model				Heterogeneous (mean-group) model			
	Median	Std	P ₅	P ₉₅	Median	Std	P ₅	P ₉₅
age	3.395	[0.439]	2.644	4.103	2.897	[0.690]	1.760	4.030
openness	0.562	[0.165]	0.285	0.826	-0.359	[0.516]	-1.199	0.501
govsize	5.990	[1.534]	3.451	8.515	4.075	[1.713]	1.243	6.926
captax	0.233	[0.488]	-0.547	1.065	-1.342	[0.889]	-2.801	0.116
contax	-2.008	[1.004]	-3.747	-0.357	-1.941	[1.465]	-4.325	0.492
labtax	-2.985	[0.636]	-4.062	-1.971	-1.565	[1.049]	-3.326	0.149
time fixed effects	crisis dummies (2008/2009)				crisis dummies (2008/2009)			

Bold numbers: 90% credible interval does not include zero.

Moreover, allowing for heterogeneous effects across countries renders this effect insignificant. Moreover, we find a meaningful effect of government size on output volatility, when controlling for openness and the different tax channels. While the standard errors are very large, a zero effect can be ruled out in both specifications. The positive sign of the government size coefficient indicates that larger public consumption creates a more uncertain economic environment. Interestingly, an insignificant effect is obtained when output volatility is regressed only on demographics and government size.¹² This reinforces the need to control for openness and the tax mix when evaluating the role of government size. When considering the homogeneous specification, the tax effects are partly in line with Posch (2011). Labour and consumption taxes are found to have a stabilising effect on the economy while no clear effect is obtained for capital taxes. The heterogeneous model suggests negative effects of all three tax types on volatility whereas none of the coefficients remains significant. However, the 90% credible intervals for labour and capital taxes come very close to excluding zero. We hypothesise that a larger dataset would allow to obtain significant results even under coefficient heterogeneity. Surprisingly, under the latter scenario the sign of capital taxes changes. Overall, these findings are in line with previous results from Posch (2011) and suggest that the stabilising effect of fiscal policy works mainly through (labour) taxation as an automatic stabiliser. Earlier results on a negative effect of government size are possibly due to missing control for the tax mix. However, we note that there might exist a trade-off between stabilisation and efficiency, as discussed by Martinez-Mongay and Sekkat (2005) and Posch (2011) among others. Specifically, while higher distortionary taxes can work in favour of output stabilisation, there exist well-described arguments on their negative effect on long-run growth.¹³

neous. Phillips and Moon (1999) derive asymptotic distributions for the pooled estimator in non-stationary panels. However, the DGP needs to be known in order to identify the appropriate expression for the standard errors. Hence, the standard errors reported here need to be considered with caution.

¹²Results are not reported here, but available on request.

¹³Evaluating the effects on first and second moments of output growth simultaneously is beyond the scope of this paper.

Counterfactual analysis

In order to demonstrate the contribution of the explanatory variables to the evolution of output volatility over time, we construct a selection of counterfactual volatility series by holding constant one or more of the explanatory variables. Specifically, we take the estimated effects from the heterogeneous (baseline) model as given, but assume that the respective variable stays constant at a value equal to the 5-year average at the beginning of the sample.¹⁴ Counterfactual scenarios are not based on the mean group estimators, but on country-specific slope coefficients. Moreover, we construct a counterfactual series at every iteration of the Gibbs sampling algorithm to obtain the full posterior distribution. Thus, the credible bands around the counterfactuals take into account all sources of filtering and parameter uncertainty within the model. We focus on the effects of demographics and the fiscal policy variables. Here, we present only a selection of countries in order to keep the analysis brief. Figure 5 plots demographics counterfactual series for France, Germany, the United Kingdom, and the United States.

The counterfactual series reflect a working age population with no demographic shifts, i.e. the share of young and very old workers is constant over the full sample. In all four countries considered, demographics explains most of the long-run swings in output volatility. When the age share variable is constant, the series still exhibit some distinct short-run fluctuations. The common long-run decline in volatility, however, is completely absent (e.g. France and United States) or less pronounced in the counterfactual (e.g. United Kingdom). Overall, the graphical analysis is in line with the notion that a higher share of prime-age workers reduces output volatility. As most industrialised countries experience important shifts towards an ageing population, actual volatility in the last two decades lies below the counterfactual series that is based on the demographic composition from 40-50 years ago. In Germany, for example, the counterfactual volatility is almost twice as large as the actual series during the years 2000 to 2005. However, there is large uncertainty around the median volatility estimates. The large difference comes as no surprise as Germany is one of the fastest aging countries. Turning to the United States, we find supporting evidence that output volatility in the last 5 decades was in large parts driven by demographics. As argued by Jaimovich and Siu (2009) the “baby boom” in the United States led to a large inflow of young workers during the 1970s and subsequently to a large share of prime-age workers since the 1990s. Note that our estimated volatility series indeed shows a large upward deviation from the counterfactual during the 1970s and 1980s, before falling below the counterfactual in the 1990s. However, there remains a persistent long-run decline in output volatility even after removing the influence of demographics. The results for the four countries presented here do, however, not hold for the entire sample. Of the remaining 18 countries only Japan and New Zealand show significant deviations of the counterfactuals from the actual volatility series. While especially Japan certainly underwent significant demographic changes also other countries are facing an ageing labour force. Overall, the absent volatility effect in these countries raises the question which factors can explain heterogeneity in the effect of demographic changes on output volatility across countries. We leave this for future research.

When we hold constant all four fiscal variables, i.e. government size as well as consumption, capital, and labour taxes, we obtain the series plotted in Figure 6. In contrast to the effect of demographics, the fiscal variables account mainly for the short-run fluctuations in volatility. See for example the case of Germany, where the counterfactual exercise leads to a very smooth series that still exhibits a hump-shaped pattern. However, the very large credible bands around the German counterfactual indicate that the effect of fiscal variables is not well identified. In France, the counterfactual series lies below the realised series for large parts of the sample period whereas the opposite is true in case of the United States. This indicates that fiscal policy had an overall destabilising effect on these economies. However, we emphasise that results from this exercise should be handled carefully, as it assumes policy-invariance of the parameters.¹⁵

¹⁴We use the average only to account for possible outliers at the beginning of the sample.

¹⁵In other words, the usual Lucas critique applies.

Figure 5: Counterfactual volatility series: Constant demographics

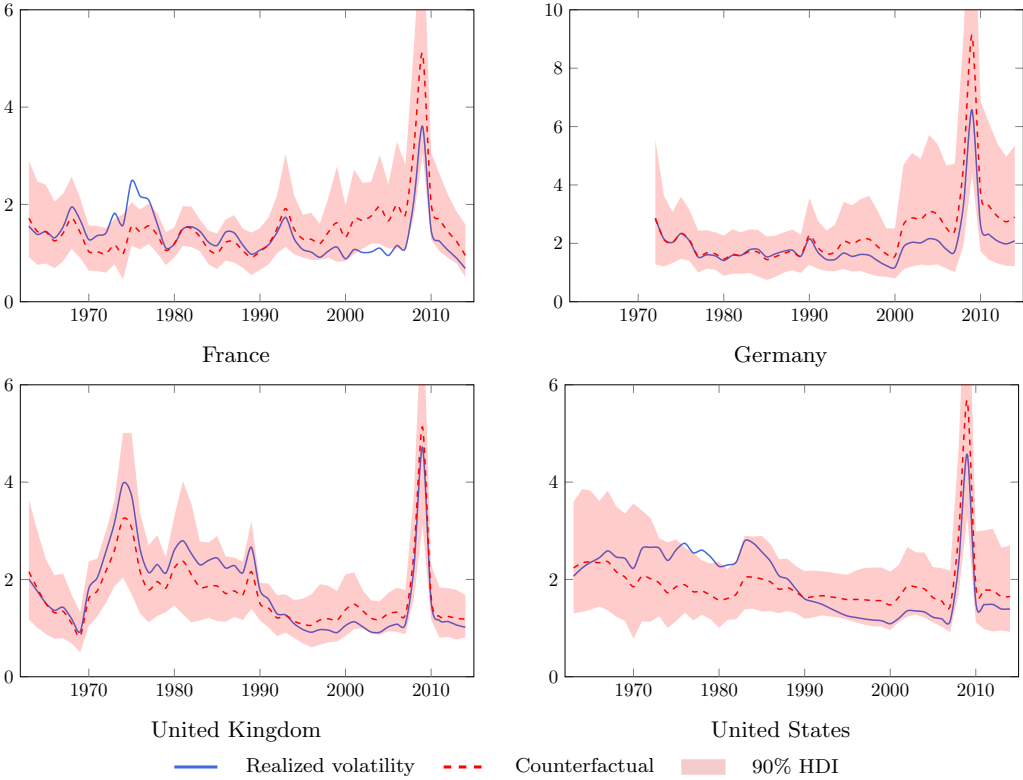
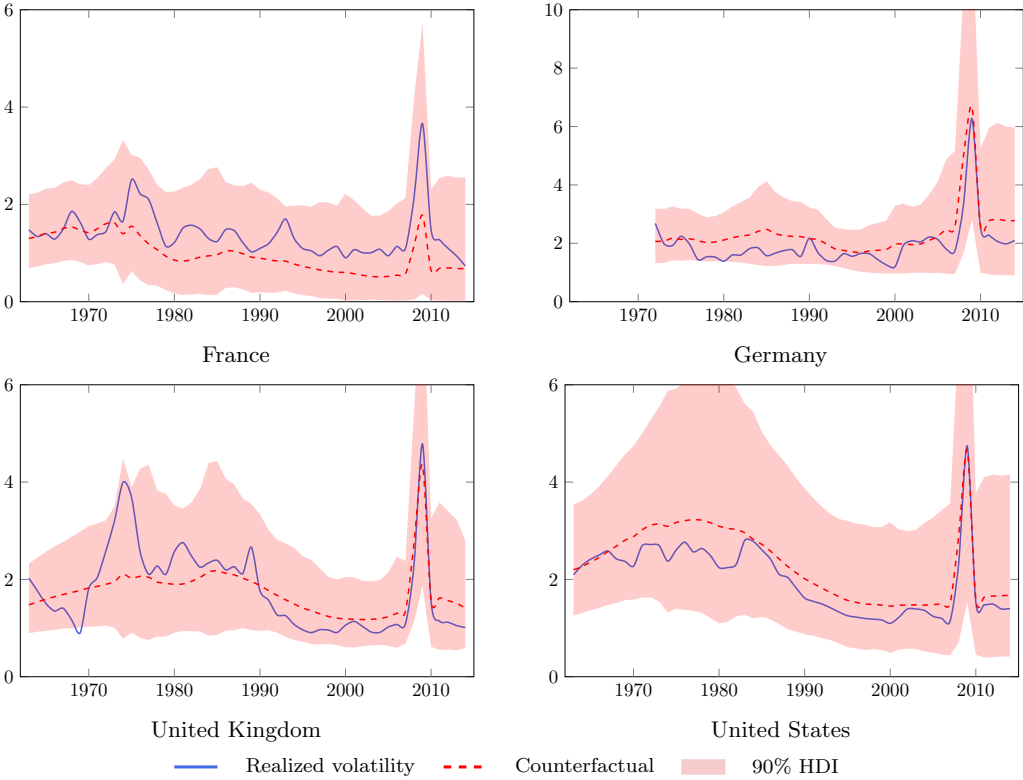


Figure 6: Counterfactual volatility series: Constant fiscal policy



6. CONCLUSIONS AND POLICY IMPLICATIONS

This paper studies the determinants of output volatility in an unbalanced panel of 22 OECD countries. We avoid using ad hoc volatility measures based on rolling standard deviations. While these are easy to implement, the resulting measure carries several problems especially if used in a subsequent regression analysis. Moreover, we explicitly account for the possibility of non-stationary factors driving output volatility. In contrast to the existing literature, the volatility series arises endogenously from an unobserved components model, that treats output volatility as a latent and possibly non-stationary process. A Bayesian model selection procedure is used to test for the presence of non-stationary error components in the volatility equation, similar to a cointegration test. This paper merges the literature on the role of government size in output stabilisation with recent studies on the effect of demographics on business cycle volatility. Moreover, the model controls for international openness and the tax mix when investigating the role of government size. Our results suggest that demographics played an important role for the evolution of output volatility during the last decades in many advanced economies. The evidence on the role of fiscal policy is mixed. When controlling for trade openness and the tax mix, government size measured as public consumption appears to have distortionary effects. The impact of taxes is ambiguous with labour taxes appearing to have a stabilising effect. This finding is in line with the concept of taxes as automatic stabilisers in the Keynesian sense. Finally, we construct counterfactual series for a selection of countries and show that while demographic changes can account to a large extent for long-run swings in volatility, fiscal policy mostly explains short-run fluctuations.

The findings presented in this paper carry implications for economic policy. While the present study suggests an important link between demographics and business cycle volatility, demographics itself is usually not seen as a policy variable that can be a tool for macroeconomic stabilisation. Nevertheless, our findings suggest that demographics should enter into predictions about future volatility. Moreover, in a large integrated economic area, such as the European Union, the demographic composition of individual Member States can be an important factor in order to explain differences in the sensitivity to common shocks. Thus, policy measures could serve as an instrument in so far as they can focus on non-prime age groups. In this regard, the present study suggests to pay attention to the overall macroeconomic effects of labour market policies targeted at changing the participation of specific age groups.

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APPENDIX A. GIBBS SAMPLING ALGORITHM

The structure of the Gibbs sampling algorithm is based on Frühwirth-Schnatter and Wagner (2010) and the description draws heavily from Berger, Everaert, and Vierke (2016). To linearise the nonlinear volatility specification, we follow the procedure by Kim, Shephard, and Chib (1998) and approximate the non-Gaussian distribution in the volatility equation by a mixture distribution. Specifically, we re-arrange and then linearise the growth equation in the following way

$$y_{i,t} = \mu_{i,t} + \rho_{1,i}(y_{i,t-1} - \mu_{i,t-1}) + \rho_{2,i}(y_{i,t-2} - \mu_{i,t-2}) + \exp\{\beta' x_{i,t}\} \exp\{h_{i,t}\} \varepsilon_{i,t}, \quad (\text{A-1})$$

where $\varepsilon_{i,t} \sim i.i.d.\mathcal{N}(0, 1)$ and $h_{i,t}$ is defined as in Equation (5). Both the explained and unexplained component of volatility enter multiplicatively. The Gibbs sampling approach allows for splitting and transforming this model into blocks that are conditionally linear. Thus, given β and $x_{i,t}$, estimates for the latent non-stationary component can be obtained from the following model

$$\tilde{y}_{i,t} = \exp\{h_{i,t}\} \varepsilon_{i,t}, \quad (\text{A-2})$$

where $\tilde{y}_{i,t} = (y_{i,t} - \mu_{i,t} - \rho_{1,i}(y_{i,t-1} - \mu_{i,t-1}) - \rho_{2,i}(y_{i,t-2} - \mu_{i,t-2}))(\exp\{\beta' x_{i,t}\})^{-1}$. This expression can be linearised by taking the natural-log of the squares

$$\ln(\tilde{y}_{i,t}^2 + c) = 2h_{i,t} + \varepsilon_{i,t}, \quad (\text{A-3})$$

where $c = 0.001$ is an offset constant and $\varepsilon_{i,t} = \ln(\varepsilon_{i,t}^2)$. The last term follows a log-chi-square distribution, which can be approximated by the following mixture of normal distributions

$$f(\varepsilon_{i,t}) = \sum_{j=1}^M q_j f_{\mathcal{N}}(\varepsilon_{i,t} | m_j - 1.2704, \nu_j^2), \quad (\text{A-4})$$

where q_j is the component probability of a specific normal distribution with mean $m_j - 1.2704$ and variance ν_j^2 . This mixture can equivalently be expressed in terms of component probabilities

$$\varepsilon_{i,t} | (\iota_{i,t} = j) \sim \mathcal{N}(m_j - 1.2704, \nu_j^2) \quad \text{with } Pr(\iota_{i,t} = j) = q_j. \quad (\text{A-5})$$

We follow Omori, Chib, Shephard, and Nakajima (2007) and use a mixture of $M = 10$ normal distributions to proxy the log-chi-square distribution. With this linearisation at hand, the Gibbs sampling algorithm consists of the following steps:

Block 1: Sampling the binary indicators \mathcal{M} and the hyperparameters ϕ

Block 1(a): Sampling \mathcal{M} , h_0 and σ_h

For notational convenience, let us define a general regression model

$$w = z^{\mathcal{M}} b^{\mathcal{M}} + e, \quad e \sim \mathcal{N}(0, \Sigma), \quad (\text{A-6})$$

with w a vector including observations on a dependent variable w_t and z an unrestricted predictor matrix containing the state processes \tilde{h}_t that is relevant for explaining w_t . The corresponding unrestricted parameter vector with the relevant elements from ϕ is denoted b . $z^{\mathcal{M}}$ and $b^{\mathcal{M}}$ are then the restricted predictor matrix and restricted parameter vector that exclude those elements in z and b for which the corresponding indicator in \mathcal{M} is 0. Furthermore, Σ is a diagonal matrix with elements $\sigma_{e,t}^2$ that may vary over time to allow for heteroskedasticity of a known form.

A naive implementation of the Gibbs sampler would be to sample \mathcal{M} from $f(\mathcal{M} | \tilde{h}, w, \phi)$ and ϕ from $f(\phi | \tilde{h}, \mathcal{M}, w)$. However, this approach does not result in an irreducible Markov chain as whenever an indicator in \mathcal{M} equals zero, the corresponding coefficient in ϕ is also zero which implies that the chain

has absorbing states. Therefore, as in Frühwirth-Schnatter and Wagner (2010) we marginalise over the parameters ϕ when sampling \mathcal{M} and next draw the parameters ϕ conditional on the indicators \mathcal{M} . The posterior distribution $f(\mathcal{M}|\tilde{h}, w)$ can be obtained using Bayes' theorem as

$$f(\mathcal{M}|\tilde{h}, w) \propto f(w|\mathcal{M}, \tilde{h})p(\mathcal{M}), \quad (\text{A-7})$$

with $p(\mathcal{M})$ being the prior probability of \mathcal{M} and $f(w|\mathcal{M}, \tilde{h})$ being the marginal likelihood of the regression model (A-6) where the effect of $b^{\mathcal{M}}$ and σ_e^2 is integrated out. The closed form solution of the marginal likelihood in the case of heteroskedasticity $\Sigma = \text{diag}(\sigma_{e,1}^2, \dots, \sigma_{e,T}^2)$, under the normal conjugate prior $b^{\mathcal{M}} \sim \mathcal{N}(a_0^{\mathcal{M}}, A_0^{\mathcal{M}})$, is given by

$$f(w|\mathcal{M}, \tilde{h}) \propto \frac{|\Sigma|^{-0.5} |A_T^{\mathcal{M}}|^{0.5}}{|A_0^{\mathcal{M}}|^{0.5}} \exp\left(-\frac{1}{2} \left(w' \Sigma^{-1} w + (a_0^{\mathcal{M}})' (A_0^{\mathcal{M}})^{-1} a_0^{\mathcal{M}} - (a_T^{\mathcal{M}})' (A_T^{\mathcal{M}})^{-1} a_T^{\mathcal{M}} \right)\right), \quad (\text{A-8})$$

with

$$a_T^{\mathcal{M}} = A_T^{\mathcal{M}} \left((z^{\mathcal{M}})' \Sigma^{-1} w + (A_0^{\mathcal{M}})^{-1} a_0^{\mathcal{M}} \right), \quad (\text{A-9})$$

$$A_T^{\mathcal{M}} = \left((z^{\mathcal{M}})' \Sigma^{-1} z^{\mathcal{M}} + (A_0^{\mathcal{M}})^{-1} \right)^{-1}. \quad (\text{A-10})$$

Following George and McCulloch (1993), instead of using a multi-move sampler in which all the elements in \mathcal{M} are sampled simultaneously, we use a single-move sampler in which each of the binary indicators δ_i (for $i = 1, \dots, N$) is sampled separately.

Using Equation (5), Equation (A-3) can be rewritten in the general linear regression format of (A-6) as

$$\overbrace{g_{i,t} - (m_{i,t} - 1, 2704)}^{w_t} = 2 \overbrace{\begin{bmatrix} 1 & \delta_i \tilde{h}_{i,t} \end{bmatrix}}^{z_t^{\mathcal{M}}} \overbrace{\begin{bmatrix} h_{i,0} \\ \sigma_{h,i} \end{bmatrix}}^{b^{\mathcal{M}}} + \overbrace{\tilde{\epsilon}_{i,t}}^{e_t}, \quad (\text{A-11})$$

for $i = 1, \dots, N$, with $\tilde{\epsilon}_{i,t} = \epsilon_{i,t} - (m_{i,t} - 1, 2704)$ is $\epsilon_{i,t}$ recentred around zero and where $g_{i,t} = \ln(\tilde{y}_{i,t}^2 + c)$. The marginal likelihood $f(w|\delta_i, h)$ can be calculated as in Equation (A-8). The binary indicator δ_i can then be sampled from the Bernoulli distribution with probability $p(\delta_i = 1|\tilde{h}_i, w)$ calculated from

$$p(\delta_i = 1|\tilde{h}_i, w) = \frac{f(\delta_i = 1|\tilde{h}_i, w)}{f(\delta_i = 0|\tilde{h}_i, w) + f(\delta_i = 1|\tilde{h}_i, w)}, \quad (\text{A-12})$$

Next, $b^{\mathcal{M}}$ can be sampled from $\mathcal{N}(a_T^{\mathcal{M}}, A_T^{\mathcal{M}})$ with $a_T^{\mathcal{M}}$ and $A_T^{\mathcal{M}}$ as defined in Equations (A-9) and (A-10). Note that $b^{\mathcal{M}} = (h_{h,0}, \sigma_{h,i})'$ when $\delta_i = 1$ and $b^{\mathcal{M}} = h_{h,0}$ when $\delta_i = 0$. In the latter case, we set $\sigma_{h,i} = 0$.

Block 1(b): Sampling ρ

Using the general notation from (A-6), define

$$\overbrace{\begin{bmatrix} y_{i,t} - \mu_{i,t} \end{bmatrix}}^{w_t} = \overbrace{\begin{bmatrix} y_{i,t-1} - \mu_{i,t-1} & y_{i,t-2} - \mu_{i,t-2} \end{bmatrix}}^{Z_t} \overbrace{\begin{bmatrix} \rho_{1,i} \\ \rho_{2,i} \end{bmatrix}}^{b_t} + \overbrace{\exp\{h_{i,t} + \beta' x_{i,t}\} \epsilon_{i,t}}^{e_t} \quad (\text{A-13})$$

with $\Sigma = \text{diag}(\exp\{h_{i,t} + \beta'x_{i,t}\}^2, \dots, \exp\{h_{i,T} + \beta'x_{i,T}\}^2)$. The parameters can be sampled according to (A-9) and (A-10).

Block 1(c): Sampling $\sigma_{\mu,i}^2$

Again, we use the more general notation from (A-6) and sample the variance conditional on $\mu_{i,t}$ according to

$$\overbrace{[\mu_{i,t} - \mu_{i,t-1}]}^{w_t} = \overbrace{[\eta_{i,t}^\mu]}^{e_t}, \quad (\text{A-14})$$

where $\sigma_{\mu,i}^2$ can be sampled from $\mathcal{IG}(c_T, C_T)$ with $C_T = C_0 + 0.5(\eta^\mu \eta^\mu)$ where η^μ is calculated from $\eta_t^\mu = \mu_{i,t} - \mu_{i,t-1}$, and where $c_T = c_0 + T/2$.

Block 1(d): Sampling the β_i

Starting from (A-1), we condition on $h_{i,t}$ and linearise again by taking the log of the squares

$$\ln(\tilde{y}_{i,t}^2 + c) = 2\beta_i'x_{i,t} + \epsilon_{i,t}, \quad (\text{A-15})$$

where $\tilde{y}_{i,t} = (y_{i,t} - \mu_{i,t} - \rho_{1,i}(y_{i,t-1} - \mu_{i,t-1}) - \rho_{2,i}(y_{i,t-2} - \mu_{i,t-2})) \exp\{h_{i,t}\}^{-1}$ and $\epsilon_{i,t}$ follows a log-chi-square distribution. Similar to (A-11), we use the more general notation

$$\overbrace{g_{i,t} - (m_{i,t} - 1, 2704)}^{w_t} = \overbrace{2\beta_i}^{z_t} \overbrace{x_{i,t}}^b + \overbrace{\tilde{\epsilon}_{i,t}}^{e_t}, \quad (\text{A-16})$$

where the predictor matrix and corresponding parameter vector are always unrestricted and $g_{i,t} = \ln(\tilde{y}_{i,t}^2 + c)$. β_i can then be sampled from $\mathcal{N}(a_T, A_T)$ similar to (A-9) and (A-10), where all elements are unrestricted.

Block 2: Sampling mixture indicators ι and latent components μ and \tilde{h}_i

Block 2(a): Sampling ι

Following Del Negro and Primiceri (2015), the mixture indicators are sampled before the stochastic non-stationary volatility component. Specifically, we use Equation (A-3) and sample the indicator from its conditional probability mass

$$p(\iota_{i,t} = j | h_{i,t}, \epsilon_{i,t}) \propto q_j f_{\mathcal{N}}(\epsilon_{i,t} | 2h_{i,t} + m_j - 1.2704, \nu_j^2), \quad (\text{A-17})$$

with the values for q_j, m_j , and ν_j^2 taken from Omori, Chib, Shephard, and Nakajima (2007).

Block 2(b): Sampling \tilde{h}_i

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 unobserved state \tilde{h}_i based on a general state space model of the form

$$w_t = Z_t^M s_t^M + e_t, \quad e_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, H_t), \quad (\text{A-18})$$

$$s_{t+1} = R_0 + R_1 s_t + K_t v_t, \quad v_t \stackrel{i.i.d.}{\sim} \mathcal{N}(0, Q_t), \quad s_1 \stackrel{i.i.d.}{\sim} \mathcal{N}(a_1, A_1), \quad (\text{A-19})$$

where w_t is now a vector of observations and s_t an unobserved state vector. The matrices $Z_t, R_0, R_1, K_t, H_t, Q_t$ and the expected value a_1 and variance A_1 of the initial state vector s_1 are assumed to be known (conditioned upon). The vector s_t^M and the matrix Z_t^M are again restricted versions of s_t and Z_t with the elements excluded depending on the model indicators \mathcal{M} . The error terms e_t and v_t are assumed to

be serially uncorrelated and independent of each other at all points in time. As Equations (A-18)-(A-19) constitute a linear Gaussian state space model, the unknown state variables in s_t can be filtered using the standard Kalman filter. Sampling $s = [s_1, \dots, s_T]$ from its conditional distribution can then be done using the multimove simulation smoother of Carter and Kohn (1994) and De Jong and Shephard (1995).

We filter and sample the stochastic volatility terms $\tilde{h}_{i,t}$ (for $i = 1, \dots, N$) conditioning on the transformed series $g_{i,t} = \ln(\tilde{y}_{i,t}^2 + c)$ where

$$\tilde{y}_{i,t} = (y_{i,t} - \mu_{i,t} - \rho_{1,i}(y_{i,t-1} - \mu_{i,t-1}) - \rho_{2,i}(y_{i,t-2} - \mu_{i,t-2})) \exp\{\beta'_i x_{i,t}\}^{-1}, \quad (\text{A-20})$$

on the mixture indicators $\nu_{i,t}$ and on the parameters ϕ . More specifically, the unrestricted (i.e. $\delta_i = 1$) conditional state space representation is given by

$$\underbrace{\begin{bmatrix} g_t^k - (m_{\nu_{i,t}} - 1, 2704) - 2h_{i,0} \end{bmatrix}}_{w_t} = \underbrace{\begin{bmatrix} 2\delta_i \sigma_{h,i} \end{bmatrix}}_{Z_t^M} \underbrace{\begin{bmatrix} \tilde{h}_{i,t} \end{bmatrix}}_{s_t^M} + \underbrace{\begin{bmatrix} \tilde{\epsilon}_t^k \end{bmatrix}}_{e_t}, \quad (\text{A-21})$$

$$\underbrace{\begin{bmatrix} \tilde{h}_{i,t+1} \end{bmatrix}}_{s_{t+1}} = \underbrace{\begin{bmatrix} 1 \end{bmatrix}}_{R_1} \underbrace{\begin{bmatrix} \tilde{h}_{i,t} \end{bmatrix}}_{s_t} + \underbrace{\begin{bmatrix} 1 \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \tilde{\eta}_{i,t}^h \end{bmatrix}}_{\nu_t}, \quad (\text{A-22})$$

with $H_t = \nu_{i,t}^2$, $Q_t = 1$ and where $\tilde{\epsilon}_t^k = \epsilon_t^k - (m_{\nu_{i,t}} - 1, 2704)$ is ϵ_t^k recentred around zero. The random walk components \tilde{h}_t^k are initialised by setting $a_1 = 0$ and $A_1 = 0.0001$.

In the restricted model (i.e. $\delta_i = 0$), Z^M and s^M are empty. In this case, no forward-filtering and backward-sampling is needed and \tilde{h}_t^k can be sampled directly from its prior using Equation (5). Using draws for $h_{i,0}$, $\sigma_{h,i}$ and $\tilde{h}_{i,t}$, $h_{i,t}$ can easily be reconstructed from Equation (6).

Block 2(c): Sampling μ_i

We sample the unobserved state μ_i based on the general state space model from (A-18) and (A-19), where all elements are unrestricted. Conditioning on the observed series $y_{i,t}$, the time-varying volatility $h_{i,t}^* = \exp\{h_{i,t} + \beta' x_{i,t}\}$, and the parameters $\sigma_{\mu,i}^2$ and ρ_i , the state space representation is given by

$$\underbrace{\begin{bmatrix} y_{i,t} - \rho_{1,i}y_{i,t-1} - \rho_{2,i}y_{i,t-2} \end{bmatrix}}_{w_t} = \underbrace{\begin{bmatrix} 1 & -\rho_{1,i} & -\rho_{2,i} \end{bmatrix}}_{Z_t} \underbrace{\begin{bmatrix} \mu_{i,t} \\ \mu_{i,t-1} \\ \mu_{i,t-2} \end{bmatrix}}_{s_t} + \underbrace{\begin{bmatrix} \epsilon_{i,t} \end{bmatrix}}_{e_t}, \quad (\text{A-23})$$

$$\underbrace{\begin{bmatrix} \mu_{i,t+1} \\ \mu_{i,t} \\ \mu_{i,t-1} \end{bmatrix}}_{s_{t+1}} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}}_{R_1} \underbrace{\begin{bmatrix} \mu_{i,t} \\ \mu_{i,t-1} \\ \mu_{i,t-2} \end{bmatrix}}_{s_t} + \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}}_{K_t} \underbrace{\begin{bmatrix} \eta_{i,t}^\mu \end{bmatrix}}_{\nu_t}, \quad (\text{A-24})$$

with H_t a matrix with diagonal elements $\exp\{h_{i,t}^*\}^2$, $Q_t = \sigma_{\mu,i}^2$, and where $\mu_{i,t}$ is diffusely initialised by setting $a_1 = 0$ and $A_1 = 10$.

Block 3: Random sign switch on σ_h and \tilde{h}

For each cross section, a random sign switch is performed on $\sigma_{h,i}$ and $\{\tilde{h}_i\}_{t=1}^T$ with probability 0.5.

APPENDIX B. MONTE CARLO SIMULATION

This appendix presents the results of a Monte Carlo simulation in order to demonstrate the effectiveness of our unobserved components model in revealing the link between the volatility of a stochastic process and a (possibly incomplete) set of non-stationary explanatory variables. To this end, we consider the following data generating process (DGP):

Model (DGP):

$$y_{i,t} = \exp(h_{i,t}^*)\varepsilon_{i,t} \quad (\text{A-25})$$

$$h_{i,t}^* = x'_{i,t}\beta_i \quad (\text{A-26})$$

$$x_{i,t}^k = x_{i,t-1}^k + u_{i,t}^k \quad \forall k = 1, \dots, K \quad (\text{A-27})$$

$$\varepsilon_{i,t} \sim N(0, 1), \quad u_{i,t}^k \sim N(0, \sigma_{u,i}^2) \quad (\text{A-28})$$

In order to keep the analysis brief we will consider only two exogenous regressors ($K = 2$) in the volatility Equation (A-26) of the DGP. The shock variance for the random walk processes of the explanatory variables is set to: $\sigma_{u,i}^2 = 0.1^2$. Moreover, x_2 will be considered an unobserved I(1) variable, i.e. only β_1 will be estimated. While the estimated model always allows for heterogeneous coefficients and hence mean group estimates will be reported, we distinguish between homogeneous and heterogeneous parameters in the DGP. More specifically, in the homogeneous case we impose identical true parameter values across countries, i.e. $\beta_i = \beta \forall i = 1, \dots, N$. Depending on the values of $\beta = [\beta_1 \ \beta_2]'$ we can distinguish three scenarios.

1) Spurious regression: $\beta = [0 \ 1]'$: h^* and x_1 are independent random walks.

2) Cointegration: $\beta = [1 \ 0]'$: h^* and x_1 are cointegrated.

3) Long-run relation but no cointegration: $\beta = [1 \ 1]'$: omitted I(1) variable.

In the heterogeneous case, i.e. $\beta_i = [\beta_{1i} \ \beta_{2i}]'$, the coefficients are independently drawn from $\mathcal{N}(1, 0.25^2)$ or set to zero depending on the scenario under consideration. Finally, we distinguish between an uncorrelated unobserved I(1) component and one that induces cross-sectional dependence. In the former case x_2 is independent across countries. In the latter case x_2 is identical across countries and hence acts as a common factor whereas β_{2i} now represents a country-specific loading. For each scenario we generate $M = 2000$ samples using the DGP as described above.

The model parameters are estimated for each of these samples using the Gibbs sampling approach outlined in Section 2 and APPENDIX A.¹⁶ The estimated model specification is a slightly simplified version of the stochastic volatility model (SV) presented in Section 2 where the time-varying intercept and the AR terms in the mean Equation (1) are dropped to match the DGP. The prior distributions for the model parameters are given in Table A-1. These priors are very loose in order to demonstrate the robustness of our approach to situations, where there is large uncertainty about parameters values.

¹⁶The number of Gibbs iterations is set to 3000 with 1000 iterations being discarded as "burn-in".

Table A-1: Prior distributions Monte Carlo simulation

Name	Description	Density	Specification	
			a_0	$\sqrt{A_0}$
$\beta_{1,i}$	Slope coefficients	$\mathcal{N}(a_0, A_0)$	true value	10.0
$h_{i,0}$	Constant country-specific volatility	$\mathcal{N}(a_0, A_0)$	0.0	1.0
$\sigma_{h,i}$	Std. of latent I(1) component	$\mathcal{N}(a_0, A_0)$	0.0	1.0
			Success rate p	
$p(\delta_i = 1)$	Inclusion probability of latent I(1) component	Bern(p)	0.5	

Notes: The prior mean for β_1 equals the true value of the data generating process. In the homogeneous case this is 0 in the spurious regression case and 1 otherwise. In the heterogeneous case this is again 0 in the spurious regression case. Otherwise, the prior mean for each cross section equals the drawn β_i .

We start by discussing the results of the scenario where the unobserved I(1) component is cross-sectionally independent. Table A-2 presents summary results of our Monte Carlo study over all iterations. The left hand side refers to the model, where the true parameters are homogeneous, whereas the right hand side shows results of the model with heterogeneous parameters in the DGP. First of all, the UC model provides an unbiased estimate of $\mathbb{E}[\beta_1] = \frac{1}{N} \sum_{i=1}^N \beta_{1i}$ in both cases. In addition, the UC model allows for correct inference under all three scenarios. The error rate, given by the fraction of MC iterations for which the 95% credible interval does not contain the true population value, equals (or comes very close to) the theoretically expected 5%. This is in line with the Bayesian interpretation of an x% credible interval, which holds the true population value (given completely uninformative priors) with probability of x%. The stochastic model specification search (SMSS) becomes more precise as T grows large whereas it should be noted that the precision obviously depends on the strength of the signal in the data.¹⁷

The model we propose, where the volatility of a stochastic process is determined by both observed exogenous regressors and an unobserved I(1) component is highly non-standard. Estimation of stochastic volatility models (SV) in general poses a challenge due to the unobservability of the volatility process and the fact that the latter is not purely deterministic, as for example in ARCH/GARCH models. The commonly used approach to estimate SV models are Bayesian Markov Chain Monte Carlo (MCMC) methods as developed in Kim, Shephard, and Chib (1998). However, augmenting the volatility equation by including explanatory variables causes further complications as the application of standard estimators for non-stationary panels is problematic in a MCMC setting. In standard non-stationary panel regressions, the mean group estimator provides asymptotically correct inference when using the non-parametric estimator for the covariance matrix of the mean group estimator as derived in Pesaran and Smith (1995). This also holds in case of omitted non-stationary variables. Coakley, Fuertes, and Smith (2001) present Monte Carlo evidence for the performance of the mean group estimator in non-stationary panels with (uncorrelated) integrated errors. In strong contrast to this, the sampling-based approach used in this paper causes the mean group estimator to be inconsistent when the error term is indeed non-stationary. In particular, Gibbs sampling requires country-by-country sampling of the individual coefficients β_i as outlined in **APPENDIX A** which are then used to compute the mean group estimator. If the non-stationarity in the error term is not explicitly modelled, each β_i will be sampled from an erroneous distribution. Consequently, the mean group estimator based on these individual β_i will also be inconsistent. This is clearly different from a standard panel regression where no sampling is required and only the point estimates of the β_i are used to obtain the mean group estimator. Importantly, inference on the mean group estimator is not based on the (inconsistently estimated) standard errors of the individual β_i . By explicitly modelling omitted non-stationary variables, our model restores correct inference on the individual β_i and thus allows for correct sampling. This in turn leads to the correct posterior distribution for the mean group estimator.

¹⁷In our baseline simulation the shock variances of both the observed and the unobserved I(1) variable are identical. If the shock variance of the unobserved I(1) variable would be relatively higher, average indicator values would increase in small samples.

Table A-2: Results Monte Carlo simulation: Independent omitted I(1) variable

Scenario	N	T	UC model (DGP: homogeneous slopes)					UC model (DGP: heterogeneous slopes)				
			bias	SE	rmse	error	SMSS	bias	SE	rmse	error	SMSS
Spurious regression	1	50	0.00	0.91	0.91	0.05	0.27	-0.02	0.96	0.96	0.06	0.29
		100	-0.01	0.66	0.66	0.12	0.35	-0.02	0.66	0.66	0.12	0.36
		250	0.01	0.39	0.39	0.11	0.75	0.01	0.38	0.38	0.12	0.72
		500	0.00	0.26	0.26	0.06	0.97	0.01	0.26	0.26	0.07	0.94
	5	50	0.00	0.42	0.42	0.05	0.27	-0.01	0.41	0.41	0.05	0.27
		100	0.01	0.29	0.29	0.09	0.34	0.01	0.29	0.29	0.08	0.34
		250	0.00	0.17	0.17	0.07	0.74	0.00	0.17	0.17	0.07	0.72
		500	0.00	0.11	0.11	0.05	0.97	0.00	0.11	0.11	0.05	0.94
	10	50	0.00	0.30	0.30	0.05	0.26	0.00	0.29	0.29	0.05	0.27
		100	-0.01	0.20	0.20	0.07	0.35	-0.01	0.20	0.20	0.07	0.35
		250	0.00	0.12	0.12	0.07	0.74	0.00	0.12	0.12	0.07	0.71
		500	0.00	0.08	0.08	0.05	0.97	0.00	0.08	0.08	0.06	0.94
	25	50	-0.01	0.18	0.18	0.04	0.27	0.00	0.18	0.18	0.04	0.27
		100	0.00	0.13	0.13	0.07	0.35	0.00	0.13	0.13	0.07	0.35
		250	0.00	0.08	0.08	0.07	0.74	0.00	0.08	0.08	0.07	0.72
		500	0.00	0.05	0.05	0.06	0.97	0.00	0.05	0.05	0.06	0.94
Cointegration	1	50	-0.01	0.74	0.74	0.02	0.20	-0.01	0.74	0.74	0.02	0.19
		100	-0.01	0.43	0.43	0.03	0.12	0.00	0.50	0.42	0.04	0.11
		250	0.00	0.19	0.19	0.04	0.06	0.00	0.31	0.18	0.04	0.06
		500	0.00	0.09	0.09	0.06	0.04	-0.01	0.28	0.14	0.06	0.05
	5	50	-0.01	0.33	0.33	0.02	0.19	-0.01	0.35	0.33	0.02	0.19
		100	0.00	0.19	0.19	0.03	0.12	0.00	0.22	0.19	0.03	0.12
		250	0.00	0.08	0.08	0.04	0.06	0.00	0.14	0.08	0.04	0.06
		500	0.00	0.05	0.04	0.05	0.03	-0.01	0.12	0.04	0.06	0.04
	10	50	0.00	0.23	0.23	0.02	0.19	0.00	0.25	0.23	0.02	0.19
		100	0.00	0.13	0.13	0.03	0.12	0.00	0.15	0.13	0.03	0.12
		250	0.00	0.06	0.06	0.04	0.06	0.00	0.10	0.06	0.04	0.06
		500	0.00	0.04	0.03	0.05	0.03	-0.01	0.09	0.03	0.05	0.04
	25	50	-0.01	0.15	0.14	0.01	0.19	-0.01	0.15	0.14	0.01	0.19
		100	0.00	0.09	0.08	0.02	0.12	0.00	0.10	0.08	0.03	0.12
		250	0.00	0.04	0.04	0.05	0.06	0.00	0.07	0.04	0.05	0.06
		500	0.00	0.03	0.02	0.06	0.04	-0.01	0.06	0.02	0.07	0.04
Omitted I(1) variable	1	50	-0.01	0.90	0.90	0.05	0.27	-0.02	1.07	1.07	0.08	0.34
		100	-0.03	0.64	0.64	0.12	0.36	-0.04	0.68	0.63	0.11	0.35
		250	0.01	0.38	0.38	0.11	0.74	0.01	0.45	0.38	0.11	0.72
		500	-0.01	0.25	0.25	0.07	0.97	-0.02	0.37	0.27	0.07	0.94
	5	50	-0.01	0.41	0.41	0.04	0.27	-0.01	0.43	0.41	0.04	0.27
		100	0.00	0.29	0.29	0.09	0.34	0.00	0.32	0.30	0.09	0.34
		250	-0.01	0.17	0.17	0.07	0.74	-0.01	0.20	0.17	0.07	0.71
		500	-0.01	0.11	0.11	0.05	0.97	-0.02	0.16	0.11	0.05	0.94
	10	50	0.00	0.29	0.29	0.04	0.26	0.00	0.31	0.29	0.05	0.27
		100	-0.02	0.20	0.20	0.07	0.35	-0.01	0.22	0.20	0.07	0.35
		250	-0.01	0.13	0.12	0.07	0.74	-0.01	0.15	0.12	0.07	0.71
		500	-0.01	0.08	0.08	0.06	0.97	-0.02	0.11	0.08	0.06	0.94
	25	50	-0.01	0.18	0.18	0.04	0.27	-0.01	0.18	0.18	0.03	0.27
		100	0.00	0.13	0.13	0.07	0.35	0.00	0.14	0.13	0.08	0.35
		250	-0.01	0.08	0.08	0.07	0.74	-0.01	0.09	0.08	0.07	0.71
		500	-0.01	0.06	0.05	0.07	0.97	-0.02	0.07	0.06	0.07	0.94

Notes: Bias, SE, and rmse are the Monte Carlo mean bias, standard error, and root mean squared error of β_1 , respectively. Error refers to the error rate, i.e. the fraction of Monte Carlo iterations for which the 95% credible interval does not contain the true population value. SMSS is the mean indicator value over cross sections and Monte Carlo iterations.

Table A-3: Results Monte Carlo simulation: Cross-sectionally dependent omitted I(1) variable

Scenario	N	T	UC model (DGP: homogeneous slopes)					UC model (DGP: heterogeneous slopes)				
			bias	SE	rmse	error	SMSS	bias	SE	rmse	error	SMSS
Spurious regression	1	50	0.00	0.92	0.92	0.05	0.27	0.00	0.96	0.96	0.06	0.29
		100	0.01	0.64	0.64	0.11	0.35	0.01	0.63	0.63	0.11	0.35
		250	0.00	0.38	0.38	0.12	0.75	0.01	0.39	0.39	0.12	0.71
		500	0.00	0.26	0.26	0.07	0.97	0.00	0.25	0.25	0.07	0.94
	5	50	0.00	0.41	0.41	0.04	0.27	0.00	0.41	0.41	0.04	0.27
		100	0.01	0.29	0.29	0.08	0.34	0.00	0.29	0.29	0.07	0.35
		250	0.00	0.17	0.17	0.07	0.75	0.00	0.17	0.17	0.08	0.72
		500	0.00	0.12	0.12	0.06	0.97	0.00	0.12	0.12	0.06	0.95
	10	50	0.00	0.30	0.30	0.04	0.26	0.01	0.30	0.30	0.04	0.27
		100	0.00	0.20	0.20	0.07	0.35	0.00	0.20	0.20	0.07	0.35
		250	0.00	0.12	0.12	0.07	0.74	0.00	0.12	0.12	0.07	0.71
		500	0.00	0.08	0.08	0.05	0.97	0.00	0.08	0.08	0.04	0.95
	25	50	0.00	0.19	0.19	0.04	0.27	0.00	0.19	0.19	0.04	0.27
		100	0.01	0.13	0.13	0.07	0.34	0.00	0.13	0.13	0.07	0.35
		250	0.00	0.08	0.08	0.07	0.74	0.00	0.08	0.08	0.07	0.71
		500	0.00	0.05	0.05	0.05	0.97	0.00	0.05	0.05	0.05	0.94
Cointegration	1	50	0.00	0.76	0.76	0.02	0.19	-0.01	0.76	0.76	0.02	0.20
		100	0.00	0.41	0.41	0.04	0.12	0.01	0.48	0.41	0.04	0.12
		250	0.00	0.18	0.18	0.04	0.06	0.00	0.31	0.18	0.04	0.07
		500	0.00	0.09	0.09	0.05	0.04	-0.01	0.26	0.10	0.06	0.04
	5	50	-0.01	0.33	0.33	0.02	0.19	-0.02	0.34	0.32	0.01	0.19
		100	0.00	0.19	0.19	0.03	0.12	0.00	0.22	0.19	0.03	0.12
		250	0.00	0.08	0.08	0.04	0.06	0.00	0.14	0.08	0.04	0.06
		500	0.00	0.05	0.04	0.05	0.03	-0.01	0.12	0.04	0.05	0.04
	10	50	0.01	0.24	0.24	0.02	0.19	0.01	0.25	0.23	0.02	0.19
		100	0.00	0.13	0.13	0.03	0.12	0.00	0.16	0.13	0.03	0.12
		250	0.00	0.06	0.06	0.05	0.06	0.00	0.10	0.06	0.05	0.06
		500	0.00	0.03	0.03	0.05	0.03	0.00	0.09	0.03	0.05	0.04
	25	50	0.00	0.15	0.15	0.02	0.19	0.00	0.16	0.15	0.02	0.19
		100	0.00	0.09	0.08	0.03	0.12	0.00	0.10	0.08	0.03	0.12
		250	0.00	0.04	0.04	0.05	0.06	0.00	0.07	0.04	0.04	0.06
		500	0.00	0.03	0.02	0.06	0.04	-0.01	0.06	0.02	0.06	0.04
Omitted I(1) variable	1	50	0.01	0.92	0.92	0.05	0.27	0.00	1.05	1.05	0.08	0.34
		100	-0.01	0.63	0.63	0.11	0.35	-0.01	0.66	0.61	0.10	0.35
		250	0.00	0.39	0.39	0.11	0.74	0.00	0.46	0.38	0.10	0.72
		500	-0.01	0.25	0.25	0.06	0.97	-0.02	0.34	0.26	0.08	0.95
	5	50	-0.01	0.41	0.41	0.04	0.27	0.00	0.42	0.40	0.03	0.27
		100	0.00	0.29	0.29	0.08	0.34	0.00	0.32	0.29	0.08	0.35
		250	-0.01	0.17	0.17	0.08	0.75	-0.01	0.21	0.18	0.08	0.71
		500	-0.02	0.12	0.12	0.07	0.97	-0.01	0.17	0.12	0.06	0.94
	10	50	0.01	0.29	0.29	0.05	0.26	-0.01	0.30	0.28	0.04	0.27
		100	-0.01	0.21	0.20	0.07	0.35	-0.01	0.22	0.20	0.07	0.34
		250	0.00	0.12	0.12	0.07	0.73	-0.01	0.14	0.12	0.07	0.70
		500	-0.02	0.08	0.08	0.06	0.97	-0.02	0.12	0.08	0.06	0.94
	25	50	0.00	0.18	0.18	0.04	0.27	-0.01	0.20	0.19	0.04	0.27
		100	0.00	0.13	0.13	0.07	0.34	0.00	0.14	0.13	0.07	0.34
		250	-0.01	0.08	0.08	0.07	0.74	-0.01	0.10	0.08	0.08	0.70
		500	0.00	0.05	0.05	0.05	0.97	-0.01	0.08	0.07	0.08	0.95

Notes: Bias, SE, and rmse are the Monte Carlo mean bias, standard error, and root mean squared error of β_1 , respectively. Error refers to the error rate, i.e. the fraction of Monte Carlo iterations for which the 95% credible interval does not contain the true population value. SMSS is the mean indicator value over cross sections and Monte Carlo iterations.

Next, we present results when allowing the unobserved I(1) component to induce cross-sectional dependence in the volatility equation. This scenario possesses great relevance for practical economic applications where global factors which influence all countries are often unobserved and thus difficult to include into econometric models. Since countries can load differently on these unobserved common factors, time fixed effects are mostly inappropriate to capture these. As can be seen from Table A-3, results for the UC model remain essentially unchanged both in terms of bias and inference. This is not surprising as the UC model includes an independent random walk component for each cross section. Ex ante no cross-country correlation is imposed on these components. However, ex post these unobserved components can be correlated. This is exactly what makes the UC approach robust to whether the omitted I(1) variable in the DGP induces cross-sectional dependence.

Summing up, this Monte Carlo simulation shows that the approach of Everaert (2011) is appropriate to correctly identify the link between two (or more) I(1) variables even if relevant non-stationary variables are omitted from the model. Moreover, the performance is unaffected by the presence of cross-sectional dependence. In particular, the approach works well in a stochastic volatility setting as applied in this paper where standard estimators are not available.

APPENDIX C. DATA

This appendix elaborates on how the dataset used in Section 2 was composed. While most variables are obtained from standard macroeconomic databases, we focus on how average effective tax rates on capital income, consumption, and labour income were computed. Table A-4 contains variable descriptions along with the corresponding sources.

Table A-4: Data description and sources

Variable	Description	Source
<i>y</i>	Annual growth rate of real GDP	World Bank national accounts data
<i>age</i>	Share of the working age population (15-64) aged 15-29 and 60-64, see Jaimovich and Siu (2009)	World Population Prospects: The 2015 Revision
<i>openness</i>	Sum of exports and imports as a share of GDP	World Bank national accounts data
<i>govsize</i>	General government final consumption expenditure as a share of GDP	World Bank national accounts data
<i>captax</i>	Average tax rate on capital income	} McDaniel (2007) & Posch (2011) & authors' calculations following Mendoza, Razin, and Tesar (1994)
<i>contax</i>	Average tax rate on consumption expenditures	
<i>labtax</i>	Average tax rate on labour income (incl. payroll tax and tax on household income)	

The major part of our dataset on effective tax rates is identical with the dataset of Posch (2011) who follows Mendoza, Razin, and Tesar (1994) in computing average effective tax rates for 22 OECD economies over the period 1970-2007. We augment this dataset for the 1960s by the tax rates of McDaniel (2007) which are however only available for 15 out of the 22 countries. In order to take into account the most recent years as well, we compute tax rates using the method proposed by Mendoza, Razin, and Tesar (1994), which builds on the OECD Revenue Statistics and national accounts data. Unfortunately, not all necessary time series are available from the OECD database. To be more specific,

- Wages and salaries (W): Not available for Australia and New Zealand (replaced by compensation of employees, received).
- Government final consumption expenditure (G): Not available from OECD database for Canada,

New Zealand, and Switzerland. Replaced by series obtained from the Federal Reserve Economic Data (FRED) database.

- Compensation of government employees: Not available for Australia.
- Operating surplus of private unincorporated enterprises: Not available for Korea and New Zealand.
- Household's property and entrepreneurial income (PEI) defined as,
PEI = Mixed income (gross) - consumption of fixed capital + property income - interests paid - (land) rents paid. For Australia and Canada: Only property income available. For Korea and New Zealand: only property income - interest paid - (land) rents paid available.

In order to be able to assess the impact of these missing series, we computed tax rates for the period 1995-2014. This allows for various consistency checks with the dataset of Posch (2011) by comparing the evolution of tax rates for the period 1995-2007 in both datasets. Since the number of missing series is very limited and no essential data is missing, both series evolve very similar and are for some countries, if any, characterised by a level difference. We normalise our tax rates such that both series have identical values in 2007. This removes the level difference (if existing) while preserving the dynamic pattern and provides us with a consistent (unbalanced) panel dataset covering the period 1961-2014.

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