FORECASTING AND ANALYSING CORPORATE TAX REVENUES IN SWEDEN USING BAYESIAN VAR MODELS*

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Abstract

Corporate tax revenue forecasts are important for governmental agencies, but are complicated to achieve with high precision and generally also difficult to connect to governments' macroeconomic forecasts. This paper proposes a solution to these problems by decomposing corporate tax revenues and connecting the components to different determinants using Bayesian VAR models. Applied to Sweden, we find that most of the variation in forecasting errors of net operating surplus and net business income are attributable to shocks in factors identified in the literature, and that the forecasting performance is improved by conditioning on the macroeconomic development. (JEL: C53, H25, H68).

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1. Introduction

It is generally of central importance for governments to improve the accuracy of corporate tax revenue forecasts, since they typically constitute an important source of income in the central budget.[1] More precise forecasts will usually improve the overall forecast of central budget income, and thus contribute to a more reliable basis for government planning. Moreover, emphasising consistency, governments are inclined to connect budget forecasts to in-house macroeconomic forecasts within a coherent framework. In this respect, connecting corporate tax revenue to the macroeconomic development could increase the overall understanding and be used for policy purposes and risk assessments. Previous studies have shown that decomposing corporate tax revenues is valuable to understand its development. The purpose of this paper is to provide a framework that connects a decomposition of corporate tax revenues to macroeconomic forecasts, via corporate earnings. In this particular study, we consider corporate tax revenue forecasts in Sweden, which is a small open economy. However, we propose that the framework may be applied to any other economy, as long as necessary adjustments are made to the included variables.

Forecasting corporate tax revenues, as with any macroeconomic aggregate, is subject to a high degree of uncertainty. In Sweden, corporate tax revenue is among the taxes with the largest forecast errors, as stated by The Swedish National Audit Office (2007). There are some distinctive considerations and difficulties when forecasting and analysing corporate tax revenues. *First*, Corporate incentives, behaviour and ability to reduce their taxable profits are many and significant. Tax codes vary among countries, but do often allow corporates to make deductions, allocations, group contributions, offsetting of taxes paid abroad, etcetera. This makes it difficult to connect firms' accounting profit to their taxable profit as determined by the tax authorities. *Second*, corporates' taxes are settled with a considerable delay. In Sweden, the tax on corporate profits is settled in December of the year after the income year.[2] The long lag between forecast and outcome causes therefore great difficulties in forecasting corporate tax revenues. *Third*, corporates can minimize their tax payments by changing their financing strategy. In Sweden, the capital cost of assets financed with borrowed capital is lower than for assets financed with equity because corporates are allowed to make deductions for their interest costs. This provides incentives for debt financing of investments. *Fourth*, in a small open economy with many multinational companies, tax payments can be further minimized, for example through transfer pricing of intra-group transaction, and shifts in location of taxable activities due to establishment of subsidiaries in a particular country. Such decisions can be hard to predict, but are often related to taxes, prices, wages, requirements for construction, legislation governing cross-border trade, and legal protections governing investors, contracts, insolvencies, and so on. *Fifth,* data of corporate tax revenues are often observed in a low frequency, normally yearly, with a small number of data points, resulting in difficulties of accurate modelling, such as running in to scarce degrees of freedom for statistical models.

Given the aforementioned difficulties, the structural decomposition of tax receipts tends to also vary over time. A number of studies have demonstrated this. For instance, Auerbach and Poterba (1987) developed a methodology for decomposing and attributing changes in corporate tax revenues to different sources, and showed that falling average tax rates and a decline in profitability have contributed to lower corporate taxes. Desai (2003) examines the relationship between book income and tax income and demonstrates that this relationship

1 In 2014, Swedish state revenues from the corporate income tax amounted to SEK 97 billion, representing 5.8 per cent of total tax revenue. The OECD continuously makes a compilation of various tax revenues as share of GDP (https://stats.oecd.org). The Swedish corporate tax revenue was 2.6 percent in 2014, which was also the average corporate tax revenue among all OECD countries, ranging between 0.4 and 7.1 percent.

2 A first preliminary outcome is available in August.

has broken down because of different treatments of depreciation, the reporting of foreign source income, and in particular the changing nature of employee compensation. Auerbach (2007) uses the same decomposition as in Auerbach and Poterba (1987) and finds offsetting trends in the ratio of profits to GDP (which is declining over time) and in the average tax on profits (which is increasing over time). Dyreng et al. (2017) finds even at the microeconomic level a clear decrease in effective tax rates.

Quite naturally, decomposing tax revenues in line with some of the previous studies might lead to insights also in terms of forecasting. In this paper, we therefore make a decomposition based on the definition of corporate tax receipts, and then tie the macro economy to the components using Bayesian vector autoregressive (BVAR) models. This is done in several steps: First, we estimate a quarterly BVAR model for net operating surplus and its determinants. Second, we bridge net operating surplus and estimate a yearly BVAR model for net business income, that is, the tax base, and tax adjustments made by the corporates and discretionary fiscal policy measures within the area of corporate taxation. Output from the second BVAR model is then used to forecast and analyse the tax base, which, in turn, may be extrapolated to forecast corporate tax revenues. In a small forecast evaluation, the extrapolations from the BVAR forecasts are compared with direct tax revenue forecasts from a mixed data sampling (MIDAS) equation and typical naïve forecasts from simple integrated autoregressive models with exogenous variables (ARIX). Our tax revenue sample is small. However, the results suggest that (i) a considerable part of the variation in forecasting errors of the net operating surplus, as well as net business income, can be attributed to shocks in the factors identified in the literature, (ii) the forecasting performance for these variables can be improved when the forecasts are conditioned on the macroeconomic development, and (iii) combining forecasts from BVAR, MIDAS and ARIX is an appropriate approach for corporate tax revenue forecasting. Standard sensitivity and scenario analyses indicate that the BVAR models are robust and produce reasonable conditional forecasts. We therefore propose that the empirical framework proposed in this paper is reliable and can be used as a policy tool to forecast and analyse corporate tax revenues.

The rest of the paper has the following structure. Section 2 motivates the choice of models. Section 3 defines corporate tax revenues and uses its main determinants found in the literature to discuss the variable selection. Section 4 introduces the BVAR framework. Section 5 summarises the empirical findings and investigates the robustness of the results in a sensitivity analysis. Section 6 concludes. Time series graphs for the included variables are collected in Appendix A, and tables related to the sensitivity analysis are collected in Appendix B.

2. Motivation behind the choice of empirical models

The academic literature on tax revenue forecasting is scarce. However, according to Jenkins et al. (2000), the main methods used to forecast corporate tax revenues, in various ministries of finance and other agencies, are (i) the extrapolation of tax revenue method, (ii) the underlying tax development method, (iii) the auditing method, (iv) the elasticity method and (v) macroeconomic regression models. The extrapolation of tax revenue method uses ARIMA models to estimate the development of tax revenue. The underlying tax development method estimates the 'structural' or 'underlying' tax base, after which information on tax rules, legislation and corporate tax behaviour are used to calculate the underlying corporate tax revenue. The auditing methodology uses the difference between the calculated tax and extra tax paid by the firm when the tax is settled on the audit day to make assessments about the tax revenue level. The elasticity method is a conditional projection, where the future tax revenue is calculated based on a starting point, combined with an estimate of the ratio of the change in tax revenues and the change in the appropriate macroeconomic variable (see, for instance, Wolswijk, 2007). Finally, macroeconomic regression models estimate functional relationships between sets of macroeconomic variables and the tax revenue in question.

Concerning macroeconometric time series models, Baghestani and McNown (1992) assume that expenditures and revenues are random walks and estimate integrated autoregressive models, such as ARIMA models, cointegrated VAR models, and error-correction models, and show that, in general, such models have good predictive abilities compared with official forecasts. A decade later, Basu et al. (2003) evaluated the different forecast methods for corporate tax and showed that expert judgment forecasts tend to outperform strict model-based projections for short forecast horizons. Gamboa (2002) came on the other hand to the overall conclusion that the elasticity method is preferable.

The extrapolation method, the elasticity methods and macroeconomic regression models do not fully take into consideration the interaction between tax revenues, the underlying base and the macro economy. Certainly, this interaction is important for structural analyses, which are generally conducted by governmental agencies. In this paper, we stress that tax revenues can be decomposed. The main components are then tied to the macro economy using BVAR models, which tend to have high forecasting precision compared with classical VAR models; especially when the number of predictors is large (see, e.g., Krol, 2010). In doing so, we wish to not only improve the corporate tax revenue forecast (or nowcast) ability, but also enable consistency between institutions' corporate tax revenue forecasts and their assessments of the macroeconomic outlook.

3. Determinants of corporate tax revenues

For any given year, the corporate tax revenues (*TAX*) in Sweden are by definition calculated as

(1) $TAX_t = \tau \times \max(0, NBI_t) + ROT_t$,

where τ is the corporate tax rate, *ROT* (reduction of taxes) is adjustment for taxes paid by the companies in other countries, *NBI* (net business income) is the taxable income (often referred to as the tax base) and max(a, b) is function which returns the maximum value of the real numbers a and b. Equation (1) is simply based on the income tax return that limited liability companies, economic associations, etc., fill in each year and send to the Swedish Tax Agency.

Based on Equation (1), a forecast at horizon h for the corporate tax revenue in levels could be found from

(2) $\widehat{TAX}_{t+h} = \tau \times \max(0, \widehat{NBI}_{t+h}) + \widehat{ROT}_{t+h}$,

provided we have forecasts for the net business income, $\widehat{NBI}_{t+h}$, and the reduction of taxes, $\widehat{ROT}_{t+h}$. The main idea in this paper is to divide the forecast for *TAX* into one part which we believe is conditionally forecastable from the macro economy, namely *NBI*, and one part which we believe is not, namely *ROT*. Because the current tax rate τ is known, and its future path is controlled by the government, we treat it as a known constant. We will also find it useful to express the nominal variables in Equation (1) as shares of nominal GDP. Their developments in Sweden 1995–2014 are shown in Figure 1. By construction, *TAX* and *NBI* tend to move together. Yet, we believe they should have slightly different characteristics. Because corporate profits is related to economic activity and cannot increase more than the growth in the economy over a longer time period, *NBI* as share of GDP should behave as a bounded stationary process. Meanwhile, *ROT* is an irregular component that depends on time-varying structural factors in different countries (see Section 1). We will therefore make the explicit assumption that the spread between *NBI* and *TAX* is driven by the constant τ and a bounded random walk *ROT*. That is, we assume that *TAX* (as share of GDP) is the sum of a scaled bounded stationary process and a bounded non-stationary (random walk) process, so that *TAX* is itself a bounded non-stationary process,

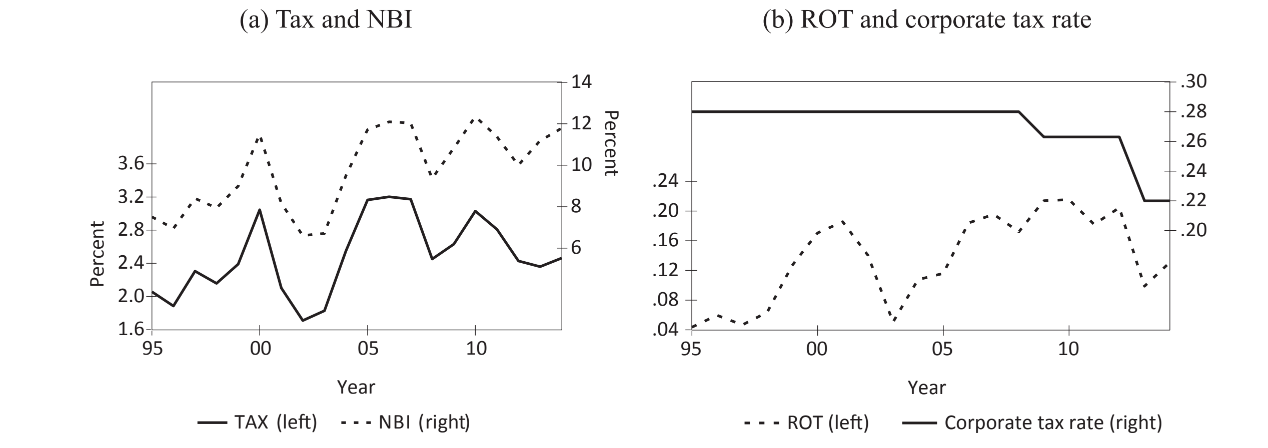

Figure 1. Elements of corporate tax revenues as shares of GDP 1995–2014
Source: The Swedish Tax Agency and the Swedish Ministry of Finance.

with random walk-like behaviour. In essence, this is in line with Baghestani and McNown (1992), who explicitly assume that revenues are random walks. Note that *ROT* is much smaller in size than *NBI*. Hence, even when our assumptions are correct, the dominant force in *TAX* is still a stationary process. For forecasting purposes, our assumptions imply that we should use the latest observed value on *ROT* as its forecast at any horizon, $\widehat{ROT}_{t+h} = ROT_t$, for all h.[3] Meanwhile, we will link *NBI* to the macro economy as follows.

By definition, *NBI* is calculated by adjusting companies' earnings before interest and tax (*EBIT*) for different tax adjustments (*TA*),

(3) $NBI_t = EBIT_t + TA_t$.

Unfortunately, aggregated information of *EBIT* and *TA* are not available from the Swedish official statistics. Therefore, in this paper, net operating surplus is used as a proxy for *EBIT,* whereas *TA* is approximated by the sum of net allocations to tax allocation reserves (including imputed income applied to tax allocation reserves) and loss carry forwards.[4] Whereas *EBIT* exists in both annual and quarterly frequency, *NBI* and (the approximation of) *TA* exist only in annual frequency. Because macroeconomic data is available on quarterly frequency, we will forecast *EBIT* through the macro economy. This forecast will then be bridged to forecast *NBI*. The model setup for this is specified in Section 4.

In what follows, we motivate the variables used to forecast *EBIT*. All selected variables, including those that are used to model *NBI*, are shown in Table 1, together with their means and standard deviations, after suitable transformations.

Financial markets: According to the academic literature, the cost of capital and labour is of central importance for firms' investment decisions, production capacity and profits (see, e.g., Copeland and Weston, 2004). In addition, this literature emphasises the importance of including some variables that capture credit availability and stress in the financial markets. The lending rate (*LR*) is the interest rate firms actually pay for their loans, and is a central variable for the cost of capital. It is expressed

3 The Dickey-Fuller test cannot reject the null hypothesis of a unit root in ROT at the 5 % significance level.

4 Net operating surplus is defined as the value added after deducting compensation of employees, taxes on production and imports less subsidies, and depreciation. At the company-level, net operating surplus may differ from profits shown on an accounting basis for several reasons, in particular as only a subset of total costs are subtracted from net output to arrive at national accounts estimate of net operating surplus.

as an average of the lending rates offered to companies for different maturities. The share price deviation from its historical trend (the share price gap, *XGAP*) is used as a proxy for stock market development and return on equity. The share price gap is defined as the deviation of the Stockholm OMX index from its trend, divided by the trend. The real share price gap captures whether developments in the stock market are following the historical trend. Here, the trend is calculated through a one-sided HP filter with the help of a smoothing parameter lambda equal to 400,000, as suggested by Drehmann et al. (2010). The credit gap (*CGAP*) is used to identify possible credit constraints. It is constructed technically in the same way as the share price gap. As a first step the credit ratio is generated (lending to the corporates in relation to GDP at current prices). The credit gap is then defined as the deviation of the credit ratio from its trend, divided by the trend. The financial stress index measures uncertainty in financial markets, which is considered to be important for corporates' option to postpone their investments. The index is an average of (i) stock market volatility, (ii) currency market volatility, (iii) the interest rate spread between housing and government bonds, and (iv) the interest rate spread between the interbank rate and the interest rate on treasury bills.

Macro domestic: GDP growth (at market and constant prices) in Sweden (*GDP*) is used to measure the increase in demand for firms' products. Inflation is used to measure domestic purchasing power and demand for firms' products, as high inflation undermines the value of money. Higher inflation contributes to firms' profits by increasing their incomes and costs in nominal terms, and may decrease their willingness to invest. The inflation is calculated using the consumer price index with fixed interest rate (*CPIF*). The real effective exchange rate (*KIX*) is included, since Sweden is a small open economy. The real exchange rate captures uncertainty about domestic purchasing power and the demand for corporates' products. It is a weighted average for the 16 largest trading partners of Sweden, where the weights are calculated according to Erlandsson and Markowski (2006).

Macro abroad: GDP growth in the rest of the world (*GDPA*) is used to measure the international demand for firms' products. Here, weighted GDP for the 16 largest trading partners of Sweden is used, where the weights are those that are used to calculate the effective exchange rate KIX (see aforementioned).

Labour market: Employment (*E*) along with unemployment (*U*) provide a good picture of labour force and labour market trends, which are of central importance for firms' output capacity. They are measured by the number of employed and unemployed persons, respectively, in the population of working age (persons aged 15–74), thousands of people. Wages per hours worked (*w*) provides a good picture of the labour cost and is used as a proxy for the marginal cost of labour.

Policy: The interest rate on three-month treasury bills (*ITB*) is directly affected by monetary policy and is therefore used as a good monetary policy indicator.

The variables discussed above will be used to model *EBIT* on quarterly frequency. For *NBI*, on yearly frequency, the fiscal policy measures (*FP*) reported by the Government in the area of corporate taxation as a percentage of GDP in current prices is used as an indicator of fiscal policy stance in this area. Starting in 1995, data on *NBI*, *FP* and *TA* are available yearly only until 2014, because of the fact that corporate tax revenues are settled the year after the year the income was acquired. Thus, the number of observations for these variables is 20. The number of observations for the quarterly variables is 90 and covers 1993Q1–2015Q2. The reason for choosing the starting point 1993Q1 is that between 1990 and 1992 Sweden reformed its tax system, and in 1992 the framework for the economic policy was reformed, introducing a flexible exchange rate system. Graphical illustrations of the variables in Table 1 are provided in Appendix A.

Table C1 in Appendix C shows cross-correlations between *TAX* (in first differences) and the variables in Table 1, including correlations with *TAX* itself. The table shows that the variables are fairly correlated with changes in corpo-

Table 1. Summary of variables

Variable	Unit	Name	Mean	Stdev
	Quarterly frequency			
Net operating surplus	Percentage of GDP	*EBIT*	13.60	1.96
Macro domestic				
Inflation	Percentage change	*CPIF*	0.39	0.48
GDP	Percentage change	*GDP*	0.64	0.92
Real exchange rate	Percentage change	*KIX*	0.19	2.47
Macro abroad				
GDP in the rest of the world	Percentage change	*GDPA*	0.59	0.51
Financial markets				
Financial stress index	Index	*SI*	0.14	0.97
Share price gap	Per cent	*XGAP*	7.81	26.48
Credit gap	Per cent	*CGAP*	–0.48	11.27
Lending rate	Per cent	*LR*	5.06	2.44
Labour market				
Unemployment	Per cent	*U*	8.03	1.58
Employment	Percentage change	*E*	0.18	0.50
Wage per hour worked	Percentage change	*W*	0.36	1.30
Monetary policy				
Interest rate on three month treasury bill	Per cent	*ITB*	3.25	2.40
	Yearly frequency			
Fiscal policy in the area of corporate tax	Percentage of GDP	*FP*	–0.02	0.09
Tax adjustments	Percentage of GDP	*TA*	0.76	0.71
Net operating surplus	Percentage of GDP	*EBIT*	13.46	1.91
Net business income	Percentage of GDP	*NBI*	9.75	1.98

rate tax revenues, suggesting that at least some of the variables could be useful in univariate or multivariate modelling of corporate tax revenues directly. The main proposal in this paper, however, is to jointly relate *all* of the variables in Table 1 to corporate tax revenues in a coherent framework by using VAR models at different frequencies. Additionally, we will exploit the fact that the macro variables are available well before corporate tax revenues are settled.

4. The Bayesian VAR framework

In Section 3, we demonstrated that tax revenues can be decomposed into *NBI* and reductions before taxes, where the latter is a highly irregular component, and where *NBI* can be further decomposed into *EBIT* and associated adjustments. Additionally, we proposed that *EBIT*, and therefore also *NBI*, can be tied to the macro economy. This connection is important, since tying the taxable income to the macro economy could improve the precision in tax revenues forecasts. To forecast *EBIT* and *NBI*, we use VAR models. Because our data consists of short time series, the classical unrestricted VAR model will tend to be over-parametrised. By applying Bayesian shrinkage, however, we are able to handle large unrestricted VARs; see e.g. Banbura et al. (2010a), and references therein. In this paper, we also use priors on the unconditional mean, the VAR steady state, following the methodology in Villani (2009).

The Bayesian VAR framework that we use in this paper is outlined as follows. Let $x_t = (x_{1,t}, x_{2,t}, \dots, x_{n,t})'$ be an $n \times 1$ vector with stationary variables, and let L be the lag-operator such that $Lx_t = x_{t-1}$. The Gaussian VAR model can be written as

(4) $\Pi(L)x_t = c + \varepsilon_t$,

where $\Pi(L) = I - \Pi_1 L - \cdots - \Pi_p L^p$ is a vector lag polynomial of order p, c is a constant and ε_t is an n-dimensional multivariate Gaussian error which is independent and identically distributed over time with mean zero and covariance matrix Σ. The mean-adjusted, or steady state, Gaussian VAR model can be written as

(5) $\Pi(L)(x_t - \mu) = \varepsilon_t$,

where $\mu = E(x_t) = \Pi^{-1}(1)c$ is the unconditional mean of x_t.

As outlined in Section 3, we aim to tie quarterly *EBIT* to the macro economy, and then bridge and tie *EBIT* to yearly *NBI, TA* and *FP*, which, in turn, can be used to forecast yearly corporate tax revenues from Equation (2). First, based on Equation (3), we define a VAR model on yearly frequency with vector

(6) $x_t = (FP_t, EBIT_t, TA_t, NBI_t)'$

We refer to this model as the NBI model. In estimating the NBI model, annual data from 1995 is used, with two lags (i.e. $p = 2$). Second, to tie *EBIT* to the macro economy, we use a VAR model on quarterly frequency with vector

(7) $x_t = (GDPA_t, KIX_t, CPIF_t, w_t, E_t, U_t, GDP_t, XGAP_t, CGAP_t, ITB_t, LR_t, EBIT_t, SI_t)'$

We refer to this model as the EBIT model. Its specification follows partly Jenkins et al. (2000). In estimating the EBIT model, quarterly data starting in 1993Q1 is used, with four lags (i.e. $p = 4$). Because Sweden is a small open economy, we expect foreign GDP to affect all variables, but not vice versa. Therefore, *GDPA* is treated as block exogenous (achieved by imposing the necessary restrictions on the polynomial $\Pi(L)$, whereas the other variables are treated as endogenous.

Consider the VAR parametrisation (4). A Bayesian approach requires prior distributions of the model parameters $\Pi_1, \ldots, \Pi_p$, c and Σ. To impose the prior belief, we follow, in large, Adolfson et al. (2007) and Österholm (2010). That is, for , we apply Minnesota type priors in the spirit of Litterman (1986), who proposed to shrink the prior mean for processes in levels towards independent random walks, such that Π_1 is the identity matrix and Π_j are zero for $j > 1$. However, for variables in levels, the prior mean on the first lag coefficients is set to 0.9, reflecting the idea of a persistent stationary series. For variables in growth rates, the prior mean for the first lag is set to zero, which is consistent with a random walk expressed in first differences. The prior distribution variance is controlled by three hyperparameters that concern, respectively, the overall tightness, the cross-variable tightness, and the lag decay. The overall tightness parameter is set to 0.2, the parameter that controls cross-variable tightness is set to 0.5, and the lag decay parameter is set to 1 implying that variances shrink linearly with the lengths of the lags. For the covariance matrix Σ, the standard non-informative prior $|\Sigma|^{-(n+1)/2}$ is used. We set the number of draws to $B = 20{,}000$.

We also consider setting a prior distribution on the VAR unconditional mean μ. Because μ is a function of the parameters, it will always have an implied prior. This implied prior is important, since long-term forecasts will approach the unconditional mean. By re-parametrising the VAR into the steady state form (5), we can impose a prior distribution on μ directly; see Villani (2009).[5] This way, there is instead an implied prior on the constant c in the VAR parametrisation (4).

Table 2 presents all steady state priors as 95 per cent probability intervals for the relevant variables. Where available, these priors follow Adolfson et al. (2007) and Österholm (2010). In other cases we use broad intervals encompassing most of the data in the sample. In the

5 A practical concern: In the simulation of the posterior distribution it is possible to obtain draws which imply a non-stationary VAR process. However, we enforce the VAR to be stationary by discarding these draws, which is standard practice.

Table 2. Prior probability intervals for variable steady states

Variable	95% prior P.I.	Variable	95% prior P.I.
	EBIT model, quarterly frequency		
GDPA	(0.25, 0.75)	*XGAP*	(–2, 2)
R	(–3, 3)	*CGAP*	(–2, 2)
CPIF	(0.35, 0.65)	*ITB*	(3, 4.5)
W	(0.15, 1.575)	*LR*	(4, 5.5)
E	(5.8, 6.8)	*EBIT*	(9, 18)
S	(–0.3, 0.7)	*SI*	(–2, 2)
GDP	(0.5, 0.625)		
	NBI model, yearly frequency		
FP	(–2, 2)	*TA*	(–2, 3.4)
EBIT	(9, 18)	*NBI*	(0, 19.45)

Note: P.I. abbreviates probability interval. All steady state priors follow the normal distribution.

EBIT model, GDP growth is assumed to have a steady state value centred on 0.56 per cent, which is equivalent to an annual growth of 2.25 per cent. Foreign GDP growth is assigned a narrower interval centred on 0.5 per cent. Swedish inflation is centred on 2 per cent at an annual rate, the Swedish central bank's inflation target. The prior for the short-term interest rate is centred on 3.75 per cent, while the lending rate is assumed to have the same interval as the short-term interest rate but one percentage point higher. This constitutes approximately the historical spread between the two interest rates. Unemployment is centred on 6.2 per cent, and the real exchange rate is centred on zero, with fairly broad intervals. The credit gap and share price gap are centred on zero due to the definition of the gap (see Section 3) and may therefore deviate from the historical average. The stress index is centred on zero, which by construction is its mean value. The remaining variables are centred on their historical averages, unless otherwise stated. For the variables in the NBI model, broad probability intervals are chosen. All posterior steady state intervals are shown in the graphs of the respective variables in Appendix A.

In Sweden, corporate tax revenues are settled in December of the year after the income year, a considerable time after macroeconomic data are released. Therefore, conditional short-term forecasts for the current or preceding year corporate tax revenues are often nowcasts.[6] Considering the importance of such nowcasts, in this paper, we consider one-step forecasts.

4.1 Identfication

The orderings of the variables in the vectors specified by Equations (4) and (5) matter for the structural implications of the model. Here, we motivate the selected order of the variables by some previous orderings found for similar models in the literature.

Hubrich et al. (2013) place foreign variables first, followed by output, inflation and interest rates, which is also the case in Christiano et al. (1999). Eichenbaum and Evans (1995) place the real exchange rate subsequent to production and inflation. Christiano et al. (1996) also place unemployment after production and inflation.

The macroeconomic variables are then followed by financial variables. However, for the financial variables, there seems to be no clear guidance on how to order them. Abildgren (2012), Adalid and Detken (2007), and Hubrich et al. (2013) all agree that the macroeconomic variables should precede the financial variables. Abildgren (2012) place credit after share prices. Adalid and Detken (2007) place equity prices prior to private credit growth. Goodhart and Hofmann (2008) similarly put house prices before credit.

The ordering in Equation (6) is motivated by the identification assumptions made in previous studies as discussed above. The ordering in Equation (7) is done using the definition of corporate tax revenues and net business income in Equation (1) and Equation (3).[7] That is, we expect *NBI* to react contemporaneously to shocks

6 Nowcasting refers to the prediction of the very recent past, the present or the very near future using contemporary high frequency information that is released before the main variable of interest; see, e.g., Banbura et al. (2010b).

7 The identifications of shocks in the models implied by Equations (6) and (7) are both motivated using orderings in previous studies and based simply on timing convention. One way to expand the structural analysis is to deliver identifying constraints by imposing sign restrictions, see, e.g., Fry and Pagan (2011), and references therein.

in *FP*, *EBIT* and *TA*. We put *FP* first because of the findings in the corporate finance literature that corporate tax rules have impact on corporates financing and investment behavior, and, consequently, on their net operating surplus as well as their willingness to make tax allocations (see, e.g., Copeland and Weston, 2004). Moreover, *TA* is placed after *EBIT* because we believe that shocks in corporate profits should have a contemporaneous impact on the decisions to make tax allocations.

5. Empirical results

5.1 Forecast performance

In Sweden, corporate tax revenues are settled in December the year following the income year. Therefore, the conditional forecast for the current year and preceding year tax revenues, i.e. the nowcast, is particularly important. Here, we undertake a small forecast evaluation to estimate the ability of the EBIT model and the NBI model to forecast, respectively, net operating surplus and net business income, and subsequently the ability to forecast corporate tax revenues based on the forecast of *NBI*, itself dependent on the *EBIT* forecast.

We first turn to the EBIT models. Two different forms of BVAR forecasts are evaluated: unconditional forecasts, and forecasts conditional on macroeconomic information. The conditional forecasts would typically arise in the second quarter of the year, when the national accounts have been released. By then, macro variables for the preceding year are available, whereas tax revenue data are not. For each type of BVAR forecast, we consider both the standard non-steady state priors, and steady state priors, respectively. This renders four BVAR models, that we denote, respectively, BVAR-U (unconditional), BVAR-C (conditional), BVAR-US (unconditional with steady-state priors), and BVAR-CS (conditional with steady-state priors). For each model, the one-step ahead forecast for the th draw is given by

$$\hat{x}_{i,t+1} = \hat{c} + \hat{\Pi}_{i,1} x_t + \hat{\Pi}_{i,2} x_{t-1} + \hat{\Pi}_{i,3} x_{t-2} + \hat{\Pi}_{i,4} x_{t-3},$$

where x_t is defined as in equation (7). The one-step ahead forecast x_{t+1} is given by the median forecast among $\hat{x}_{i,t+1}$, for $i = 1,2 \ldots, B$, where B is the number of draws (see Section 3).

The forecasts from the BVAR models are compared to one-step ahead forecasts from two naïve models: a random walk (no-change forecast), and a stationary first-order AR process of order 1,

$$(8)\ EBIT_{t+1} = EBIT_t + \varepsilon_{t+1},$$

$$(9)\ EBIT_{t+1} = c + \phi EBIT_t + \varepsilon_{t+1},$$

where c and ϕ are coefficients that are estimated by ordinary least squares (OLS), and ε_{t+1} is the regression error. Both models would be natural choices to forecast *EBIT*. Following standard time series notation, the models (8) and (9) are denoted ARI(0,1) and ARI(1,0), respectively, where ARI(a,b) abbreviates an autoregressive process of order a, integrated of order b. That is, the first difference of the ARI(0,1) is ARI(0,0), i.e. white noise, whereas the ARI(1,0) is simply a stationary AR(1).

The forecast evaluation period is 2006Q1–2015Q2, increasing the initial estimation window 1993Q1–2005Q4 by one quarter for each new forecast. For the point forecasts we calculate the mean error (ME), mean absolute error (MAE), and root mean square error (RMSE). The results are displayed in Table 3. Because the EBIT model is used to bridge *EBIT* into the yearly model for *NBI*, we also evaluate how these yearly aggregates (as ratios of GDP) compare against yearly forecasts from the ARI models. The results are displayed on the right side of Table 3, and cover the sample 2006–2015.

For this period, the MAE is lower for the conditional forecasts, indicating that these models can be used to incorporate information of macroeconomic development or bridge macroeconomic forecasts to improve the forecast ability for *EBIT*. The BVAR-C model (in bold numbers) has the lowest ME, MAE, and RMSE for both quarterly and yearly forecasts.

Table 3. Forecast error aggregates for net operating surplus (EBIT)

	Quarterly: 2006Q1–2015Q2			Yearly: 2006–2014		
Model	ME	MAE	RMSE	ME	MAE	RMSE
ARI(0,1)	0.06	0.46	0.62	0.28	1.33	1.66
ARI(1,0)	0.10	0.46	0.63	0.22	0.94	1.09
BVAR-U	0.22	0.42	0.60	0.30	0.79	0.86
BVAR-C	**0.05**	**0.29**	**0.36**	**0.14**	**0.46**	**0.57**
BVAR-US	0.22	0.41	0.60	0.29	0.93	1.09
BVAR-CS	0.05	0.32	0.40	0.18	0.60	0.83

Note: Errors are expressed as shares of GDP, where ME is the mean error, MAE is the mean absolute error and RMSE is the root mean square error. BVAR-U is unconditional, BVAR-C is conditional on macro, BVAR-US is unconditional with steady state priors, and BVAR-CS is conditional on macro with steady state priors.

We turn next to *NBI*. The forecast evaluation period is now yearly 2010–14. The period is simply chosen by estimation limitations due to the small number of observations. Again, we consider one-step ahead forecasts, increasing the estimation window by one year for each new forecast. We consider the same BVAR setup as before, but where forecasts now are given by the median forecast from

$$\hat{x}_{t+1} = \hat{c} + \hat{\Pi}_{i,1}\tilde{x}_t + \hat{\Pi}_{i,2}\tilde{x}_{t-1}, \qquad (i = 1,2,\dots,B)$$

where x_t is defined as in Equation (6). Here, the tilde in $\tilde{x}_t$ denotes that *EBIT* has been bridged from the EBIT model, whereas the hat in $\hat{x}_{t+1}$ denotes a forecast. For the conditional forecasts (BVAR-C and BVAR-CS), *EBIT* is bridged by

$$EBIT_t^Y = \frac{\sum_{j=1}^{4}(EBIT_{t-j/4}^Q \times GDP_{t-j/4}^Q)}{GDP_t^Y}$$

where $EBIT_t^Q$ and $EBIT_t^Y$ are observed as shares of GDP on quarterly and yearly frequency, respectively, and GDP_t^Q and GDP_t^Y are observed in levels on quarterly and yearly frequency, respectively. For notational simplicity, the time index for quarterly observations is defined as a fraction of the year. For the unconditional models (BVAR-U and BVAR-US), *EBIT* is simply bridged by the mean of the quarterly forecasts for each corresponding year.

The performances of the BVAR models one-step ahead forecasts for *NBI* are compared with the one-step ahead forecasts from an ARI(0,1), i.e. a random walk model, and an ARI(1,0), i.e. a stationary AR(1). Because the number of observations is so small, we disregard RMSE and calculate only ME and MAE. Table 4 shows the results. For each BVAR model, the MAE is lower when incorporating the net operating surplus forecasts conditioned on information of the macro economy. Again, BVAR-C (in bold numbers) has the lowest MAE.

Table 4. Forecast errors for net business income (NBI)

Model	2010	2011	2012	2013	2014	ME	MAE
ARI(0,1)	–1.52	0.97	1.37	–1.17	–0.62	–0.19	1.13
ARI(1,0)	–2.03	0.12	0.86	–1.21	–1.05	–0.66	1.05
BVAR-U	–1.07	0.89	0.74	–1.18	–0.51	–0.23	0.88
BVAR-C	**–0.63**	**0.57**	**0.46**	**–1.32**	**–0.77**	**–0.34**	**0.75**
BVAR-US	–1.19	0.88	0.93	–1.05	–0.50	–0.19	0.91
BVAR-CS	–0.91	0.64	0.81	–1.25	–0.77	–0.30	0.88

Note: Errors are expressed as shares of GDP, where ME is the mean error and MAE is the mean absolute error. BVAR-U is unconditional, BVAR-C is conditional on macro, BVAR-US is unconditional with steady state priors, and BVAR-CS is conditional on macro with steady state priors.

Finally, we consider direct forecasting of corporate tax revenues. Following the procedures outlined in Section 3, we use Equation (2) by plugging in forecasts for *NBI* from the conditional BVAR models BVAR-C and BVAR-CS, respectively, and using a no-change forecast for *ROT*. We compare performance of the BVAR-based forecasts, a random walk (no-change) forecast (denoted ARI(0,1) as before), and forecasts from the following five naïve forecasting models,

(10) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \varepsilon_{t+1}$,

(11) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \alpha GDP_{t+1} + \varepsilon_{t+1}$,

(12) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \alpha GDP_{t+1} + \beta w_{t+1} + \varepsilon_{t+1}$,

(13) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \alpha GDP_{t+1} + \beta CPIF_{t+1} + \varepsilon_{t+1}$,

(14) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \alpha GDP_{t+1} + \beta LR_{t+1} + \varepsilon_{t+1}$,

where GDP_t is yearly percentage change in GDP, w_t is the yearly percentage change in wage per hour worked, $CPIF_t$ is the yearly percentage change in prices, LR_t is the yearly lending rate, and c, ϕ, α and β are parameters that are estimated by OLS. Thus, the models in Equations (11) – (14) add macroeconomic information to the ARI(1,1) model in Equation (10). Following again standard notation, we denote the models (11) through (14) ARIX1(1,1) to ARIX4(1,1), where ARIX means ARI with exogenous variables. We use integrated processes because we view corporate tax revenues as share of GDP as a non-stationary, yet bounded, variable (see Section 3). All of the six alternative models are natural choices of ARIX models for forecasting corporate tax revenue. Additionally, we consider the MIDAS equation

(15) $\Delta TAX_{t+1} = c + \phi \Delta TAX_t + \beta B(L^{1/4}; \theta) GDP_{t+1} + \varepsilon_{t+1}$,

where c, ϕ, β and θ are regression parameters that are estimated with nonlinear least squares, and B is a polynomial defined as $B(L^{1/4}; \theta) = \sum_{k=0}^{K} b(k; \theta) L^{k/4}$, a function of the quarterly lag-operator $L^{k/4} GDP_t = GDP_{t-k/4}$, where, as before, the time index for quarterly observations is defined as a fraction of the year. For the functional form of $b(k; \theta)$, we choose the exponential Almon lag with one shape parameter, as proposed by Andreou et al. (2013), and we set $K = 7$, implying current and preceding year GDP. Note that the MIDAS function (15) is regressing tax revenues directly onto quarterly GDP, and that the parameters depend on the forecast horizon $h = 1$. MIDAS is well-known to be efficient for forecasting with mixed frequencies; see, for instance, Schumacher (2016), and references therein.

The results for the forecasts for *TAX* are shown in Table 5. Our sample is small. However, we conclude that MIDAS, the conditional BVAR (BVAR-C) and ARIX1 (in bold numbers) perform best, with the lowest MAEs. It is well-known that forecast combinations, in form of weighted averages of model forecasts, may produce smaller forecast errors than the separate models (see, e.g., Timmermann, 2006). Indeed, forecast combinations consisting of simple averages from the three best performing models, ARIX1, MIDAS and BVAR-C, produce lower MAE (denoted by the ampersand &). This suggests that all of these models contribute jointly with useful information when forecasting the tax revenues. The best performing combination is an average of MIDAS and BVAR-C. The forecast error for this combination is 0.03 percentage points smaller than for the next best performing combination. In 2014 that would have been equal to roughly SEK 1.2 billion, or about 1.2 per cent of total corporate tax revenues, which is a non-negligible amount for policy purposes. The difference is more than two times larger when comparing to the best single model, MIDAS. Due to the

Table 5. Forecast errors for corporate tax revenue

Model	2010	2011	2012	2013	2014	ME	MAE
ARI(0,1)	0.40	–0.22	–0.38	–0.07	0.10	–0.03	0.23
ARI(1,1)	0.34	–0.32	–0.44	–0.08	0.08	–0.08	0.25
ARIX1(1,1)	**0.14**	**–0.25**	**–0.29**	**–0.07**	**0.07**	**–0.08**	**0.16**
ARIX2(1,1)	–0.28	–0.18	–0.22	–0.23	0.01	–0.18	0.18
ARIX3(1,1)	0.55	–0.37	–0.85	–0.47	–0.32	–0.29	0.51
ARIX4(1,1)	–0.66	–0.34	–0.39	–0.29	–0.20	–0.38	0.38
MIDAS	**–0.18**	**0.05**	**–0.29**	**–0.13**	**0.06**	**–0.10**	**0.14**
BVAR-U	–0.28	0.20	0.22	–0.15	–0.08	–0.02	0.19
BVAR-C	**–0.16**	**0.11**	**0.14**	**–0.18**	**–0.14**	**–0.05**	**0.15**
BVAR-US	–0.31	0.20	0.27	–0.12	–0.08	–0.01	0.20
BVAR-CS	–0.24	0.13	0.24	–0.17	–0.14	–0.04	0.18
BVAR-C & MIDAS & ARIX1	0.04	–0.10	–0.24	–0.01	0.09	–0.04	0.10
MIDAS & ARIX1	–0.02	–0.10	–0.29	–0.10	0.06	–0.09	0.11
BVAR-C & ARIX1	0.15	–0.18	–0.22	0.05	0.10	–0.02	0.14
BVAR-C & MIDAS	**–0.01**	**–0.03**	**–0.22**	**0.02**	**0.09**	**–0.03**	**0.07**

Note: Errors are expressed as shares of GDP, where ME is the mean error and MAE is the mean absolute error. BVAR-U is unconditional, BVAR-C is conditional on macro, BVAR-US is unconditional with steady state priors, and BVAR-CS is conditional on macro with steady state priors. The ampersand & denotes a simple average.

small number of yearly observations, the evaluation results for the *NBI* and *TAX* forecasts are only indicative. However, considering that the quarterly forecasts for *EBIT* perform well, we have reason to believe that also the precision in the yearly forecasts for *NBI* and *TAX* will carry over to larger samples.

5.2 Structural analysis

Governmental agencies may have an interest to analyse the determinants and mechanisms behind the development of corporate tax revenue for policy purposes and risk assessment. A structural analysis could be used to try to isolate, for example, the effect of increased financial stress on tax revenue. Here, we shortly demonstrate that the BVAR approach is suitable for this task. Many structural forms may be considered. We consider a simple case of orthogonalisation of shocks based on the identification assumptions given in Section 4.1. Technically, ε_t in the right hand side of Equation (4) is replaced with the process $A\varepsilon_t$, where A is the lower triangular matrix from the Cholesky decomposition of the error covariance matrix, such that $\Sigma = AA'$. This allows us to recursively identify shocks in the system; see, e.g., Adolfson et al. (2007).

5.2.1 Forecast error variance decomposition

We first turn to forecast error variance decompositions. They show how much of the forecast error variances of EBIT and NBI that can be explained by exogenous shocks to the other variables in their respective VAR models. To facilitate interpretation of the empirical results, we group the variables as in Table 1.

Figure 2 (a) shows the variance decomposition of the forecast errors for EBIT from an unconditional BVAR model without steady state priors. It indicates that external shocks, macroeconomic shocks, as well as financial shocks explain a substantial part of the forecasting error variance.

Figure 2 (b) shows the decomposition of the variance in forecast errors for *NBI* from

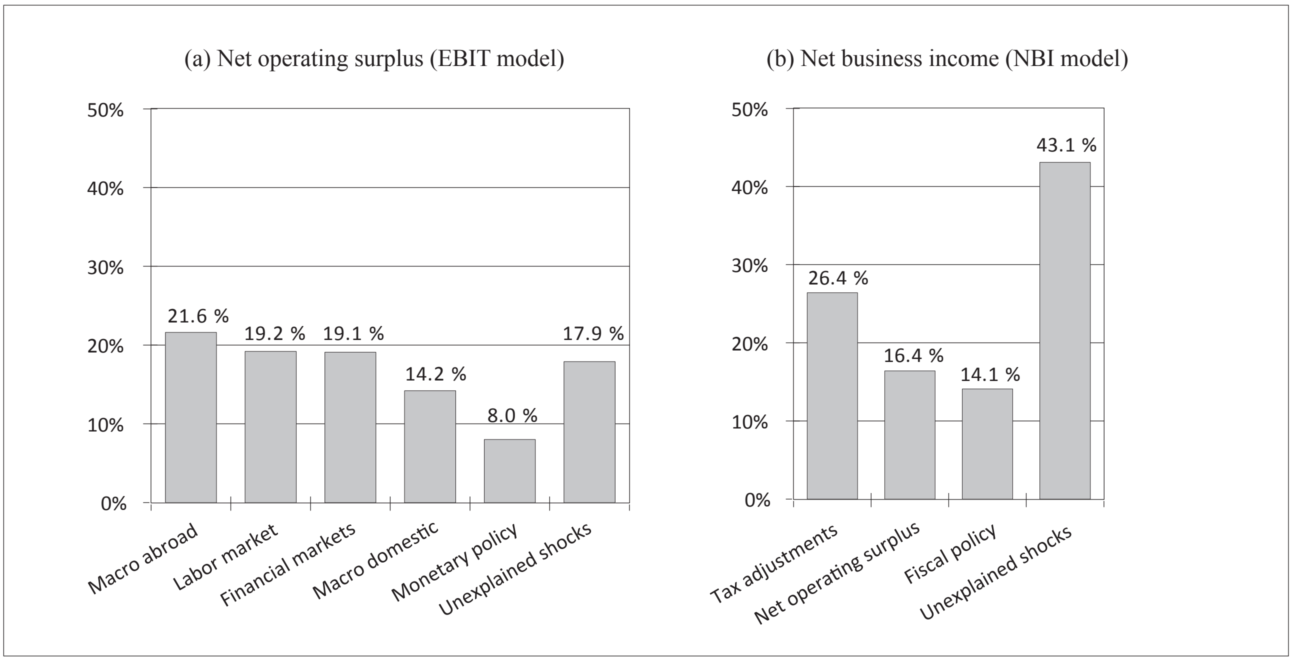

Figure 2. Variance decomposition of the median forecast deviation

an unconditional BVAR model without steady state priors. About 57 per cent of the variance in the in-sample forecast errors is attributed to its determinants. That is, about 43 per cent of the variance is unexplained. Indeed, shocks in *EBIT* only explain about 16 per cent of the variance in forecast errors. This could also indicate that, as a proxy for *EBIT*, net operating surplus may not be the best candidate. Naturally, if a better proxy were to be available, then the user may simply replace the proxy in the current framework.

One way of supplementing the variance decomposition analysis is with an impulse response analysis. Though left out, an examination of the impulse responses shows that the majority of the responses are as expected even if some have broad posterior probability intervals encompassing zero.[8]

5.2.2 Scenario analysis

A scenario analysis makes it possible to examine the extent of which NBI, and thereby corporate tax revenues, will deteriorate as a consequence of negative development in financial markets. As a short illustration, we compare two fictive scenarios. The first scenario (a main scenario) is conditioned upon the Ministry of Finance forecast for GDP growth abroad. The second scenario (a financial stress scenario) has the same condition but with the addition of imposed shocks in the financial markets. This scenario simulates a recurrence of the 2008 financial crisis development in stress index and share prices, now starting 2015Q4; see Figure 3. Compared to the main scenario, the financial stress scenario leads to a lower EBIT between 2015 and 2017 and a higher EBIT between 2018 and 2020 (see Table 6). This leads to a similar development of NBI. Further, the forecasts for corporate tax revenues initially decline under the financial stress scenario (see Figure 4).[9] Thus, the BVAR models' conditional forecasts are reasonable, in the sense that corporate tax revenues deteriorate as a consequence of negative development in financial markets.

8 The impulse responses can be supplied by the authors upon request.

9 The EBIT model scenario forecasts for GDP and CPIF are used to calculate proxy-forecasts for nominal GDP.

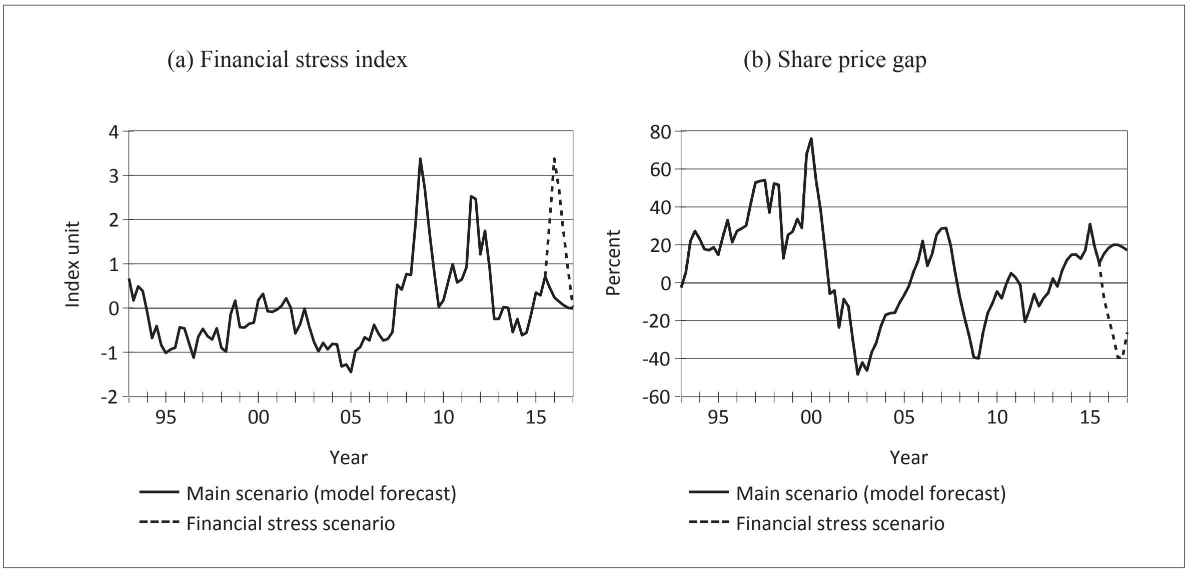

Figure 3. Scenarios for the financial stress index and share price gap

Table 6. Scenario forecasts for net operating surplus and net business income

	2015	2016	2017	2018	2019	2020
	Net operating Surplus (EBIT)					
Main scenario	12.06	11.90	11.77	11.60	11.61	11.91
Financial stress scenario	12.03	11.19	11.44	12.15	12.24	12.14
Difference	–0,03	–0.71	–0.33	0.55	0.43	0.23
	Net business income (NBI)					
Main scenario	11.79	11.72	11.39	11.05	10.74	10.56
Alternative scenario	11.79	11.71	11.03	10.84	10.94	10.81
Difference	0.00	–0.01	–0.36	–0.21	0.20	0.25

Note: Values are expressed as percentage of GDP.

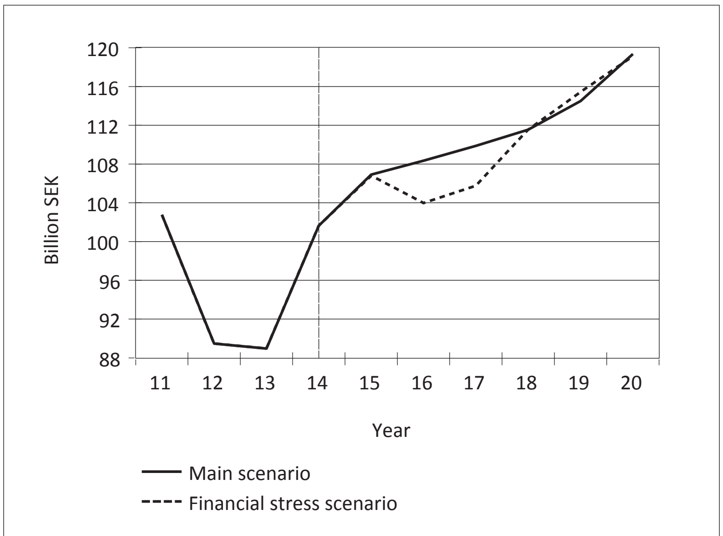

Figure 4. Scenario forecasts for corporate tax revenues

5.3 Sensitivity analysis

We investigate the robustness of the results by making forecasts for *NBI* and *EBIT* 2015–18 and calculating forecast error variance decompositions under different prior and structural assumptions. The baseline models for the EBIT models and NBI models, respectively, are those with steady state priors as described in Section 4. By comparing to these models we can contain the impact of individual changes to the steady states. The case without steady state priors are also compared to the baseline models. All changes are made one by one. The results from the sensitivity analysis are provided in Tables B1-B4 in Appendix B. Tables B1 and B2 show the results for the EBIT models, and Tables B3 and B4 show the results for the NBI models.

Two different types of changes in steady state priors are considered. First, we let all prior probability intervals keep their length, but shift their centre downwards by one sample standard deviation of the specific variable. Second, the centres of prior probability intervals are unchanged, but the lengths of the intervals are doubled. For the hyperparameters, the parameters controlling the overall tightness (λ_1) and the cross-variable tightness (λ_2) are changed to 0.1 and 0.2, respectively, which increase their informativeness, and the parameter controlling the lag decay (λ_3) is changed to 0.5, which relaxes its informativeness. Additionally, alternative orderings of the variables are considered. For the EBIT model we put financial market variables in front of macro variables and for the NBI model an arbitrary alternative ordering is considered.

The results in Table B1 suggest that the forecasts for *EBIT* are essentially insensitive to changes in the steady states (rows 3-15 and 16-28), with the exception of the steady states for unemployment, the credit gap and the share price gap. When the steady state of unemployment is increased, the model predicts lower *EBIT* in the long run. In the case of the credit gap and share price gap, the steady state priors are set tightly to zero, indicating that the gaps should close in the long run. As this is far from their particular sample unconditional means, a change in their prior has a relatively large impact on the overall forecasts in these cases. The hyperparameter changes (rows 29-31) have larger impact, which is expected as they can be seen as equivalent to changing the model specification. The specific alternative ordering of the variables (row 32) does not seem to have a major impact on forecasts.

Table B2 shows that the forecast error variance decomposition of *EBIT* is insensitive to changes in steady state priors (rows 3-28) and alternative orderings of the variables (row 32), but not when it comes to the hyperparameters (rows 29-31). A smaller part of the forecast error variance is explained by the determinants when the data is suppressed by tighter hyperparameters.

The results in Tables B3 and B4 suggest that the changes in steady state priors (rows 3-10) as well as an arbitrary ordering of variables (row 14) do not have any major impact on the forecasts or the forecast error variance decomposition of *NBI*. This is also the case when the hyperparameters are changed (rows 11-13).

6. Conclusions

This paper decomposes Swedish corporate tax revenues and connects the tax base to the macro economy and other relevant variables using BVAR models. A number of studies have demonstrated that the structural decomposition of tax receipts tends to vary over time and that such decomposition is valuable for analysing tax revenues. Thus, decomposing tax revenues might lead to insights also in terms of forecasting. In light of this, we use the conventional wisdom that tax revenues are essentially random walks, but then stress that a decomposition of the tax base may be connected to the macro economy and other determinants found in the literature. The BVAR models are used to analyse how important different shocks are for profits and the tax base, and to make forecasts for corporate tax revenues.

Our empirical results indicate that external shocks, macroeconomic shocks, as well as financial shocks explain a substantial part of the forecasting error variance of corporates' profit, and that shocks in profits, tax adjustments and fiscal measures explain a major part of the forecasting error variance of the tax base for corporate tax. These factors are all identified in the literature, and the implications of our findings can be of broad importance for understanding the way different factors impact corporate earnings, and essentially, corporate tax revenues. This is especially important because firms can decide when, how and in what way they would like to report their profits due tax deductions, transfer pricing, group contributions and other special arrangements.

Furthermore, our results indicate that the predictive performance of net operating surpluses, net business income and corporate tax revenues can be improved when they are conditioned on obtained macroeconomic information that is available before the tax revenue outcome, and, additionally, that combining forecasts from BVAR models, MIDAS models and ARIX models is a viable approach for forecasting corporate tax revenues.

Whereas our quarterly sample for net operating surplus is fairly large, our yearly tax revenue sample is short. Therefore, the results for the yearly tax revenue forecasts are only indicative. However, since the quarterly forecasts for net operating surplus perform well, we have reason to believe that also the precision in the yearly forecasts for net business income and corporate tax revenues will carry over to larger samples.

For consistency, governments are typically inclined to connect budget forecasts to their macroeconomic forecasts. A key benefit of the forecasting models proposed in this paper is that they clearly link the forecast for corporate tax revenues to macro variables and other determinants. Because of these links, the models provide tools to assess a range of corporate tax revenues given different scenarios for the determinants. The model-based input can be of great importance for forecasting of government's corporate tax revenues as well as analysing the sensitivity of these revenues in alternative macroeconomic environments.

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Appendix

Appendix A: Variables and posterior steady state intervals
The figures in this Appendix show each variable in Table 1 with posterior steady states based on the steady state priors shown in Table 2.

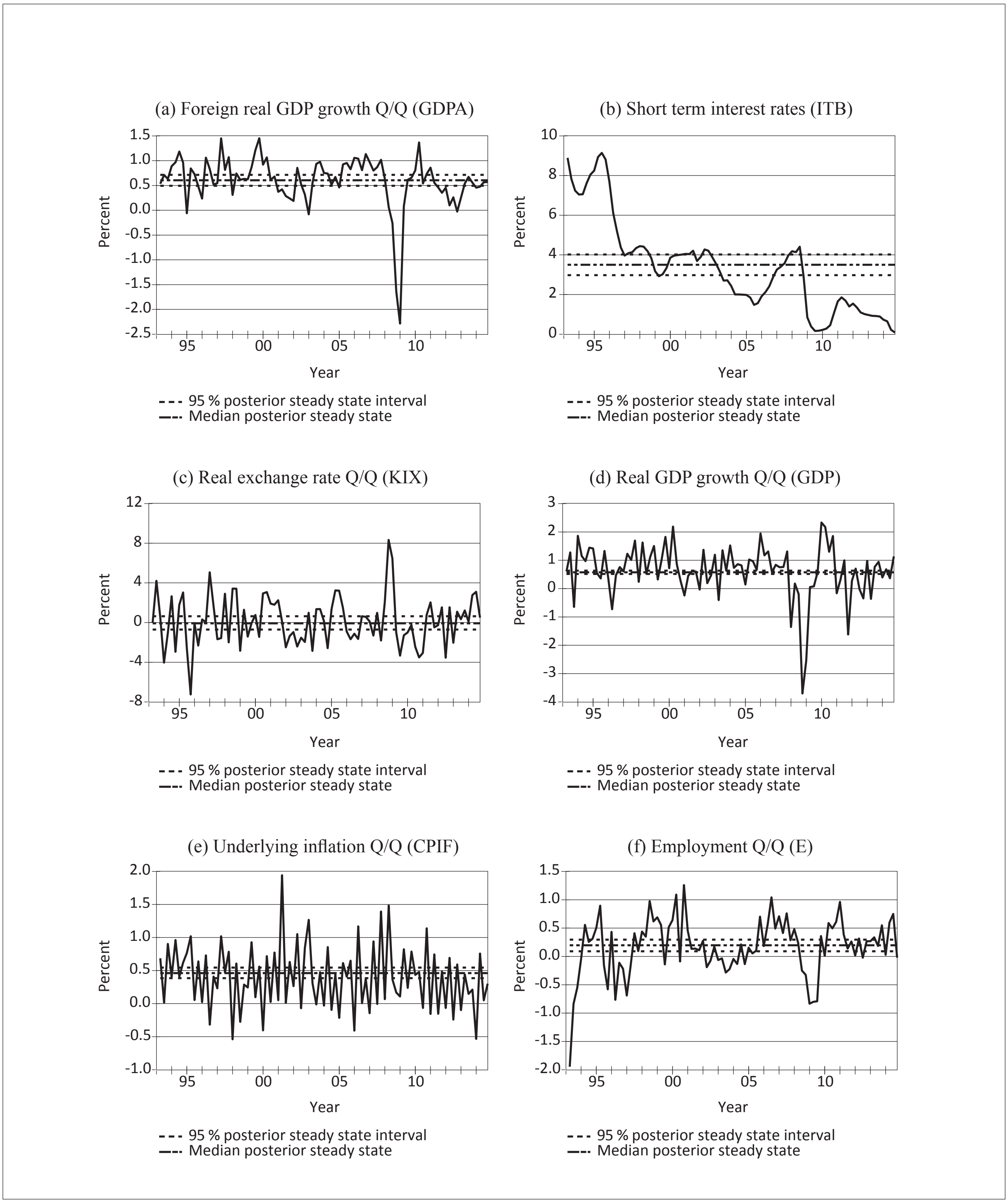

Figure A1. Variables in the EBIT model with posterior steady states

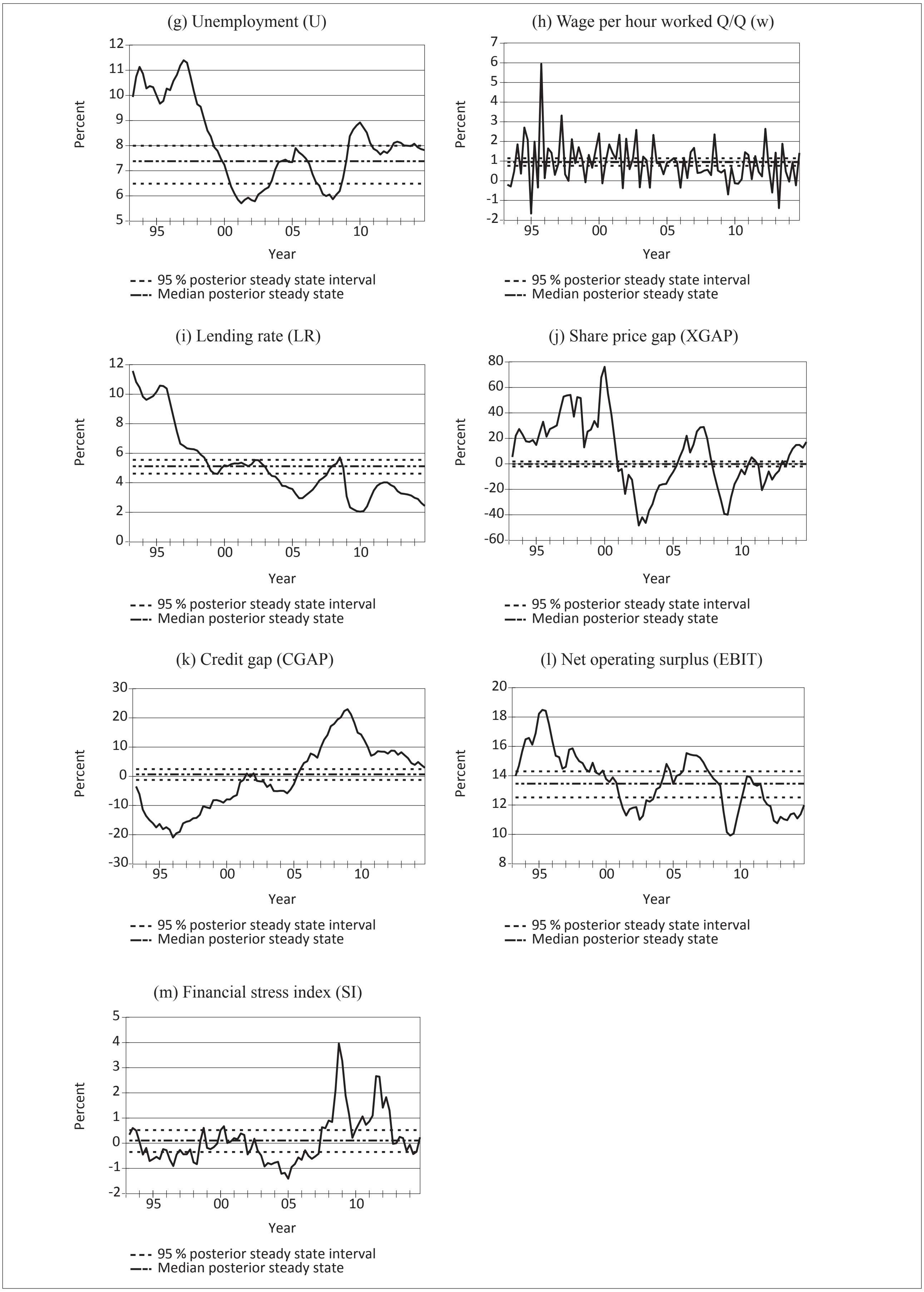

Figure A1, cont'd. Variables in the EBIT model with posterior steady states

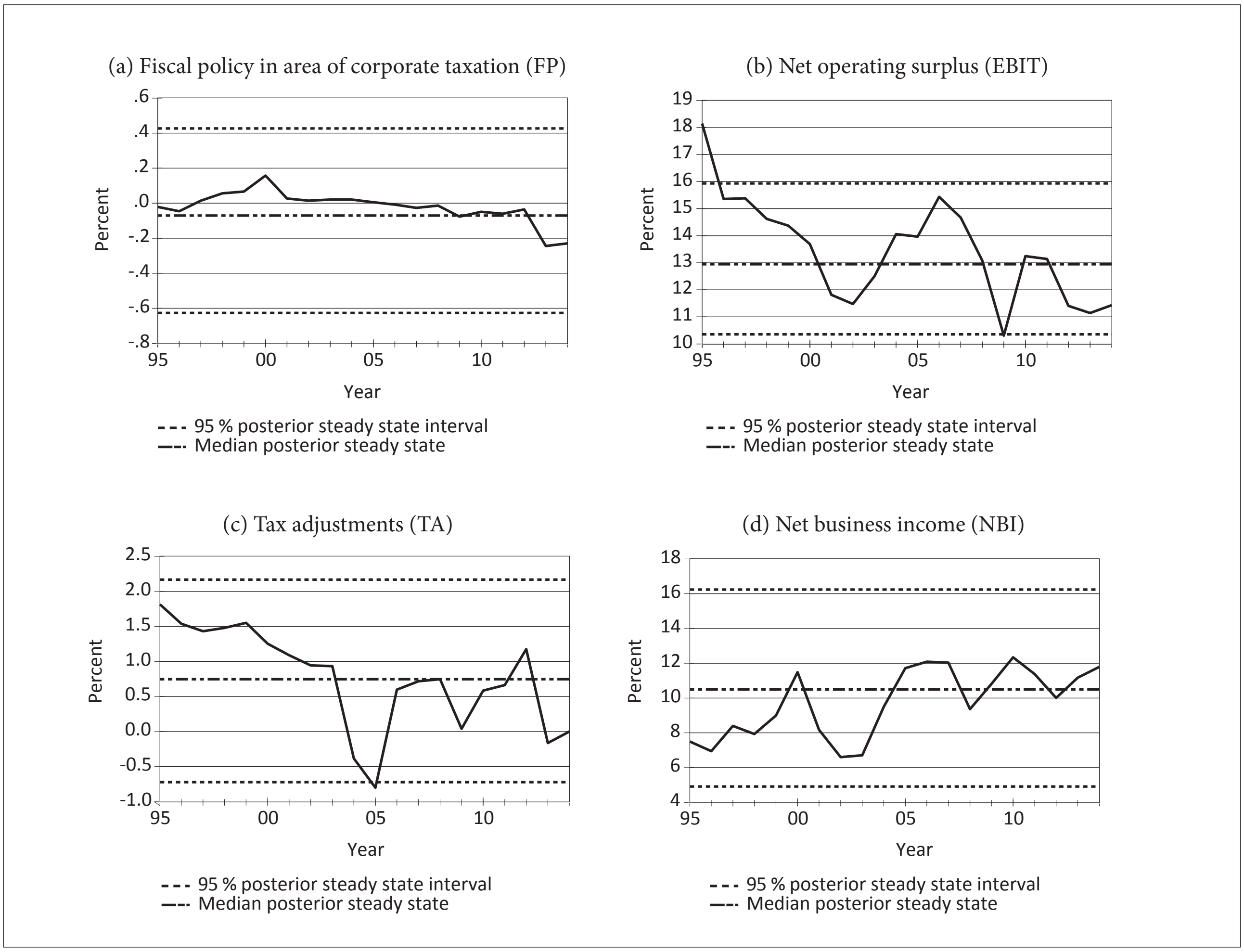

Figure A2. Variables in the NBI model with posterior steady states

Appendix B: Tables related to the sensitivity analysis

Table B1. Sensitivity analysis of the forecasts for EBIT

		2015	2016	2017	2018
Baseline		12.13	12.10	11.89	11.81
One standard deviation negative change in the steady state mean	*GDPA*	–0.06	–0.13	–0.11	–0.04
	KIX	0.01	0.00	–0.03	0.02
	CPIF	0.05	0.06	0.09	0.06
	w	0.02	0.05	0.01	0.01
	U	–0.02	–0.04	-0.09	–0.22
	E	–0.01	0.00	0.00	0.01
	GDP	–0.02	–0.04	0.03	0.07
	CGAP	0.04	0.04	–0.09	–0.21
	XGAP	0.00	0.08	0.18	0.32
	ITB	0.06	0.12	0.03	–0.07
	LR	–0.01	–0.02	–0.02	–0.01
	EBIT	–0.02	–0.06	–0.12	–0.08
	SI	0.01	0.01	0.00	0.01
Doubling of the steady state interval	*GDPA*	–0.06	–0.13	–0.11	–0.04
	KIX	0.01	0.00	–0.03	0.02
	CPIF	–0.01	–0.02	–0.04	0.06
	w	0.01	–0.03	–0.03	0.01
	U	0.04	0.06	0.00	0.01
	E	0.00	0.01	–0.04	–0.04
	GDP	–0.03	0.00	0.00	0.03
	CGAP	–0.02	–0.07	–0.07	–0.03
	XGAP	0.01	0.01	0.04	0.06
	ITB	–0.01	0.02	–0.02	–0.02
	LR	–0.01	–0.02	–0.02	–0.01
	EBIT	–0.02	–0.06	–0.12	–0.08
	SI	0.01	0.01	0.00	0.01
Changes in hyperparameters	$\lambda_1 = 0.1$	–0.17	–0.24	–0.32	–0.25
	$\lambda_2 = 0.2$	–0.21	–0.41	–0.58	–0.55
	$\lambda_3 = 0.5$	0.01	0.05	–0.01	–0.01
Alternative order: $x_t = (GDPF_t, CGAP_t, XGAP_t, ITB_t, LR_t, KIX_t, CPIF_t, w_t, U_t, E_t, GDP_t, EBIT_t, SI_t)'$		0.01	–0.02	–0.02	0.04
No steady state prior		0.04	0.09	0.11	0.15

Note: Values are expressed in differences from Baseline. For hyperparameters, λ_1 refers to the overall tightness, λ_2 refers to the cross-variable tightness and λ_3 refers to the lag decay.

Table B2. Sensitivity analysis of forecast error variance decomposition for EBIT

		Macro abroad	Macro domestic	Labour market	Financial factors	Monetary policy	*EBIT*
Baseline		21.1	14.3	19.2	19.2	7.8	18.4
One standard deviation negative change in steady state mean	*GDPA*	18.4	14.2	20.2	20.4	7.5	19.4
	KIX	21.0	14.6	19.8	18.4	8.0	18.3
	CPIF	20.3	13.4	20.4	20.3	7.6	18.0
	W	20.4	14.5	19.0	18.9	8.7	18.5
	U	23.8	14.7	18.4	17.2	9.1	16.9
	E	21.4	13.9	19.4	18.3	8.4	18.6
	GDP	19.8	13.3	20.0	20.1	7.0	19.8
	CGAP	20.4	14.2	19.7	19.3	7.5	18.9
	XGAP	19.9	14.2	18.2	22.5	8.0	17.2
	ITB	21.8	14.3	19.1	16.7	10.2	17.8
	LR	19.5	14.2	19.9	18.7	8.9	18.8
	EBIT	21.2	14.1	19.5	18.6	7.9	18.8
	SI	19.8	14.4	19.9	20.0	7.7	18.1
Doubling of the steady state interval	*GDPA*	22.0	14.3	18.7	18.8	8.1	18.1
	KIX	21.2	13.9	19.3	18.8	8.4	18.3
	CPIF	20.6	14.0	19.2	19.6	8.0	18.6
	W	20.9	14.4	19.5	18.4	8.1	18.8
	U	21.8	14.0	18.8	18.5	8.4	18.5
	E	21.4	14.0	19.3	18.8	7.9	18.6
	GDP	21.3	14.1	19.4	18.8	8.5	17.9
	CGAP	21.2	14.1	19.1	19.0	8.6	18.1
	XGAP	21.2	14.7	19.3	18.9	8.2	17.8
	ITB	21.9	13.8	19.8	18.2	7.9	18.5
	LR	21.1	14.6	19.6	18.1	8.4	18.2
	EBIT	21.9	14.1	19.5	17.9	8.0	18.6
	SI	21.7	13.9	19.5	18.8	8.2	17.9
Changes in hyperparameters	$\lambda_1 = 0.1$	16.3	11.2	24.3	13.6	6.6	27.9
	$\lambda_2 = 0.2$	16.4	11.5	25.5	10.2	5.9	30.6
	$\lambda_3 = 0.5$	25.7	14.2	17.9	18.6	8.7	14.8
Alternative order: $x_t = (GDPA_t, CGAP_t, XGAP_t, ITB_t, LR_t, KIX_t, CPIF_t, w_t, U_t, E_t, GDP_t, EBIT_t, SI_t)'$		21.2	6.0	13.2	23.0	17.7	18.9
No steady state prior		21.6	14.2	19.2	19.1	8.0	17.9

Note: Values are expressed in percentage share. For hyperparameters, λ_1 refers to the overall tightness, λ_2 refers to the cross-variable tightness and λ_3 refers to the lag decay.

Table B3. Sensitivity analysis of the forecasts for NBI

		2015	2016	2017	2018
Baseline		11.79	11.77	11.57	11.49
One standard deviation negative change in the steady state mean	*FP*	–0.01	–0.04	–0.14	–0.09
	EBIT	0.05	0.11	–0.01	–0.03
	TA	–0.04	–0.04	–0.18	–0.17
	NBI	–0.02	0.06	–0.08	–0.07
Doubling of the steady state interval	*FP*	–0.02	0.07	–0.05	–0.03
	EBIT	–0.01	0.05	–0.01	0.01
	TA	0.07	0.17	0.15	0.16
	NBI	0.02	0.12	–0.01	–0.01
Changes in hyperparameters	$\lambda_1 = 0.1$	–0.03	–0.03	–0.23	–0.23
	$\lambda_2 = 0.2$	0.00	0.07	–0.06	–0.06
	$\lambda_3 = 0.5$	0.02	0.08	0.02	0.02
Alternative order: $x_t = (EBIT_t, NBI_t, FP_t, TA_t)'$		0.01	0.01	–0.12	–0.12
No steady state prior		–0.09	–0.07	–0.23	–0.27

Note: Values are expressed in differences from Baseline. For hyperparameters, λ_1 refers to the overall tightness, λ_2 refers to the cross-variable tightness and λ_3 refers to the lag decay.

Table B4. Sensitivity analysis of forecast error variance decomposition for NBI

		FP	*EBIT*	*TA*	*NBI*
Baseline		11.9	16.2	26.8	45.0
One standard deviation negative change in the steady state mean	*FP*	12.1	16.0	26.9	44.9
	EBIT	11.8	16.5	27.6	44.0
	TA	12.0	17.0	26.1	44.9
	NBI	12.2	16.4	27.1	44.3
Doubling of the steady state standard deviation	*FP*	12.4	16.2	27.3	44.1
	EBIT	11.9	16.2	26.4	45.5
	TA	12.1	16.0	27.2	44.7
	NBI	11.8	16.1	27.4	44.6
Changes in hyperparameters	$\lambda_1 = 0.1$	9.2	18.4	25.4	47.0
	$\lambda_2 = 0.2$	9.2	17.5	25.2	48.1
	$\lambda_3 = 0.5$	12.4	15.3	27.3	45.0
Alternative order: $x_t = (EBIT_t, NBI_t, FP_t, TA_t)'$		5.8	1.6	18.7	73.9
No steady state prior		14.1	16.4	26.4	43.1

Note: Values are expressed in percentage share. For hyperparameters, λ_1 refers to the overall tightness, λ_2 refers to the cross-variable tightness and λ_3 refers to the lag decay.

Appendix C: Cross-correlations with changes in corporate tax revenues

Table C1. Yearly cross-correlations with changes in corporate tax revenues

j	ΔTAX_{t-j}	$EBIT_{t-j}$	TA_{t-j}	FP_{t-j}	GDP_{t-j}	$GDPA_{t-j}$	E_{t-j}	U_{t-j}
0	1	0.33	–0.35	0.16	0.38	0.26	–0.25	0.30
1	0.06	–0.06	–0.11	–0.12	–0.27	–0.37	–0.52	0.24
2	–0.36	–0.24	0.04	–0.03	–0.22	–0.18	–0.22	–0.13
	w_{t-j}	$CPIF_{t-j}$	LR_{t-j}	KIX_{t-j}	ITB_{t-j}	$CGAP_{t-j}$	$XGAP_{t-j}$	SI_{t-j}
0	–0.63	–0.44	–0.28	–0.02	–0.28	–0.26	0.35	–0.43
1	–0.09	0.09	0.04	–0.08	–0.04	–0.20	–0.30	–0.28
2	0.14	0.30	0.29	–0.05	0.27	–0.04	–0.40	–0.04