PhD THESIS DECLARATION

The undersigned

SURNAME *Lenarčič*
FIRST NAME *Andreja*
PhD Registration Number *1203587*

Thesis title: *Essays in Macroeconomics*

PhD in *Economics*, Cycle *22*
Candidate's tutor: *Tommaso Monacelli*
Year of thesis defence: *2014*

DECLARES

Under her responsibility:

1) that, according to Italian Republic Presidential Decree no. 445, 28th December 2000, mendacious declarations, falsifying records and the use of false records are punishable under the Italian penal code and related special laws. Should any of the above prove true, all benefits included in this declaration and those of the temporary embargo are automatically forfeited from the beginning;

2) that the University has the obligation, according to art. 6, par. 11, Ministerial Decree no. 224, 30th April 1999, to keep a copy of the thesis on deposit at the "Bilioteche Nazionali Centrali" (Italian National Libraries) in Rome and Florence, where consultation will be permitted, unless there is a temporary embargo protecting the rights of external bodies and the industrial/commercial exploitation of the thesis;

3) that the Bocconi Library will file the thesis in its "Archivio istituzionale ad accesso aperto" (institutional registry) which permits online consultation of the complete text (except in cases of a temporary embargo);

4) that, in order to file the thesis at the Bocconi Library, the University requires that the thesis be submitted online by the candidate in unalterable format to Societá NORMADEC (acting on behalf of the University), and that NORMADEC will indicate in each footnote the following information:

   - thesis *Essays in Macroeconomics*;
   - by *Lenarčič Andreja*;
   - defended at Universitá Commerciale "Luigi Bocconi" – Milano in *2014*;
   - the thesis is protected by the regulations governing copyright (Italian law no. 633, 22th April 1941 and subsequent modifications). The exception is the right of Universitá Commerciale "Luigi Bocconi" to reproduce the same for research and teaching purposes, quoting the source;

5) that the copy of the thesis submitted online to NORMADEC is identical to the copies handed in/sent to the members of the Thesis Board and to any other paper or digital copy deposited at the University offices, and, as a consequence, the University is absolved from any responsibility regarding errors, inaccuracy or omissions in the contents of the thesis;

6) that the contents and organization of the thesis is an original work carried out by the undersigned and does not in any way compromise the rights of third parties (Italian law, no. 633, 22nd April 1941 and subsequent integrations and modifications), including those regarding security of personal details; therefore the University is in any case absolved from any responsibility whatsoever, civil, administrative or penal, and shall be exempt from any requests or claims from third parties;

7) that the PhD thesis is not the result of work included in the regulations governing industrial property, was not produced as part of projects financed by public or private bodies with restrictions on the diffusion of the results, and is not subject to patent or protection registrations, and therefore not subject to an embargo;

Date *31 January 2014*

SURNAME *Lenarčič*
FIRST NAME *Andreja*

Contents

List of Figures

List of Tables

Acknowledgements

First and foremost, I wish to thank my advisor Tommaso Monacelli for his academic support, helpful comments, patience and motivation during my PhD studies. Besides my advisor, I would like to thank my other professors that were involved in the process of writing this thesis at different stages: Francesco Giavazzi, Carlo Favero, Luca Sala and Antonella Trigari for their encouragement, support and insightful comments. I owe many of my programming skills to Marco Maffezzoli, thank you.

I am very grateful to my officemate and co-author Szabolcs Deak for all the help and knowledge he shared. Many thanks also to my ECB co-authors, Dieter Gerdesmeier and Barbara Roffia. Thank you for the fruitful collaboration, support and valuable professional experience. I am also grateful for the hospitality of the Monetary Policy Stance Division at the European Central Bank, where the common project with Barbara and Dieter started.

Part of this thesis has been written while I was working at the Economics and Research Department at the Bank of Slovenia. I am grateful to all my colleagues for their support and encouragement during the last few years. Special thanks goes to Mateja Gabrijelčič, Damjan Kozamernik and Matija Lozej for their very useful advice, readiness to help, motivation and understanding.

I would also like to thank my fellow PhD students at Bocconi. Thanks for making the long hours of work more fun and the PhD stress more bearable. Big thank you also to my good friends that believed in me throughout all these years, Špela, Marta, Gerry and Nenad.

I am also very thankful to my parents for their love, support and the good foundations they gave me.

And finally, I am deeply grateful to my love and best friend Damijan for being there for me at all times, for the moral support and for making me a happier person despite the continuous pressures of the PhD life. I dedicate this thesis to him.

Chapter 1

The Fiscal Multiplier and the State of Public Finances

The Fiscal Multiplier and the State of Public Finances[1]

Szabolcs Deák
Surrey University[2]

Andreja Lenarčič
Bocconi University[3]

February 3, 2014

[1]Early drafts of this paper were circulated under the title "The Macroeconomic Effects of Fiscal Policy Shocks in Good Times and Bad". We are indebted to Carlo Favero, Ana Galvão, Francesco Giavazzi, and Massimiliano Marcellino for sharing their data and computer codes. We are also grateful to Gianni Amisano, Michael Ehrmann, Carlo Favero, Francesco Giavazzi, Róbert Lieli, Helmut Lütkepohl, Tommaso Monacelli, Roberto Perotti, Morten Ravn, Luca Sala and seminar participants at Università Bocconi, EIEF, ECB, MNB and EUI for helpful comments. Parts of this paper was written while the authors were visiting the European Central Bank, whose hospitality is gratefully acknowledged.

[2]Research Fellow, Centre for International Macroeconomic Studies (CIMS), Surrey University, Guildford. E-mail: s.deak@surrey.ac.uk

[3]PhD candidate, Department of Economics, Università Commerciale Luigi Bocconi, Milan. E-mail: andreja.lenarcic@phd.unibocconi.it

Abstract

Can fiscal policy always stimulate output? We address this question empirically using a regime-switching model where the size of the fiscal multiplier is conditional on the state of public finances. We make two contributions. First, we estimate several model specifications using postwar U.S. data which differ in the number of regimes and the conditioning variable used as a proxy for the state of public finances. We find that a model with two regimes and the debt-to-GDP ratio as a conditioning variable fits the data better than other nonlinear specifications or the benchmark linear model. Second, we compute fiscal multipliers conditional on the debt-to-GDP ratio based on the impulse responses from our model. We find that the fiscal multiplier is decreasing in the debt-to-GDP ratio. Every percentage point increase in the debt-to-GDP ratio decreases the peak spending multiplier by 0.06 points and the peak revenue multiplier by 0.10 points. These results indicate that there are diminshing returns to the use of deficit financed fiscal stimulus.

Keywords: fiscal policy, fiscal multiplier, public debt, regime switching threshold autoregression

JEL Classification: E62, C34, H60

1.1 Introduction

The recent financial and economic crisis has triggered a rapid deterioration of the health of public finances in many countries. Large government bailouts, declining tax revenues, and the workings of the automatic stabilizers have all contributed to a series of large deficits and, consequently, to the rapid accumulation of debt. Against this background, policy makers turned towards fiscal policy as a key tool for stimulating aggregate demand as the scope of conventional monetary policy to provide stimulus became limited by the zero lower bound.

In this paper we investigate empirically whether the ability of fiscal policy to stimulate aggregate demand depends on the state of public finances. We use a regime switching structural VAR to estimate state-dependent fiscal multipliers, defined as the dollar response of output to an exogenous dollar change in government expenditures or revenues, for the United States for the period 1960-2007.

At least three existing strands of models formalize how fiscal multipliers vary with the state of public finances. First, Blanchard [1990], Sutherland [1997] and Perotti [1999] illustrate how the wealth effect generated by fiscal policy shocks depends on the level of sovereign debt when taxes are distortionary. A tax cut, for example, represents an intertemporal reallocation of tax distortions in these models via the intertemporal government budget constraint. Because tax distortions are assumed to be convex in the tax rate the same tax cut induces a higher change in the present discounted value of the tax distortions, and hence a stronger wealth effect, the higher the tax rate is today. The latter is, in turn, a positive function of the initial debt via the intertemporal government budget constraint.

Second, Bohn [1998] provides empirical evidence that fiscal policy in the US is characterized by spending reversals, defined as a systematic negative response of deficit to the level of public debt, that are becoming stronger as the debt-to-GDP ratio increases. Corsetti, Meier, and Müller [2009] demonstrate that incorporating these features into a standard New Keynesian model gives rise to state-dependent fiscal multipliers. An expenditure shock in this framework increases aggregate demand in the short-run and at the same time creates expectations of government spending below trend in the future. These expectations lower the long-run interest rate and modify the time profile of the fiscal multiplier: the short-run spending multiplier is increasing while the long-run multiplier is decreasing in the strength of debt stabilization.

Third, potential nonlinearities arise also in the presence of sovereign default risk. Bi [2010], Ghosh, Kim, Mendoza, Ostry, and Qureshi [2011] and Juessen, Linnemann, and Schabert [2011], among others, develop models where the interest rate on government bonds increases nonlinearly with the level of government liabilities. At low levels of government debt, interest rates are unresponsive to the level of debt. As the economy approaches its fiscal limit, the level of debt above which it cannot be rolled-over, financial markets start to demand a risk premium on government bonds that is steeply increasing in the level of debt.

We estimate state-dependent fiscal multipliers in two steps. First, we address the question which variable we should use as a proxy for the state of public finances to define the regimes of our model. We estimate several alternative specifications of our regime switching structural VAR that differ in the conditioning variable we use and compare them in terms of their fit to the data. Motivated by the flow and intertemporal budget constraints of the government we use threshold variables related to the cost of servicing the debt, the stationarity and the stock of accumulated debt, and to the primary deficit. Furthermore, we use threshold variables that are meant to capture nonlinearities arising from the possibility of sovereign default risk. While we believe that investors considered sovereign default risk negligible in the United States over our sample period, we do not want to exclude this possibility a priori. Second, we compute state-dependent fiscal multipliers based on the impulse responses of our model.

We find that the model with the debt-to-GDP ratio as a threshold variable fits the data best. The estimated threshold value of debt that triggers the regime switch is at 42.5 percent of GDP and it splits the sample such that approximately one quarter of the observations are during bad times, a term we will use to refer to the regime characterized by high debt-to-GDP ratio. This estimated threshold value should not be interpreted as a fiscal limit above which public finances are not sustainable since the data strongly rejects sovereign default risk as the source of nonlinearities in our sample.

We find that deficit financed fiscal stimulus is characterized by diminishing returns. The strong asymmetries in the response of output across regimes imply a negative relationship between the fiscal multiplier and the debt-to-GDP ratio. Every additional dollar spent by the government increases output by 0.89 dollar less in bad times than in good, while the corresponding difference for a dollar decrease in government revenues is 1.03 dollar. Diminishing returns arise since deficit financed fiscal stimulus increases the debt-to-GDP ratio and, consequently, leads to a decrease in the fiscal multiplier.

The different time profile of the output response in the two regimes indicate that spending reversals are the source of the asymmetric response of output. The output response to a government expenditure shock in bad times is higher at shorter and lower at longer horizons compared to good times. Moreover, similarly to Bohn [1998], we find evidence that spending reversals are becoming stronger as the debt-to-GDP ratio increases. During good times spending reversal occurs with delay, but during bad times the deficit response to changes in the debt is negative already on impact and it is getting stronger in the short-run before returning to zero. Consequently, the persistence of the fiscal expansion is lower during bad times. In order to determine whether the observed differences in the fiscal multiplier are driven by the less persistent fiscal expansion only, we perform a counterfactual analysis in which we control for the differences in the estimated fiscal rules. We find that the lower persistence of the fiscal expansion cannot account for the differences in the multipliers, which suggests that they are driven by the asymmetric response of the private sector.

We derive two additional policy implications from our model. First, in a nonlinear model the fiscal multiplier is not only a function of the threshold variable, but it also depends on the size and sign of the fiscal policy shock. We have varied the fiscal policy shocks used in our simulations from a fiscal expansion equivalent to 5 percent of GDP to a contraction with the same magnitude. We find that expenditure cuts are associated with a higher output loss than revenue increases at shorter horizons during bad times. At longer horizons our results are consistent with Alesina, Favero, and Giavazzi [2012] who find that revenue based fiscal consolidations have been associated with mild and short-lived recessions while tax-based adjustments have been associated with prolonged and deep recessions. Moreover, our results show that more expansionary shocks lead to smaller multipliers which lends further support to our earlier argument that there are diminishing returns to the use of deficit financed fiscal stimulus. Intuitively, since our impulse response analysis has shown that the fiscal multiplier is a decreasing function of the debt-to-GDP ratio, the more expansionary the fiscal shock is the more debt is accumulated and the smaller the multiplier gets. Second, in a counterfactual exercise we have simulated the effects of the American Recovery and Reinvestment Act of 2009 using both our linear and nonlinear models. While both models seem to agree regarding the cost of the stimulus package in terms of accumulated debt, the expansionary effects on output are considerably smaller and insignificant in the nonlinear model.

The closest to our work are the papers by Choi and Devereux [2005] and Kirchner, Cimadomo, and Hauptmeier [2010] who study how the ability of government expenditures to stimulate aggregate demand changes with the state of public finances. Choi and Devereux [2005] condition the effects of government expenditure shocks on the real treasury bill rate in order to capture nonlinearities related to the cost of financing the debt in the United States. They find that the ability of fiscal policy to boost economic growth is decreasing in the interest rate which gives rise to very different policy implications from ours. The real interest rate on treasury bills has been very low since the onset of the financial crisis hence their results support the increased use of fiscal measures. Kirchner, Cimadomo, and Hauptmeier [2010] use time-series data for the Euro Area and, in accordance with our results, find a negative relationship between the expenditure multiplier and the debt-to-GDP ratio. According to their results every percentage point increase in the debt-to-GDP ratio decreases the spending multiplier by 0.01 points. This is considerably lower than our corresponding estimate which is due both to a smaller historical variation in the debt-to-GPD ratio in the US and a smaller elasticity of the spending multipler with respect to public debt in the Euro Area.

To our best knowledge, we are the first to estimate a threshold value of the debt-to-GDP ratio in a nonlinear model for the US economy. Panel data studies by Perotti [1999], Corsetti, Meier, and Müller [2010] and Ilzetzki, Mendoza, and Végh [2010] all find that higher indebtedness leads to weaker or even contractionary response of output to fiscal stimulus. But contrary to our approach, these studies impose threshold values in the neighbourhood of 100 percent of the debt-to-GDP ratio to the whole cross-section of countries uniformly to define the regimes in their models. As such, they are not applicable to the US economy that has historically recorded lower debt-to-GDP ratios compared to other countries in their sample.

Although we limit our analysis to estimating the fiscal multiplier conditional on the state of public finances, a growing body of literature shows that other determinants are also important. These determinants include the business cycle [Auerbach and Gorodnichenko, 2010, 2011, Fazzari, Morley, and Panovska, 2012, Batini, Callegari, and Melina, 2012, Canzoneri, Collard, Dellas, and Diba, 2011, Michaillat, 2012], the exchange rate regime [Corsetti, Meier, and Müller, 2010, Ilzetzki, Mendoza, and Végh, 2010], financial factors [Corsetti, Meier, and Müller, 2010, Kirchner, Cimadomo, and Hauptmeier, 2010, Afonso, Baxa, and Slavík, 2011] and openness to trade [Ilzetzki, Mendoza, and Végh, 2010, Kirchner, Cimadomo, and Hauptmeier, 2010]. In addition, a number of papers have analyzed the behavior of the fiscal multiplier when the monetary policy is constrained at the zero lower bound [Cogan, Cwik, Taylor, and Wieland, 2010, Mertens and Ravn, 2010, Christiano, Eichenbaum, and Rebelo, 2011, Eggertsson, 2011, Bilbiie, Monacelli, and Perotti, 2012].

The paper is organized as follows. Section 2 presents the empirical methodology used to estimate the reduced form models and the strategy to choose the benchmark specification. Section 3 describes our identification strategy and how the fiscal multiplier is computed. Section 4 discusses the results relevant to the choice of the benchmark specification and section 5 presents the estimated effects of fiscal policy in the linear and nonlinear models. Section 6 examines the robustness of our results. Section 7 concludes.

1.2 Empirical methodology

This section outlines the empirical methodology used to estimate the reduced form model. First, we describe both the linear and the nonlinear models used in the paper and their estimation. We employ a multivariate endogenous threshold autoregressive model (ET-VAR) to model explicitly the dependence of the transmission mechanism on initial conditions that differ across regimes. We discuss the methodology in terms of the two regime model, but everything can be readily extended to a model with more regimes. Then, we briefly describe how the endogenous variables of the model are constructed and we give details of the threshold variables we consider as proxies for the state of public finances. Finally, we discuss our strategy to choose our benchmark specification.

1.2.1 The (almost) linear model

In order to keep our exercise comparable to the existing literature, we estimate a type of structural VAR estimated by Blanchard and Perotti [2002] and Perotti [2004]. In particular, we adopt the specification of Favero and Giavazzi [2007] because it combines a linear VAR with the flow government budget constraint within the same model and can be easily extended to model endogenous regime switches in a nonlinear VAR. While the model can be estimated as any other linear VAR the nonlinearity of the flow government budget constraint makes the model behave as a nonlinear model when computing the impulse response functions.

The model consists of two parts. The first is a standard linear autoregression of the form:

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{\Phi}\mathbf{X}_t + \mathbf{\Gamma}\mathbf{D}_t + \varepsilon_t \tag{1.1a}$$

where $\mathbf{Y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{X}_t = [\ \mathbf{Y}'_{t-1} \ \cdots \ \mathbf{Y}'_{t-p}\ ]'$ is an $np \times 1$ vector of lagged values, $\mathbf{D}_t = [\ d_{t-1} \ \cdots \ d_{t-k}\ ]'$ is a $k \times 1$ vector of lagged values of the level of the debt-to-GDP ratio, $\mathbf{c}$, $\mathbf{\Phi}$ and $\mathbf{\Gamma}$ are $n \times 1$, $n \times np$ and $n \times k$ coefficients matrices. The second part of the model is the flow government budget constraint:

$$d_t = \frac{1+i_t}{1+\Delta p_t}\frac{1}{1+\Delta y_t}d_{t-1} + \frac{\exp(g_t)-\exp(t_t)}{\exp(y_t)} \tag{1.1b}$$

where i_t is the nominal interest rate on government debt, Δp_t is inflation, y_t is log real GDP, g_t is log government expenditure net of interest payments and t_t is log government revenues net of interest receipts.

To close the model, Favero and Giavazzi [2007] defines the vector of endogenous variables to be $\mathbf{Y}_t = [\ g_t \quad t_t \quad y_t \quad \Delta p_t \quad i_t\ ]'$. This way the dynamics of all the variables that enter the right-hand side of (1.1b) are modeled by the autoregression in (1.1a) and the model endogenizes debt dynamics in a way that is consistent with the flow government budget constraint.[1]

Notice that the flow government budget constraint (1.1b) is an identity and has no parameters to be estimated. Since (1.1a) is linear in its coefficients it can be estimated as any other linear VAR. However, the endogenous variables depend on the lagged values of the debt-to-GDP ratio that is, in turn, a nonlinear function of the lagged endogenous variables. This implies that we need resort to simulation to compute the impulse response functions of the endogenous variables.

1.2.2 The nonlinear model

Multivariate threshold autoregressive models (TVARs) combine two piecewise linear models with different sets of coefficients over two subsamples (regimes) into a nonlinear VAR [Tsay, 1998]. The two regimes are determined by an observed threshold variable, a value of that threshold variable that separates the two regimes and a delay parameter. The linear model of the previous section generalizes to the following nonlinear model:

$$\mathbf{Y}_t = \begin{cases} \mathbf{c}^{(1)} + \mathbf{\Phi}^{(1)}\mathbf{X}_t^{(1)} + \mathbf{\Gamma}^{(1)}\mathbf{D}_t + \varepsilon_t^{(1)} & \text{if } z_{t-d} \leq r \\ \mathbf{c}^{(2)} + \mathbf{\Phi}^{(2)}\mathbf{X}_t^{(2)} + \mathbf{\Gamma}^{(2)}\mathbf{D}_t + \varepsilon_t^{(2)} & \text{if } z_{t-d} > r \end{cases} \tag{1.2a}$$

$$d_t = \frac{1+i_t}{1+\Delta p_t}\frac{1}{1+\Delta y_t}d_{t-1} + \frac{\exp(g_t)-\exp(t_t)}{\exp(y_t)} \tag{1.2b}$$

where z_t is the threshold variable, d is the delay parameter and r is the threshold value that triggers a regime switch. Each regime has a different set of coefficients indexed by superscript (j), possibly different number of endogenous lags (p_j) and we also allow for regime specific covariance matrices for the residuals, that is $\varepsilon_t^{(j)} \sim N(0, \mathbf{\Sigma}^{(j)})$.

For a given threshold variable and lag lengths p_j and k the model can be estimated in three steps. First, for given values of the threshold variable, r, and the delay parameter, d, the model reduces to two linear VARs. The (regime specific) coefficient and covariance matrices of the two piecewise linear models, $\hat{\mathbf{c}}^{(j)}(r,d)$, $\hat{\mathbf{\Gamma}}^{(j)}(r,d)$, $\hat{\mathbf{\Phi}}^{(j)}(r,d)$ and $\hat{\mathbf{\Sigma}}^{(j)}(r,d)$, can be estimated with least squares formula using observations from regime j.

Second, for a given value of the delay parameter d we estimate the threshold value by maximizing the conditional likelihood over a grid of values for the threshold value. Galvão [2006] shows that conditional maximum likelihood works better than least squares estimation when the covariance matrices are regime specific, hence $\hat{r}(d)$ is obtained as

[1] Chung and Leeper [2007], instead, include the debt in their VAR as one of the endogenous variables and impose the intertemporal budget constraint of the government as a set of cross-equation restrictions.

$$\hat{r}(d) = \arg\min_{r \in R} \sum_{j=1}^{2} \frac{T_j}{2} \log |\hat{\mathbf{\Sigma}}^{(j)}(r,d)| = \arg\min_{r \in R} \sum_{j=1}^{2} \frac{T_j}{2} \log \left| \frac{1}{T_j} \sum_{i=1}^{T_j} \hat{\varepsilon}_t^{(j)}(r,d) \hat{\varepsilon}_t^{(j)}(r,d)' \right|$$

where $|\hat{\mathbf{\Sigma}}^{(j)}(r,d)|$ is the determinant of the estimated covariance matrix, T_j is the number of observations in regime j and R denotes the grid of values for the threshold value. We form this grid using all observations of the threshold variable excluding the lowest and highest 20 percent of the observations. This ensures that we have at least 20 percent of the observations in each regime.[2]

Third, the delay parameter is also estimated by maximizing the conditional likelihood over the values $D = \{1, \ldots, 4\}$:[3]

$$\hat{d} = \arg\min_{d \in D} \sum_{j=1}^{2} \frac{T_j}{2} \log |\hat{\mathbf{\Sigma}}^{(j)}(\hat{r}(d), d)|$$

An alternative specification used by Auerbach and Gorodnichenko [2010] is the smooth transition autoregressive (STAR) where the two regimes are not mutually exclusive as in the case of TVARs. The dynamics of the endogenous variables is driven by a weighted average of the two piecewise linear functions, where weights are given by the logistic function $[1 + \exp(-\gamma(z_{t-d} - r))]^{-1}$, and it allows a smooth transition even with two regimes and may give a better approximation to the underlying nonlinearity than an ET-VAR model with several regimes. In short samples, however, that are typically available in macroeconomics the curvature parameter, γ, and/or the threshold value, r, can be estimated only very imprecisely. Auerbach and Gorodnichenko [2010] overcome this problem by calibrating rather than estimating the curvature parameter using the NBER classification for recessions as an exogenous source of information. We have chosen the ET-VAR model over the STAR model because it allows us to estimate the parameters governing the transition between regimes instead of imposing them.[4]

[2]The typical choice in applications is 10 or 15 percent. Our more conservative choice reflects the fact that we have a VAR with five endogenous variables and potentially up to four lags are included in the regressions. We also experimented both with higher and lower values, but the results are unaffected.

[3]The last two steps are equivalent to maximizing the conditional likelihood over the two dimensional grid $D \times R$. We chose to estimate them in two steps only for convenience.

[4]When Auerbach and Gorodnichenko [2010] estimate all the parameters of their model jointly they find very high point estimates for the curvature parameter γ. These high values indicate that the data can be well described by a model where regime switches occur sharply at certain threshold values.

1.2.3 Data

As mentioned before we adopt the specification of Favero and Giavazzi [2007] both in terms of model variables and identification strategy. The vector of endogenous variables includes quarterly US data on (federal) government total expenditures net of interest payments (g_t), (federal) government total receipts net of interest receipts (t_t), and GDP (y_t), all in per capita real terms, the GDP deflator inflation rate (Δp_t) and the average nominal cost of financing the debt (i_t).[5] All variables are in logs except the interest rate, which enters in levels. The exogenous regressor debt-to-GDP ratio is computed using the series Federal Debt Held by the Public.[6] The full sample goes from 1960:1 until 2007:4.[7]

While this set of endogenous variables is standard in the fiscal SVAR literature, there are some differences in the definition of the variables to ensure that the flow government budget constraint (1.1b) can track the observed dynamics of the debt accurately.[8] First, the interest rate is defined as the nominal cost of servicing the debt instead of the yield to maturity on government bonds. It is computed as the ratio between net interest payments and the end of last period stock of government debt. Second, expenditures and receipts at the federal level are used to construct the endogenous variables since the definition of debt refers to federal government debt. Third, transfer payments are considered as part of government expenditure, rather than being subtracted from government receipts.

This last difference is in line with the argument of Oh and Reis [2012] that empirical research on fiscal policy should focus on government expenditures rather than government purchases. They point out that government purchases account for only 25 percent of the total increase in US government expenditures between the last quarter of 2007 and the last quarter of 2009 and their share from the provisions of The Recovery Act of 2009 is even smaller. Moreover, the standard practice in the empirical literature on fiscal policy is to use government purchases and net taxes to define g_t and t_t, respectively.[9] Notice that, using net transfers is equivalent to assuming that all households have the same

[5]We use the GDP deflator for all variables to obtain the corresponding real values. For details on the construction of the variables and the data sources, see our Appendix or Favero and Giavazzi [2007].

[6]The time series for debt held by the public is available only from 1970:1 on the FRED website. We follow Favero and Giavazzi [2007] and use the observation for 1970:1 as an initial value and the debt dynamics equation (1.1b) to construct a debt-to-GDP series that covers our entire sample.

[7]Some of the threshold variables discussed later have smaller samples as a consequence of differencing. Computing year-on-year differences, for example, forces us to drop three observations from the beginning of the sample. When we estimate several competing specifications we restrict the sample to be the same for all models.

[8]Favero and Giavazzi [2007] carefully check whether these differences in the definition of the variables alter the estimated effects of fiscal policy shocks. They conclude that the impulse responses are similar to the results of Perotti [2004] both in their full sample (1960:1-2006:2) and in their two subsamples (1960:1-1979:4 and 1980:1-2006:2).

[9]Government purchases are defined as the sum of government consumption and investment expenditures, while net taxes are defined as the sum of tax receipts and net transfers (transfer receipts minus transfer payments).

marginal propensity to consume and any transfer is neutral with respect to aggregate quantitites. However, many theoretical papers assume that households are heterogenous in their marginal propensity to consume in order to produce empirically plausible fiscal multipliers [see Galí, López-Salido, and Vallés, 2007, for example].

1.2.4 Threshold variables considered

In this subsection we attempt to assemble a list of potential proxies for the state of public finances to use as threshold variables in our model. We collect these variables into five groups (Table 3.4). We motivate this grouping by the flow and the intertemporal budget constraints of the government.

[Table 1 about here.]

The first term on the right-hand side of the flow budget constraint (1.1b), which is repeated here for convenience

$$d_t = \frac{1+i_t}{1+\Delta p_t}\frac{1}{1+\Delta y_t}d_{t-1} + \frac{\exp(g_t) - \exp(t_t)}{\exp(y_t)} \tag{1b}$$

is the real cost of servicing the debt and we include three variables related to it. The real 3-month treasury bill rate is used by Choi and Devereux [2005] as a direct measure of the cost of financing the debt. We also consider the real cost of financing the debt and the real 10-year government bond rate among our candidates. The former is directly related in our model to the cost of financing the debt and can be computed from our model variables as $(1 + i_t)/(1 + \Delta p_t)$. The latter is a more forward looking variable than the short term rate and can be a more sensitive proxy to expectations about the sustainability of fiscal policy.

The first two terms together, the relationship between the real interest rate and the growth rate of real GDP, determine the stationarity of the accumulation equation. When the real interest rate is low relative to the growth rate of the economy, the debt stock is falling behind GDP and the debt-to-GDP ratio is decreasing. When interest rates are high relative to the growth rate of the economy, then debt is growing faster than GDP and an expansionary fiscal shock accelerates the growth of the debt-to-GDP ratio even further. Hence, this difference is often used to evaluate fiscal sustainability [see for example Callen, Terrones, Debrun, Daniel, and Allard, 2003, Fund, 2009, ECB, 2011]. We include three variables measuring the difference between the real interest rate and the growth rate of the economy where the interest rate is defined by the short-run real interest rate (3-month T-bill rate), the long-run real interest rate (10-year government bond rate) and the real cost of financing the debt.

We include three variables related to the driving force of equation (1.1b), the primary deficit-to-GDP ratio. The quarterly primary deficit-to-GDP ratio and the annual primary deficit-to-GDP ratio are used in Giavazzi and Pagano [1995] to define protracted and sizable budget cuts or expansions. The worse of the last two periods' quarterly primary deficit-to-GDP ratio follows Perotti's (1999) definition of the bad times dummy.

Iterating the flow budget constraint forward we obtain the intertemporal budget constraint of the government:

$$d_t = \sum_{s=1}^{\infty} \left[\prod_{j=1}^{s} \frac{1 + i_{t+j}}{1 + \Delta p_{t+j}} \frac{1}{1 + \Delta y_{t+j}} \right]^{-1} \frac{\exp(t_{t+s}) - \exp(g_{t+s})}{\exp(y_{t+s})} \tag{1.3}$$

which shows that the debt-to-GDP ratio can be interpreted as the PDV of the future surpluses of the government from the perspective of the current period. We include four variables related to it. The papers by Perotti [1999], Giavazzi, Jappelli, and Pagano [2000], Giavazzi, Jappelli, Pagano, and Benedetti [2005] and Corsetti, Meier, and Müller [2010] are all using the debt-to-GDP ratio as a conditioning variable.[10] Coenen, Straub, and Trabandt [2012] assume fiscal rules in their model where fiscal instruments react to, among others, the cyclical component of real per capita debt. Additionally, we consider the change in the debt-to-GDP ratio which has been used as a potential source of nonlinearity in a number of papers by Giavazzi and Pagano [1990, 1995], Alesina and Perotti [1996a,b], Giavazzi, Jappelli, and Pagano [2000], Giavazzi, Jappelli, Pagano, and Benedetti [2005] and more recently by Burriel, de Castro, Garrote, Gordo, and Prez [2009].[11] Finally, big and persistent year-on-year declines in the debt-to-GDP ratio were used in a recent paper by Nickel, Rother, and Zimmermann [2010].

The intertemporal budget constraint of the government is valid only if the government is willing and able to honor its debt. While we believe that investors considered sovereign default risk negligible in the United States over our sample period, we do not want to exclude this possibility a priori. We condition on five variables that are potential indicators of either the government's ability to service its debt or investors' perception of sovereign risk. Following Haugh, Ollivaud, and Turner [2009] we use the ratio of debt interest payments-to-government receipts to proxy for investor assessments of sovereign risk. As a joint proxy for the first three terms in (1.1b), we consider the ratio of debt interest payments-to-GDP as an indicator for government indebtedness. The last three variables

[10] The time series for debt held by the public is available only from 1970:1 on the FRED website. We follow Favero and Giavazzi [2007] and use the observation for 1970:1 as an initial value and the debt dynamics equation (1.1b) to construct a debt-to-GDP series that covers our entire sample.

[11] Favero and Giavazzi [2007] include two lags of the debt-to-GDP ratio in their linear VAR as exogenous regressors and cannot reject the restriction that the two coefficients on d_{t-1} and d_{t-2} are equal in size with opposite signs thus it is the first difference of the debt-to-GDP ratio that enters their specification.

in this category are related to the fiscal limit of the economy.[12] The models of Bi [2010], Ghosh, Kim, Mendoza, Ostry, and Qureshi [2011] and Juessen, Linnemann, and Schabert [2011] predict that the interest rate rises nonlinearly with the level of government liability. When the economy is below the fiscal limit, the sovereign risk premium is stable and interest rates vary little with government debt. As the economy approaches its fiscal limit the probability of sovereign default increases and financial markets start to demand a premium for government bonds. This mechanism increases the slope of the pricing rule of the interest rate that links government debt to the interest rate as the economy approaches its fiscal limit.[13]

1.2.5 Choosing between different specifications

We need to compare competing specifications along three different dimensions. First, given a choice of a threshold variable we need to select the lag lengths in the two regimes. Second, we need to compare models that differ in the threshold variable. Third, we need to confront the best fitting nonlinear model with the linear benchmark.

We base the first two choices on a penalized likelihood function. We follow the approach of Artis, Galvão, and Marcellino [2007] and Galvão and Marcellino [2010] for comparing competing specifications that differ in terms of the threshold variable. They use information criteria based on a penalized likelihood function, where the penalty depends on the number of estimated parameters, in particular the Akaike, Hannan and Quinn, and Schwarz information criteria. The results of Gonzalo and Pitarakis [2002] show that the most reliable information criterion to choose among the models is the one with the heaviest penalty function, i.e. the Schwarz criterion.

Following standard practice in time series analysis, we also use the information criteria to select the best lag structure of our model. First, we set the lag length of the exogenous regressor d_t to $k = 2$. Our results show that all the information criteria are increasing with the lag length k, but for values above 2 the gain is negligible. Hence estimating additional parameters do not justify the additional computational costs while they decrease the power of the estimation substantially [Hansen, 1996]. Second, in each regime the lag length can take a value from the set $P = \{1, \ldots, 4\}$. We allow for different lag lengths in the two

[12]The fiscal limit is defined as the level of debt that the government is able and willing to service. When the debt level exceeds the fiscal limit, a sovereign default occurs.

[13]For the nonlinear relationship described see Figure 6 in Bi [2010] and the discussion therein. Note that the interest rate rule depicted in the graph looks very similar to a threshold function. It shows a very sharp increase in the interest rate at the fiscal limit while it is linear away from it. Thus, the slope of the interest rate has only two values in her model. This is a direct consequence of the assumption that the default rate, δ, is constant and exogenous. If the default rate was an endogenous function of the macroeconomic fundamentals as in Juessen, Linnemann, and Schabert [2011], then the interest rate rule would take off more gradually.

regimes and thus for each threshold variable we estimate a model for all possible lag length combinations over the two dimensional grid $P \times P$ and select the combination that minimizes the given information criterion.

When comparing the best fitting nonlinear specification with the linear model we rely on two statistical tests. The first test is a variable addition test, which considers as the nonlinear alternative the specification

$$\mathbf{y}_t = \mathbf{c} + \mathbf{\Phi X}_t + \mathbf{\Gamma D}_t + \mathbf{\Psi} \begin{bmatrix} \mathbf{X}_t' & \mathbf{D}_t' \end{bmatrix}' z_{t-d} + \varepsilon_t$$

given the value of the delay parameter, d [see for example Artis, Galvão, and Marcellino, 2007, Teräsvirta, 1998]. If the true model is linear, then the coefficients in $\mathbf{\Psi}$ are jointly insignificant which can be tested using an LR test.

The second test was proposed by Tsay [1998] and it uses predictive residuals from an arranged model to construct a test statistic. Given a threshold variable, z, and a value for the delay parameter, d, the observations in the linear model are arranged according to the increasing ordering of z_{t-d}. Then a series of linear models for each value $m = m_0, \ldots, T$ are estimated using observations $i = 1, \ldots, m$ from the arranged sample to construct one step ahead prediction errors.[14] If the data were generated by a threshold model, then this arrangement transforms the model into a structural break model with observations for regime 1 at the beginning and for regime 2 at the end of this arranged sample and a structural break at an unknown date in between. In this case the predictive errors are correlated with the regressors of the arranged model. If, instead, the data were generated by a linear model, then the predictive residuals are uncorrelated with the arranged regressors and the coefficients of the regression of the predictive residuals on the arranged regressors should be jointly insignificant under the null.

There are several alternatives to these two tests in the literature [see for example Andrews and Ploberger, 1994, Hansen, 1999, Altissimo and Corradi, 2002]. We have chosen these two tests because they rely on the choice of the threshold variable to construct a test statistic, but neither the value nor the distribution of the test statistic depend on the threshold value, r, a nuisance parameter which is present only under the alternative. Thus, both of these tests are simple and have familiar limiting distributions. Furthermore, as pointed out by Galvão and Marcellino [2010], applying these alternative tests in a multivariate setting may be misleading when the variance of the disturbances is regime specific.

[14] m_0 is the sample size of the first model and T is the size of the full sample. On the selection of m_0 and details of the procedure see Tsay [1998].

1.3 Estimating the fiscal multiplier

Obtaining estimates for the fiscal multiplier requires two steps. First, we need to identify the structural shocks in the estimated models. Second, we need to compute impulse response functions to the identified fiscal policy shocks.

1.3.1 Identification

We identify the structural shocks for the fiscal variables separately for each of the regimes using the Blanchard and Perotti [2002] identification approach, extended by Perotti [2004] for the five variable VAR. Imposing the relationship

$$\left[\begin{array}{cc|ccc} 1 & 0 & -\alpha_{gy} & -\alpha_{g\Delta p} & -\alpha_{gi} \\ 0 & 1 & -\alpha_{ty} & -\alpha_{t\Delta p} & -\alpha_{ti} \\ \hline a_{31}^{(j)} & a_{32}^{(j)} & 1 & 0 & 0 \\ a_{41}^{(j)} & a_{42}^{(j)} & a_{43}^{(j)} & 1 & 0 \\ a_{51}^{(j)} & a_{52}^{(j)} & a_{53}^{(j)} & a_{54}^{(j)} & 1 \end{array}\right] \left[\begin{array}{c} e_1^{(j)} \\ e_2^{(j)} \\ \hline e_3^{(j)} \\ e_4^{(j)} \\ e_5^{(j)} \end{array}\right] = \left[\begin{array}{cc|ccc} b_{11}^{(j)} & 0 & 0 & 0 & 0 \\ b_{21}^{(j)} & b_{22}^{(j)} & 0 & 0 & 0 \\ \hline 0 & 0 & b_{33}^{(j)} & 0 & 0 \\ 0 & 0 & 0 & b_{44}^{(j)} & 0 \\ 0 & 0 & 0 & 0 & b_{55}^{(j)} \end{array}\right] \left[\begin{array}{c} u_1^{(j)} \\ u_2^{(j)} \\ \hline u_3^{(j)} \\ u_4^{(j)} \\ u_5^{(j)} \end{array}\right]$$

where $e_i^{(j)}$ and $u_i^{(j)}$ denote the reduced form innovation and the structural shock of the ith equation in regime j, respectively. The elasticities α_{gy}, $\alpha_{g\Delta p}$, α_{gi}, α_{ty}, $\alpha_{t\Delta p}$ and α_{ti} represent the automatic response of fiscal variables to economic activity and are computed using external information [see Perotti, 2004, for details].

The values of the elasticities are shown in Table 3.5. We compute the values of α_{ty} and $\alpha_{t\Delta p}$ for the linear model by computing their sample mean for the entire sample. For the nonlinear model we compute the subsample means pertaining to each of the regimes in order to capture the potential differences in the workings of the automatic stabilizers.[15] While the differences in the subsample means of the elasticities seem to be small, recall that we also allow for regime specific covariance matrices for the residuals. Hence regime specific identification can be a potential source of asymmetric impulse responses across regimes and we carefully check whether this is indeed the case.

[Table 2 about here.]

We have chosen the Blanchard and Perotti [2002] approach among the alternative identification schemes primarily because it facilitates the comparability of our results with a large pool of literature on the effects of fiscal policy shocks. Moreover, other identification approaches in the literature cannot be applied easily to the threshold VAR

[15] This is the same approach followed by Baum and Koester [2011], for example. However, they restrict the estimated covariance matrices to be the same across regimes, which implies that their identification is regime specific only due to the regime specific elasticities.

model setting. The narrative approaches of Ramey and Shapiro [1998] and Romer and Romer [2009] has too few observations to obtain reliable results after splitting the sample into two.[16]

The other alternative identification method is the sign restrictions approach of Mountford and Uhlig [2008]. This identification method requires very few restrictions and can be easily motivated by the theoretical literature when applied to a linear VAR. However, it is not readily applicable to our regime switching setting. Several papers provide empirical support in favor of contractionary fiscal expansions [Perotti, 1999, Giavazzi and Pagano, 1990, 1995, Alesina and Perotti, 1996a,b, among others], i.e. macroeconomic variables can respond qualitatively differently to fiscal shocks conditional on the state of public finances. We therefore prefer to be agnostic and avoid putting any a priori restrictions on the sign of the impulse responses.

Finally, we have to point out that our chosen identification approach is not free of criticism. It was criticized, for example, for the sensitivity of its results to the elasticities used [Caldara and Kamps, 2008] or its inability to accommodate fiscal foresight [e.g. Ramey, 2009, Leeper, Walker, and Yang, 2009]. Our primary goal in this paper is to compare impulse responses obtained from our best fitting nonlinear model and from the benchmark linear VAR. We do not have reason to believe that these models are affected asymmetrically by the shortcomings of the identification method used and we can safely compare these two sets of results. Furthermore, recent papers by Chahrour, Schmitt-Grohé, and Uribe [2010], Perotti [2011] and Caldara and Kamps [2012] show that the method of Blanchard and Perotti [2002] does a reasonable job to identify the structural shocks of the model even in the presence of foresight.

1.3.2 Computing impulse response functions and their confidence intervals

As we pointed out already, the endogenous variables of the linear model depend on the lagged values of the debt-to-GDP ratio that are nonlinear functions of the lagged endogenous variables. It implies that (1.1a) has no moving average representation and in order to derive impulse responses we need to compute generalized impulse responses even for the linear model (see Appendix 1.B for the details).

When computing impulse responses for the nonlinear model we can distinguish two cases based on whether we allow for the possibility of a regime switch following the struc-

[16] We have estimated the model using the narrative record of Romer and Romer [2009]. The smaller regime in our nonlinear model contains only 6 episodes from their dataset which prevents reliable identification in our model. Mertens and Ravn [2011] have reconciled the two approaches in the proxy SVAR framework for the three variable VAR of Blanchard and Perotti [2002], but the lack of reliable identification also applies to their approach in our model due to the same reason.

tural shock. If the possibility of a regime switch is excluded, then the impulse response functions depend only on the regime when the shock hits. It is computationally much less demanding since each piecewise linear model has its own set of impulse responses that can be computed independently from each other. However, the differences in the responses of the model variables across regimes are overestimated, as Auerbach and Gorodnichenko [2010] point out, under the assumption that the regime at the time of the shock's arrival prevails forever. It is especially true at longer horizons since the importance of initial conditions should diminish over time.

Allowing for regime switches is in particular important for threshold VAR models since the coefficients of a TVAR model are functions of the observations in their respective subsamples only. Assuming that the same regime prevails forever implies that the impulse responses also depend on those subsamples only. If we allow for the possibility of a regime switch following the structural shock instead, then the impulse response functions depend on the parameter estimates of both regimes as well as on the dynamics of the threshold variable. These impulse responses thus utilize the entire sample and alleviate the disadvantage of TVARs arising from splitting the sample.

In order to simulate regime switches we need to model the dynamics of the threshold variable. For this reason we have chosen the specification of Favero and Giavazzi [2007] that already links the dynamics of our threshold variable candidates to the endogenous variables of the model through the flow government budget constraint.

Many papers in the fiscal VAR literature report transformations of the impulse responses that give the dollar response of each variable to a dollar shock to one of the fiscal variables. In a linear model it is a matter of convenience only since the impulse response functions scale up proportionally with the size of the shock. In our nonlinear model, however, the size and the sign of the shock can matter depending on how different the estimated dynamics in the two regimes are. For this reason we use a structural shock equivalent to 1 percent of GDP during all our simulations. This allows us to interpret the impulse responses of output as dollar value multipliers without any further transformation.[17]

We use a bootstrap approach to compute confidence intervals and repeat the simulations of impulse responses for each replication.[18] We build time series $\mathbf{y}_t$ for the endogenous variables, d_t for the debt-to-GDP ratio and z_t for the threshold variable based on the estimated parameters of the model and resampled residuals.[19] We repeat the first

[17] We investigate the extent to which the fiscal multiplier changes with the size and the sign of the structural shock in Section 1.5.3.

[18] For a detailed description and discussion see Artis, Galvão, and Marcellino [2007] and Galvão and Marcellino [2010].

[19] We use 2000 replications in our plots throughout the paper.

two steps of the estimation procedure for each generated series: we keep the estimated delay parameter $\hat{d}$ fixed, but reestimate the coefficients $\hat{\mathbf{\Phi}}^{(j)}(r,d)$ and $\hat{\mathbf{\Sigma}}^{(j)}(r,d)$ and the threshold value $\hat{r}(d)$ each time. Since parameter uncertainty about the threshold value can be a major weakness to regime switching models this approach attempts to address this issue.

1.4 The best fitting nonlinear model

This section reviews the results relevant to the choice of the benchmark model specification. We compare the estimation results of the competing nonlinear specifications first. Then, we confront the best fitting nonlinear model to the linear one by means of the two nonlinear tests. Finally, we inspect the fit of our selected nonlinear specification.

As discussed in section 1.2, we estimate a nonlinear model with two regimes for every candidate threshold variable. For each estimated nonlinear model we calculate the AIC, SC and HQC information criteria to choose among the competing model specifications in terms of lag structure and alternative threshold variables. We report the values of the three different information criteria for the estimated models in Table 3.6. Given the large number of model specifications it is reassuring that the data prefer the model with the debt-to-GDP ratio as a threshold variable independently of the information criterion used.[20]

[Table 3 about here.]

The different information criteria suggest quite different number of lags, ranging from $(p_1 = 1, p_2 = 1)$ by SC to $(p_1 = 3, p_2 = 4)$ by AIC. We select the most parsimonious model specification chosen by the SC criterion for the same reason we fixed the lag length for the exogenous regressor at $k = 2$: in order to minimize the probability of overfitting due to the high cost of estimating additional parameters both in terms of computer and estimation power. This leaves us enough degrees of freedom even in the regime with the smaller number of observations for the estimation the coefficients of the model.

We plot the log likelihood function against the threshold variable to assess the fit of the model and, in particular, how strong the threshold effect is in the estimated model (Figure 3.1). The log likelihood displays a sharp spike at the estimated threshold value indicating a strong threshold effect. The dotted horizontal line marks the location of

[20] In fact the data prefer the model with the debt-to-GDP ratio as the threshold variable for almost all possible combinations of the lag lengths. Thus, this result is not driven by the specific lag structure chosen or the particular way one or the other information criterion penalizes the likelihood of the models. It implies that the choice of the threshold variable depends on the log likelihood only and is independent of the choice of the lag structure which is selected by the information criterion.

the 10 percent confidence interval around the estimated threshold value based on the LR-statistics approach of Hansen [2000]. The small confidence interval implies a tightly estimated threshold value.

[Figure 1 about here.]

The test statistics for the two nonlinearity tests, the arranged regression test of Tsay [1998] and the variable addition test of Teräsvirta [1998], are shown in Table 3.7. We already have estimated the delay parameter to be $d = 3$, but we perform the tests for delay values up to 4 in order to make sure that the result is independent of the estimated value. Both tests for all delay values reject the linear model in favor of the benchmark nonlinear model even at 1 percent significance.

[Table 4 about here.]

Based on these results we feel confident to use the model with the debt-to-GDP ratio as a threshold variable as our benchmark specification. Figure 3.2 plots the evolution of the threshold variable and the estimated threshold value, that splits the sample into two parts. The estimated threshold value implies that approximately three quarters (75.5 percent) of the observations belong to the lower regime (good times), as they correspond to the debt-to-GDP ratio (lagged two periods) lower than 42.54 percent. The rest of the observations belong to the high debt-to-GDP ratio regime (bad times) denoted with the shaded area in the plot.

[Figure 2 about here.]

Table 3.8 reports the estimated feedback from the debt-to-GDP ratio to the endogenous variables. Our results are very similar to Favero and Giavazzi [2007] in the sense that the coefficients on the first and second lags are of opposite sign but the same magnitude. This is not only true for the linear model, but also for both regimes of the nonlinear model. We have tested the restriction that the sum of the lag coefficients in each equation is zero, i.e. it is the first difference of the debt-to-GDP that enters the specification with one lag only, but rejected the restriction for both models.[21]

[Table 5 about here.]

Interestingly, the models using a threshold variable related to the sovereign risk premium provide the poorest fit (Table 3.6). Furthermore, our nonlinearity tests accept the

[21] The test statistics for the linear and the nonlinear model are 25.5 and 160.4, respectively, following a chi-squared distribution with 5 and 10 degrees of freedom. The restriction is rejected in both cases even at 1 percent significance level.

linear model against the nonlinear alternative using any of these variables as a threshold variables. This confirms our prior belief that investors considered sovereign default risk negligible in the United States over our sample period. This evidence is also in line with the results of Ghosh, Kim, Mendoza, Ostry, and Qureshi [2011] that the current debt level in the US is well below its “debt limit” beyond which fiscal solvency is in doubt; or to use their terminology, the US has considerable fiscal space, defined as the distance between the current debt level and a “debt limit”.

Before we turn our attention to the estimated fiscal multipliers we deem important to stress that our results do not imply that the debt-to-GDP ratio is the only possible source of nonlinearity among the threshold variables considered here. The information criteria do not provide us a measure of nonlinearity only rank the competing specifications in terms of likelihood. Hence, our selected threshold variable is only the most likely one given our specification and an authentic one given the results of our nonlinearity tests. Other specifications or even questions within the same specification may well require the use of the other threshold variables considered here. In fact, the nonlinearity tests reject the linear specification also in favor of some of the other nonlinear models we have disregarded here.

1.5 Can fiscal policy always stimulate output?

We present the results of our impulse response analysis in this section. We compare the fiscal multipliers between the linear model and the two regimes of the nonlinear model first. Then, we examine if our results are consistent with a mean reverting debt policy in the US. Additionally, we implement a policy counterfactual to understand the source of the asymmetric response to fiscal policy shocks across regimes. We conclude this section by reviewing some implications of our model.

1.5.1 Estimated fiscal multipliers

The main focus of this section is to characterize the size of the state-dependent fiscal multipliers based on the impulse responses from our models. For this reason, and to conserve space, we present the responses of three variables: GDP which is the main variable of interest, the debt-to-GDP ratio which is the threshold variable in our model, and the deficit-to-GDP ratio which is the main driving force of debt accumulation. Recall that we use expansionary fiscal shocks equivalent to 1 percent of GDP in all our simulations; a positive expenditure and a negative revenue shock. This allows us to interpret the impulse responses of GDP as dollar value multipliers without any further transformation.

Government spending shock. We plot the responses to a positive expenditure shock in Figure 3.3. The three columns plot the same impulse responses, but differ in the confidence intervals used. The shaded area represents a one standard deviation confidence band around the impulse responses of the linear model, good times and bad times in the first, second and third columns respectively.

[Figure 3 about here.]

At almost every horizon the output response is stronger in good times than in bad with the response of the linear model in between. The peak value of the expenditure multiplier is 1.45 in the linear model, which is in line with the estimated values for the US in the literature [see Ramey, 2011, and the references therein]. Compared to other papers in the SVAR literature, it is slightly above the estimated value by Blanchard and Perotti [2002] and Favero and Giavazzi [2007], close to the findings of Perotti [2004] and below the results of Caldara and Kamps [2008] and Caldara and Kamps [2012]. The output response peaks at 1.58 after 5 quarters in good times, slightly above the linear model. The output response in bad times is stronger on impact than in good times, but steadily decreases after that and becomes weaker after 4 quarters. Its peak value is only 0.69 and it is significantly different from zero for only two periods after impact.

The response of the deficit-to-GDP ratio is the least persistent during bad times out of the three cases. It is already the weakest on impact due to regime-specific identification and it returns to baseline faster than in good times or in the linear model. This finding is consistent with the empirical evidence of Bohn [1998] that spending reversals become stronger as the debt-to-GDP ratio increases. Moreover, the finding that output response to an expenditure shock in bad times is higher at shorter while it is lower at longer horizons compared to good times is also consistent with the prediction of the New Keynesian model with spending reversals [Corsetti, Meier, and Müller, 2009].

The response of the debt-to-GDP ratio is positive in all three cases reflecting the expansionary nature of the expenditure shock. Interestingly, fiscal expansion is the least costly in terms of debt accumulation in bad times with a peak response of only 0.6 percent of GDP 10 quarters after the shock. This is due to the dynamics of both output and deficit. The stronger impact response of output implies a weaker impact response of the debt-to-GDP ratio, while the less persistent deficit response outweighs the weaker response of output afterwards and leads to a weaker debt accumulation.

Tax receipt shock. We plot the responses to a negative revenue shock in Figure 3.4. The three columns again share the same impulse responses, but differ in the depicted confidence bands.

[Figure 4 about here.]

We find that also the revenue multiplier is decreasing in the the debt-to-GDP ratio. In contrast to the case of the expenditure shock, the output response is stronger in good times than in bad already on impact, and the revenue multiplier in bad times becomes negative between quarters 4 and 17. However, it is never significantly different from zero. The peak value of the revenue multiplier is 1.55 in the linear model, which is within the range of estimates found in the empirical literature, although it is toward the high end.[22] Blanchard and Perotti [2002], Favero and Giavazzi [2007] and Barro and Redlick [2011] all estimate values close to unity, while Caldara and Kamps [2012] report a value slightly above ours. The output response in good times is very similar to that of the linear model; it is stronger up to 14 quarters after impact and becomes weaker afterwards. The revenue multiplier is positive on impact in bad times, but turns negative after 3 quarters only to return to positive 15 quarters later. Its peak value is only 0.32, however it is never significantly different from zero and it is outside of the confidence intervals of both the linear model and the other regime for almost the entire horizon.

As opposed to the case of an expenditure shock, the response of the deficit-to-GDP ratio is more persistent during bad times than during good. This finding seems to indicate that spending reversals become weaker as the debt-to-GDP ratio increases. Given that the deficit responses to the two fiscal shocks have quite different implications for the relationship between the strength of the spending reversals and the degree of indebtedness, we will return to this question in more detail later.

The response of the debt-to-GP ratio is positive again in all three cases since we are considering an expansionary revenue shock. The response of debt is much more pronounced during bad times with a peak response of 2.36 percent of GDP 15 quarters after impact. This result is driven by both the stronger deficit and weaker output responses in that regime.

Measuring the difference An important question is whether any two of the three output responses (linear model, good times and bad) are significantly different from each other. The output response to a revenue shock in the linear model and in good times never seem to be significantly different since they both are inside each other's confidence intervals. The answer is not so obvious when one impulse response lies outside of the confidence intervals of the other but the opposite is true the other way around. However, we cannot claim that they are different even if both impulse responses lie outside of the confidence intervals of one another if the distributions forming the confidence intervals are correlated; as is the case for the two regimes of the nonlinear model.

To take into account the correlation between the distributions we compute the pair-

[22] We define the revenue multiplier as the response of output divided by the size of the shock (expressed in terms of output) multiplied by minus one, $-\frac{t}{y}\frac{\Delta y}{\Delta t}$, in order to express the expansionary effect of revenue based fiscal stimulus and to facilitate comparison with expenditure multipliers.

wise differences between the impulse responses within each replication of our bootstrap approach.[23] Figure 3.5 plots the differences in the fiscal multiplier derived from the two models and the confidence intervals around these differences. The fiscal multiplier in good times is higher than that of the linear model, but it is not significantly different from it at any horizons. The expenditure multiplier in bad times is always lower than that of the linear model and good times (with the exception of the impact multiplier), but only significantly different from the good times' multiplier starting 8 quarters after impact. The revenue multiplier in bad times is also always lower than in good times or that of the linear model and it is significantly so for most of the horizon.

[Figure 5 about here.]

To sum up, we find strong asymmetries in the response of output across regimes which imply a negative relationship between the fiscal multiplier (both the expenditure and the revenue multipliers) and the debt-to-GDP ratio. This result implies that the use of deficit financed fiscal stimulus is characterized by diminishing returns since it increases the debt-to-GDP ratio and, consequently, leads to a decrease in the fiscal multiplier.

1.5.2 Inspecting the asymmetric response to fiscal policy shocks

In this section we examine the observed differences between the fiscal multipliers in the two regimes. First, we return here to the question whether spending reversals become stronger or weaker as the debt-to-GDP ratio increases. Then, we look at the structural shocks to see if regime specific identification can contribute to these differences. Then, we carry out a counterfactual analysis to determine if we can attribute the differences to the dynamic paths of one or more variables.

Spending reversals We return here to the question whether our results imply a positive or a negative relationship between the strength of the spending reversals and the degree of indebtedness. Recall that our results from the impulse response analysis show that the response of deficit to an expenditure shock is less persistent during bad times suggesting a positive relationship (Figure 3.3). On the other hand, following a revenue shock the response of deficit shows a more pronounced fiscal expansion in bad times indicating that spending reversals become weaker in that regime (Figure 3.4).

Bohn [1998] uses annual data to estimate a fiscal reaction function for the US in a single equation framework. He finds that the primary deficit-to-GDP ratio responds negatively to changes in the debt-to-GDP ratio, which implies that the debt-to-GDP ratio should be

[23] The distributions forming the confidence intervals of the linear model and any of the two regimes of the nonlinear model are uncorrelated by construction. Taking pairwise differences this way constitutes a random matching between these two populations.

mean-reverting. Furthermore, his results show that the marginal response is increasing in the debt-to-GDP ratio, which implies that spending reversals are stronger during bad times.

However, we cannot interpret the impulse response of deficit as the response to changes in debt for two reasons. First, we could interpret our identified fiscal shocks as an innovation to debt if the implied fiscal expansion was purely deficit financed. But government expenditures, for example, respond endogenously to a revenue shock in our model and it is unlikely that the response is such that the impulse response corresponds to the case of a deficit financed revenue shock. Second, Bohn [1998] finds a positive correlation between current deficit and lagged debt while an expenditure shock in our model affects debt starting only contemporaneously.

Debt enters as an exogenous regressor into our model as well as a threshold variable. This offers us two ways to assess how debt accumulation affects the evolution of deficit. The left panel of Figure 3.6 shows how the dynamics of deficit changes with the debt-to-GDP ratio as a threshold variable. It plots the mean evolution of deficit along the simulated baseline scenarios in the two regimes. The graph corroborates the first finding of Bohn [1998] since the deficit of good times is replaced by a surplus in bad times in order to stabilize the debt-to-GDP ratio.

The right panel of Figure 3.6 shows how deficit changes with debt within the regimes as well as how its dynamics shifts between regimes. It plots the impulse responses of deficit to a "debt shock" in both regimes computed the same way detailed in Section 4.[24] The negative response at each horizon during bad times implies that the higher the debt the lower deficit is, i.e. debt stabilization occurs already on impact. During good times, however, the initially positive response of deficit to an increase in debt shows an accelerating debt accumulation which turns into negative to stabilize the debt stock only after several periods. The marked shift in the impulse responses show that the marginal response of deficit to changes in debt is decreasing in the debt, which corroborates Bohn's second finding.

[Figure 6 about here.]

Regime specific identification A potential source for the differences in our impulse responses is the impulses themselves. We could observe different impulse responses across

[24]Since deficit is a nonlinear function of the endogenous variables its response depends on the value of those variables. The impact response, for example, is given by

$$\delta\left(\frac{\exp(g_t)-\exp(t_t)}{\exp(y_t)}\right)/\delta d_t = (\gamma_{g,d_{t-1}}-\gamma_{y,d_{t-1}})\frac{\exp(g_t)}{\exp(y_t)} - (\gamma_{t,d_{t-1}}-\gamma_{y,d_{t-1}})\frac{\exp(t_t)}{\exp(y_t)}$$

where $\gamma_{v,d_{t-1}}$ is the estimated coefficient of d_{t-1} in the equation of variable v. We have plotted the mean value of the responses within each regime.

regimes even with the same lag coefficients if the variables responded to different shocks due to regime specific identification. Table 3.9 compares the reduced form equivalents of the different structural shocks used in the simulations across regimes. The revenue shocks are practically identical in both regimes while we can see a difference between the reduced form equivalents of the expenditure shock. In particular, the impacts on tax revenues and output are higher in bad times.

[Table 6 about here.]

These differences on impact can prevail if the estimated processes are persistent. To determine the extent to which these differences are important we carried out a counterfactual analysis where we used the same reduced form shocks in both regimes to derive impulse responses. The first column in Figure 3.7 shows the difference between the fiscal multipliers across regimes in the benchmark model, which we repeated from the third column of Figure 3.5 for convenience. The panels in the second and third columns show the results from the experiments using the same reduced form shock in both regimes; the identified good times shock in the second and the bad times shock in the third column, respectively. While regime specific identification contributes to the differences in the multipliers across regimes, qualitatively the results are very similar to the benchmark case.

[Figure 7 about here.]

Counterfactual analysis The previous results imply that the asymmetric response of output stems from the differences in the estimated dynamics (coefficients) of the two regimes. This section presents the results of two counterfactual experiments to analyze the contribution of the fiscal rules and the interest rate rule to these observed asymmetries.

In the first experiment we examine the contribution of spending reversals. As we discussed earlier we have found evidence of spending reversals in our sample that are becoming stronger as the debt-to-GDP ratio increases. These reversals have a direct and an indirect effect on the multipliers. First, the differences in the fiscal rules can translate directly into asymmetries in the fiscal multipliers. A less persistent fiscal expansion implies a smaller multiplier during bad times even if output responded the same way to the shock. Second, as Corsetti, Meier, and Müller [2009] point out, an expansionary fiscal shock with spending reversals creates expectations of government spending below trend in the future which alters the response of the private sector.

In order to determine how much of the asymmetric response of output we can attribute to the direct effect of the differences in the fiscal rules, we implement the following counterfactual experiment. We compare the output responses in the two regimes in a model where we control for the differences in the fiscal rules. We impose the coefficients of the first two equations of one of the regimes to the other regime as well and allow for the estimated regime specific coefficients only in the other three equations; namely the GDP, inflation and interest rate equations. Comparing the three columns in Figure 3.8 shows that asymmetries in the fiscal multipliers prevail even if we impose the same fiscal rules in both regimes. Hence, the asymmetric output response is not driven by differences in policy, which leaves the explanation that it is the response of the private sector that matters.

[Figure 8 about here.]

The second experiment provides further evidence that the estimated threshold value for the debt-to-GDP ratio should not be interpreted as a fiscal limit above which public finances are not sustainable. We compare the output responses in the two regimes in a model where we allow for regime specific coefficients only in the interest rate equation while we impose the same coefficients in all the other equations. The second and third columns in Figure 3.8 show that the interest rate equation alone is not able to generate any observable asymmetries in the fiscal multipliers. Hence, the asymmetric output response does not arise from nonlinearities related to the behavior of the sovereign risk premium.

[Figure 9 about here.]

1.5.3 Model implications

This section reviews some direct or indirect implications of our model. First, we examine an issue that is specific to the impulse response analysis of nonlinear models. We vary the size and the sign of the structural shocks to see if it leads to any noticeable differences in the fiscal multipliers presented before. Second, we implement a policy counterfactual to analyze the different policy implications of the two models for the American Recovery and Reinvestment Act of 2009 (ARRA). Finally, we assess the fit of our model in terms of how well it replicates the regime switching probabilities estimated directly from the dynamics of the threshold variable.

Size of the structural shock The impulse response functions of a linear model scale up proportionally with the size of the structural shock. Hence, using a shock equivalent to 1 percent of GDP (so the impulse response function of output can be interpreted as a dollar value multiplier without any further transformation) or rescaling the impulse responses to a unit shock to represent dollar value multipliers lead to the same results. In a nonlinear model, however, the size and the sign of the shock matter.

We have varied both the expenditure and revenue shocks from a fiscal expansion equivalent to 5 percent of GDP to a contraction with the same magnitude (Table 3.10). The general conclusion from the exercise is that the more contractionary a shock is the larger the multiplier is. The intuition behind this result is that the more expansionary the shock is the more debt is accumulated and the more time the model spends during simulations in bad times where the multiplier is smaller.

[Table 7 about here.]

The effects of the US stimulus package So far we have focused on comparing the output effects of a one-time expenditure or revenue shock equivalent to 1 percent of GDP. In this policy counterfactual we try to evaluate the different policy implications of the two models for the effects of the ARRA.

The stimulus package represents a series of both expenditure and revenue shocks over 7 quarters starting in 2009:2. These shocks are all smaller than 1 percent of GDP but accumulate to 5.8 percent of GDP (Table 3.11). While we excluded the financial crisis period from our sample, the first quarter of the stimulus package is in bad times according to our estimated threshold value.[25] Consequently, we simulate impulse responses from the nonlinear model starting in that regime.

Figure 3.10 plots the impulse responses from both the linear and the nonlinear model. According to the linear model output is significantly above the baseline already on impact and the difference is steadily increasing over the entire horizon of our simulation. By the end of the fifth year output is 7.1 percent above the baseline. Deficit is increasing until the end of the stimulus package and reaches a peak deficit of 3.6 percent of GDP above baseline. Consequently debt is accumulated quickly and it peaks by 6.0 percent of GDP above the baseline 15 quarters after the first shock.

[Table 8 about here.]

The nonlinear model gives a different view on the effects of the stimulus package. It seems to be ineffective in stimulating output for 10 quarters since output remains very close to the baseline. Then it slowly rises above the baseline and by the end of the fifth year GDP is 2 percent higher than it would have been without the fiscal expansion. The response of deficit and debt are very similar to that of the linear model peaking by 3.5 and 6.4 percent of GDP above their respective baselines. Consequently, according to the nonlinear model the stimulus package is far less successful at stimulating the economy in exchange for the same consequences on accumulated debt.

[25] We have also reestimated the model using a sample period extended until 2009:4 to include the first period of the stimulus package. The inference regarding the regime in 2009:2 remains the same.

[Figure 10 about here.]

Regime switching probabilities Recall that the dynamics of the threshold variable is determined by the flow government budget constraint (1.1b) which is an identity and has no estimated parameters. The evolution of the debt-to-GDP ratio in our simulations hence is driven indirectly by shocks to the endogenous variables. This gives us a way to assess how well our benchmark model approximates the nonlinear dynamics in the data. We can compare the dynamics of the threshold variable in our simulations to the dynamics obtained from a model where innovations to the debt-to-GDP ratio are explicitly modeled.

The key contribution of the threshold variable to the dynamics of our nonlinear model is to determine the regime. To assess how well the benchmark model can replicate this aspect of the data we plotted regime switching probabilities derived from a univariate model of the debt-to-GDP ratio and from our benchmark nonlinear model in Figure 3.11.[26] The left panel plots the regime switching probabilities at each horizon for simulations starting in good times: the probability at a given horizon is approximated by the fraction of the simulations being in bad times, i.e in which the debt-to-GDP ratio is above the estimated threshold value. The right panel computes the probabilities for bad times in a similar way.

The dynamics of the threshold variable are reproduced by the benchmark nonlinear model remarkably well despite being a piecewise linear approximation only. In bad times the probabilities are always very close and never significantly different from each other. In good times the regime switching probabilities are slightly higher in the benchmark model than in the data, but again are not significantly different for most of the horizon considered. We can observe two asymmetries between the panels which can both be explained by the differences of the two subsamples constituting the two regimes.

First, the wider confidence intervals in bad times are due to the smaller subsample which translates into larger parameter uncertainty. Second, the higher probability of a regime switch in bad times can be explained by the asymmetric distribution of the threshold variable around the estimated threshold value. The distance of the highest debt-to-GDP ratio in bad times (50.60 percent) from the threshold value is 2.5 times the distance of the lowest observation in good times (22.74 percent) from the threshold, while the same ratio for the median observations in the two regimes is 2.2. Hence, the threshold variable observations are more dispersed below the threshold value than above leading to an asymmetry in the probability of regime switches.

[Figure 11 about here.]

[26]The univariate model is an autoregressive model of the debt-to-GDP ratio in levels with four lags. We have experimented also with a model in first differences, but the results remained qualitatively similar.

1.6 Robustness

In this section we consider alternative specifications to assess whether our results are due to the particular empirical strategy chosen.

Structural break Since the observations with high debt-to-GDP ratio are concentrated in the second part of our sample, it could very well be the case that the differences in the two regimes captured with our benchmark specification are caused by a structural break. Several papers studying the effects of fiscal policy shocks split their sample around 1980 to allow for the possibility of a structural break [see for example Perotti, 2004, Favero and Giavazzi, 2007, Caldara and Kamps, 2008, among others] and find that impulse responses in the second subsample are less pronounced than in the first subsample. They attribute their findings to changes in the conduct of fiscal and/or monetary policies or the developments in the variance of shocks known in the literature as the Great Moderation.

To confront our nonlinear model with the possibility of a structural break we estimate two alternative models. First, we estimate a structural break model (SB-VAR) by splitting our sample into two subsamples (1960:1-1979:4 and 1980:1-2007:4) at roughly the same date as other papers in the literature. Second, we estimate an endogeneous structural break model (ESB-VAR) where we also estimate the most likely date of the structural break in the model based on a penalized likelihood approach. In particular, we estimate a series of SB-VARs with a possible structural break as early as 1978:1 and as late as 1987:4. The estimated endogeneous structural break that emerges from this exercise is between 1979:4 and 1980:4 depending on the information criterion used.

We list the values of information criteria for both models in Table 3.12, where we also repeat the results of our benchmark specification for convenience. While we find that both alternative models provide a better fit than most of the nonlinear specifications considered in this paper, none of the two structural break models fit the data better than the benchmark specification.

[Table 9 about here.]

Three regimes While our nonlinearity tests rejected the linear model in favor of the nolinear specification with two regimes we have no a priori reason to exclude the possibility of more regimes. In fact, if nonlinearities are strong in our sample, then more regimes should improve the fit of our models given that threshold models are only piecewise linear approximations of the underlying nonlinear process. We apply the same nonlinearity tests in a recursive fashion and estimate all the competing nonlinear specifications with three regimes to investigate this possibility.

Our nonlinear model consists of two piecewise linear models and it is assumed to be linear within each regime. Hansen [1999] shows that the estimated threshold value in the case of two regimes is a consistent estimate for one of the two estimated threshold values in a model with three regimes. Consequently, the model with two regimes can be considered as a special case of the model with three regimes where two adjoing regimes are restricted to have the same coefficients. Hence, we can apply the same nonlinearity tests on the regimes of the model with two regimes to check if this linearity assumption is valid. We find some evidence against the linearity assumption in the low debt-to-GDP ratio regime which signals that the three regime model might be preferred.[27]

Based on the results of the nonlinearity tests we repeat the estimation procedure for all our nonlinear models.[28] Also in the case of three regimes the debt-to-GDP ratio emerges as the preferred threshold variable irrespective of which information criteria we use. We focus again on the most parsimonious version of the model with one lag in each regimes selected by the SC criterion to keep comparability with the two regime case.

Figure 3.12 shows the marginal log likelihood functions for each of the two threshold values obtained as cross-sections of the three dimensional log likelihood surface. In panel (a) we fix the lower threshold value at its point estimate and plot the log likelihood as a function of the higher threshold value only; in panel (b) we plot the log likelihood as a function of the lower threshold value only while fixing the higher threshold. The estimated upper threshold value is identical to the estimated threshold value in the two regime model [in line with Hansen, 1999] while the estimated lower threshold is 27.62 percent. But the latter estimate, unlike the former, is very unprecise. The 10 percent confidence band is almost 5 percentage points wide ranging from 27.61 to 32.12 percent. Based on this large parameter uncertainty about the lower threshold value, a crucial parameter for a regime-switching model, we have chosen to use the model with two regimes for our analysis.

[Figure 12 about here.]

Identification There is a considerable disagreement in the literature about the elasticity values used for identification, in particular about the output elasticity of revenues. Moreover, Caldara and Kamps [2008] have demonstrated that the fiscal multipliers computed from a SVAR using the identification approach of Blanchard and Perotti [2002] can

[27]We consider only the subsample of observations pertaining to the larger of the two regimes in our benchmark nonlinear model since the smaller subsample is too short for the tests to give reliable results.

[28]The estimation procedure is a straightforward generalization of the case with two regimes; it only takes more time given that the dimensionality of the estimation procedure is exponentially increasing in the number of regimes. Similarly to the two regimes case we fix the lag length of the exogenous regressor at $k = 2$ and consider values for both the lag lenghts of the endogenous variables and the delay parameter up to 4. We need to estimate two threshold values, $r = (r_1, r_2)$, that split the observations into three regimes. We estimate the model over a two dimensional grid $r \in R \times R$ of all possible combinations that ensure that each regime contains at least 20 percent of the observations and calculate the log likelihood for each of them. Recall that we do not constrain the model to have the same lag lengths in the two regimes and thus the "one-step-at-a-time" approach described by Hansen [1999] cannot be used here to reduce the computational burden.

be sensitive to the value of this elasticity. Therefore, we consider two alternative values of this elasticity, one lower and one higher, to assess the robustness of our results.

The construction of the first alternative follows the methodology of Caldara [2011]. We estimate the elasticity of private consumption with respect to output, a component of the output elasticity of revenues, to be 0.56 instead of assuming a value of 1 as Perotti [2004] does. This modification lowers the output elasticity of revenues by 11 percent. The second alternative is motivated by the result of Mertens and Ravn [2011], who show that the narrative record can be reconciled with an output elasticity of revenues around 3 within their proxy SVAR framework. Hence, we increase our output elasticity of revenues by 50 percent to match their value.

We find that expenditure multipliers are robust to changes in the output elasticity of revenues. This is due to the fact that the expenditure shock is ordered first in our specification. Revenue multipliers, on the other hand, are in general increasing in the value of this elasticity. The output response is stronger in both regimes when we use the higher elasticity, but the difference between the multipliers across regimes becomes smaller and less significant. The opposite is true when we use the lower elasticity and the difference between the multipliers across regimes becomes larger and and even more significant.

Debt-to-GDP ratio as an exogenous regressor One might argue that including the debt-to-GDP ratio as an exogenous regressor could bias our results in favor of the benchmark model chosen. Given that our model specification is only an approximation, using the same variable both as a regressor and a threshold variable can help the nonlinear model to capture the underlying nonlinearities in the data better. To this end we have reestimated all the models using the same variable both as a regressor and a threshold variable, but no clear pattern emerged how the information criteria have changed compared to our earlier results. Some of the competing models have their fit improved but the benchmark model still provides the best fit.

1.7 Conclusions

Motivated by the recent deterioration of the state of public finances and a rekindled interest in the ability of fiscal policy to stimulate aggregate demand, we use a regime-switching empirical model to estimate state-dependent fiscal multipliers that depend on the state of public finances in the United States. First, we estimate several model specifications in order to see which conditioning variable we should use to proxy the state of public finances for the purpose of defining the regimes in our model. We use conditioning variables related to the cost of servicing the debt, the stationarity and the stock of accumulated debt, to the primary deficit, and to the sovereign risk premia. Comparing these model specifications in terms of their fit we find that the model with the debt-to-GDP ratio as a conditining variable fits the data best. The estimated threshold value of debt that triggers the regime switch is at 42.5 percent of GDP and it splits the sample such that approximately one quarter of the observations are in the regime characterized by high debt-to-GDP ratio.

Second, using the impulse response functions of our regime-switching model we compute fiscal multipliers conditional on the debt-to-GDP ratio. The strong asymmetries that we find in the response of output across regimes reveal a negative relationship between the fiscal multiplier and indebtedness. This finding implies that the use of deficit financed fiscal stimulus is characterized by diminishing returns since an expansionary fiscal policy shock increases the debt-to-GDP ratio and, consequently, leads to a smaller fiscal multiplier. While we estimate positive fiscal multipliers in both regimes, our results show that the ability of fiscal policy to stimulate aggregate demand has been weaker in the aftermath of the financial and economic crisis than other papers in the literature have found. Moreover, our results lend support to a policy that reduces the debt stock during booms to ensure that the fiscal multiplier is higher during recessions when fiscal stimulus is most needed.

While we find that the fiscal multiplier varies with the degree of indebtedness, related empirical papers provide evidence that fiscal multipliers depend also on other factors, including business cycle conditions, exchange rate regime and the degree of openness to trade. Future research should concentrate on creating a common econometric framework that encompasses these different factors and allows to investigate their interactions and their relative contributions to the state-dependent effects of fiscal policy. Furthermore, it would be instructive to construct DSGE models that could account for the state-dependency of fiscal multipliers and would provide a platform for policy experiments.

1.A Appendix: Data

We use quarterly data for the US economy from 1960:1-2009:4. The source of all the variables are the NIPA accounts (available on the Bureau of Economic Analysis website), except for the time series for the stock of US public debt which is obtained from the FRED database (available on the Federal Reserve of St.Louis website). The definition of the variables is as follows:

— g_t: log of real per capita federal government total nominal expenditures minus net interest payments. Quarterly observations computed as

$$g_t = \log \frac{G - INT\_PAY}{POP * GDPDEF}$$

where

- G: federal government total nominal expenditure from line 40 in Table 3.2. It is seasonally adjusted at annual rates.
- INT_PAY: federal government nominal interest payments from line 29 in Table 3.2. It is seasonally adjusted at annual rates.
- GDPDEF: The price index for GDP from line 1 in Table 1.1.4. It is seasonally adjusted and the base year is 2005.
- POP: midperiod population from line 39 of Table 2.1.

— t_t: log of real per capita federal government total receipts. Quarterly observations computed as

$$t_t = \log \frac{T - INT\_REC}{POP * GDPDEF}$$

where

- T: federal government total nominal receipts from line 37 in Table 3.2. It is seasonally adjusted at annual rates.
- INT_REC: federal government nominal interest receipts from line 13 in Table 3.2. It is seasonally adjusted at annual rates.

— y_t: log of per capita GDP. Quarterly observations computed as

$$y_t = \log \frac{GDP}{POP * GDPDEF}$$

where

- GDP: nominal GDP from line 1 in Table 1.1.5. It is seasonally adjusted at annual rates.

— Δp_t: GDP deflator inflation rate. Quarterly observations computed as

$$\pi_t = \log GDPDEF_t - \log GDPDEF_{t-1}$$

— i_t: nominal cost of financing the debt. Quarterly observations computed as

$$i_t = \frac{INT\_PAY_t}{DEBT_{t-1}}$$

where

- DEBT: Federal Debt Held by the Public recomputed by the authors.

1.B Appendix: Computing generalised impulse responses

Linear model Suppose we are interested in computing responses up to horizon $t + s$ to the structural shock ε which hits our system at time t:[29]

$$GI_y(\varepsilon) = E\{\mathbf{y}_{t,t+s}|\varepsilon\} - E\{\mathbf{y}_{t,t+s}|0\}$$

where $\mathbf{y}_{t,t+s}$ denotes the history of the endogenous variables between period t and $t + s$. We obtain $GI_y(\varepsilon)$ through the following two steps:

1. We compute the impulse responses

$$GI_y(\varepsilon, \mathbf{\Theta}_t) = E\{\mathbf{y}_{t,t+s}|\varepsilon, \mathbf{\Theta}_t\} - E\{\mathbf{y}_{t,t+s}|0, \mathbf{\Theta}_t\}$$

   that are conditional on the history of model variables, both the endogenous variables and the debt-to-GDP ratio, leading up to this period, that is $\mathbf{\Theta}_t = \begin{bmatrix}\mathbf{X}_t' & \mathbf{D}_t'\end{bmatrix}'$:

   (a) Draw a sample from the estimated residuals of the model, $\varepsilon_{t,t+s}$.

   (b) Generate a baseline simulation $\mathbf{y}^{bs,l}_{t,t+s}$ for the endogenous variables and $d^{bs,l}_{t,t+s}$ for the debt-to-GDP ratio by solving the model equations (1.1a) and (1.1b) forward conditional on the initial condition $\mathbf{\Theta}_t$. The superscript bs stands for baseline simulation, while l denotes the number of the current replication (see point 1e). Use the resampled residuals from step 1a for the simulation.

   (c) Generate an alternative simulation $\mathbf{y}^{as,l}_{t,t+s}$ for the endogenous variables and $d^{as,l}_{t,t+s}$ for the debt-to-GDP ratio by solving the model forward conditional on $\mathbf{\Theta}_t$. The superscript as stands for alternative simulation. Use the resampled residuals from step 1a for the simulation with the first realization perturbed by the shock, i.e. replace ε_t with $\varepsilon_t + \varepsilon$.

   (d) Compute the impulse response of replication l as $\mathbf{y}^{as,l}_{t,t+s} - \mathbf{y}^{bs,l}_{t,t+s}$. Notice that this response is conditional on the particular history $\varepsilon_{t,t+s}$.

[29] Artis, Galvão, and Marcellino [2007] refer to ε as the "extraordinary" shock to distinguish it from the shocks they draw from the estimated normal distribution of the residuals to simulate time series from their model. We resample the estimated residuals both for the linear and the nonlinear VAR instead to simulate time series from our model. Therefore, we will refer to ε as a structural shock, or shock for short, as opposed to the residuals.

(e) Repeat steps 1a to 1d for $l = 1, \ldots, L$ to average out the effects of future histories $\varepsilon_{t,t+s}$, which affect both the baseline and the alternative scenarios similarly.[30] Notice that we use the same draws to compute the two simulations, which guarantees that the only source of difference between them is the shock ε.

2. To obtain impulse responses $GI_y^{(j)}(\varepsilon)$ we average $GI_y(\varepsilon, \mathbf{\Theta}_t)$ over all histories within our sample.

Nonlinear model Suppose that the threshold variable is a function of the model variables:

$$z_t = f(\mathbf{Y}_t, \mathbf{X}_t, d_t, \mathbf{D}_t) \tag{2c}$$

We obtain $GI_y^{(j)}(\varepsilon)$, responses up to horizon $t+s$ to the structural shock ε which hits our system at time t through the following steps:

1. We compute the impulse responses

$$GI_y^{(j)}(\varepsilon, \mathbf{\Theta}_t^{(j)}) = E\{\mathbf{y}_{t,t+s}|\varepsilon, \mathbf{\Theta}_t^{(j)}\} - E\{\mathbf{y}_{t,t+s}|0, \mathbf{\Theta}_t^{(j)}\}$$

that are conditional on the history of model variables leading up to this period, that is $\mathbf{\Theta}_t^{(j)} = \begin{bmatrix}\mathbf{X}_t^{(j)\prime} & \mathbf{D}_t^{(j)\prime} & z_{t-d}^{(j)} & \ldots & z_t^{(j)}\end{bmatrix}'$:

(a) Draw one sample for each regimes from the estimated residuals of the model, $\varepsilon_{t,t+s}^{(i)}$ $(i = 1, 2)$.

(b) Generate a baseline simulation $\mathbf{y}_{t,t+s}^{bs,l}$ for the endogenous variables, $d_{t,t+s}^{bs,l}$ for the debt-to-GDP ratio and $z_{t,t+s}^{bs,l}$ for the threshold variable by solving the model equations (1.2a)-(2c) forward conditional on the initial condition $\mathbf{\Theta}_t^{(j)}$. The superscript bs stands for baseline simulation, while l denotes the number of the current replication. Use the resampled residuals from step 1a for the simulation.

(c) Generate an alternative simulation $\mathbf{y}_{t,t+s}^{as,l}$ for the endogenous variables, $d_{t,t+s}^{as,l}$ for the debt-to-GDP ratio and $z_{t,t+s}^{as,l}$ for the threshold variable by solving the model forward conditional on $\mathbf{\Theta}_t$. The superscript as stands for alternative simulation. Use the resampled residuals from step 1a for the simulation with the first realization perturbed by the shock, i.e. replace $\varepsilon_t^{(j)}$ with $\varepsilon_t^{(j)} + \varepsilon$.

(d) Compute the impulse response of replication l as the difference between the alternative and the baseline scenarios. Notice that this response is conditional on the particular histories $\varepsilon_{t,t+s}^{(j)}$.

[30]We use $L = 2000$ for all of our simulations throughout the paper.

(e) Repeat steps 1a to 1d for $l = 1, \ldots, L$ to average out the effects of histories $\varepsilon^{(j}_{t,t+s})$, which affect both the baseline and the alternative scenarios similarly. Notice that we use the same draws to compute the two simulations, which guarantees that the only source of difference between them is the shock ε.

2. To obtain impulse responses $GI^{(j)}_y(\varepsilon)$ we average $GI^{(j)}_y(\varepsilon, \mathbf{\Theta}^{(j)}_t)$ over all histories belonging to regime j.

Chapter 2

Public wage bill adjustment in a small open economy

Public wage bill adjustment in a small open economy

Andreja Lenarčič[1]

[1] Università Bocconi and Bank of Slovenia. The views presented do not necessarily correspond to the views of the Bank of Slovenia. I am grateful to Francesco Giavazzi, Matija Lozej, Tommaso Monacelli, Simon Savšek and Antonella Trigari for helpful comments and suggestions. All the remaining errors are mine. E-mail: andreja.lenarcic@phd.unibocconi.it.

Abstract

We build a small open economy DSGE model with private and public sector labour markets that are both subject to search and matching frictions. In this framework we analyse the effects of cuts in public sector wages and vacancies, with a focus on how the competitiveness of the economy and the trade balance change in face of such shocks. The results depend markedly on whether the unemployed can optimally choose in which sector to search for a job. If movement between the sectors is allowed, a cut in the public sector wages or vacancies leads to lower public sector employment and output. Simultaneously, private sector employment and output increase and the total unemployment decreases. Further, public wage or vacancy cuts lead to lower private sector wages after the first period which translates into lower prices of home goods and lead to higher terms of trade and an increase in exports. Increasing the degree of trade openness in the model leads to more pronounced increase in net exports following the reduction in public sector wage bill. Our results are broadly in line with the empirical impulse responses, that we get from a panel SVAR estimated on three open economies. An exception is the reaction of the real exchange rate.

Keywords: fiscal policy, labour market frictions, public wages, consolidation, open economy

JEL Classification: E62, E24, F41, J45

2.1 Introduction

Public wage bill represents a large share of total government expenditures,[2] yet most of the literature modelling the effects of government expenditures focuses on government spending in the goods and services markets. An additional motivation to study the effects of changes in the public wage bill is linked to the recent fiscal consolidation efforts in many European countries that have often introduced cuts in public sector wages or employment as part of their adjustment measures. An important question not widely addressed in the literature is how these measures affect the competitiveness of the economy.

In this paper we address this topic from an empirical and theoretical point of view. We start by estimating a structural panel VAR using quarterly data on three industrialized small open economies, Australia, Canada and the UK. We find that after a government wage cut, output gradually increases, while the unemployment rate decreases and remains suppressed for more than 20 quarters. Net exports increase on impact, while the real exchange rate appreciates. A cut in government employment produces very similar dynamics, leading to an increase in output and a decrease in unemployment. The response of the real exchange rate and net exports is insignificant for a number of periods after the shock. Our finding that the cut in government wages decreases unemployment is in line with the previous literature that explicitly models the public sector labour market [see Ardagna, 2007, Quadrini and Trigari, 2008, Gomes, 2011, Bermperoglou, Pappa, and Vella, 2013].

In the next step we verify to what extent we can replicate these results in a theoretical model. In particular, we analyse the effects of a cut in public sector wages and a cut in public sector vacancies in a small open economy model where we focus primarily on the effects of these measures on terms of trade, real exchange rate, exports and the trade balance. Additionally, we explore how the effects of the public sector wage bill reduction depend on the trade openness of the economy.

A further interesting question is how the effects of consolidation via a cut in public sector wages or vacancies compare with the effects of a cut in government consumption of goods and services. As it has been shown in the literature, the real wage reacts positively to a government consumption shock [see Monacelli, Perotti, and Trigari, 2010, Ravn and Simonelli, 2007, Ramey, 2009, Pappa, 2009]. At the same time a number of authors have shown that a cut in public sector wages reduces wages in the private sector as well Ardagna [see 2007], Quadrini and Trigari [see 2008], Gomes [see 2011], Bermperoglou, Pappa, and Vella [see 2013]. Consequently, a cut in government consumption could have similar effects as a cut in public sector wages. On the other hand, the existing literature suggests that

[2] According to Gomes [2011] in the United States the public sector wage bill represents around 60 percent of government consumption expenditure.

the response of the total unemployment after a standard government consumption shock on could differ from the effect of the government wage cut. Monacelli, Perotti, and Trigari [2010] for instance find that a positive shock in government consumption leads to lower unemployment in their SVAR. Similarly, Ravn and Simonelli [2007] find that a shock to government purchases leads to a very protracted increase in employment and real wages, while unemployment declines gradually. Given these mixed results, we compare in our theoretical model the effects of the public sector wage and vacancy cuts to the responses obtained after a cut in government consumption of goods and services.

The effects of the three fiscal shocks, a shock to public wages, public vacancies and government spending shock, are studied using a small open economy DSGE model with sticky prices, similar to Faia and Monacelli [2008], and search and matching frictions in the labour market, based on Mortensen and Pissarides [1994] and Pissarides [2000]. The workers can work or search for work in two sectors, private and public (government) sector, similar to the models by Quadrini and Trigari [2008], Gomes [2011] and Bermperoglou, Pappa, and Vella [2013]. We develop two versions of the model, one with a fixed share of unemployed searching in the public sector, and another where the workers are allowed to move between sectors. Private sector wages are determined with the standard Nash bargaining, while in public sector wages and the number of posted vacancies are determined exogenously by the government. We abstract from different possibilities of government budget financing and assume that the budget is balanced each period by adjusting lump-sum taxes.

Our main theoretical findings are as follows. First, the effects of cuts in public sector wages and vacancies in our model depend strongly on whether the share of unemployed searching in the public sector is fixed or chosen in the household optimization process. When the share is fixed, we observe no effects of the public sector wage shock on most of the variables and the responses following the public sector vacancy shock are quite different from the case with a flexible share. At the same time, the effects of the government spending shock are the same for most of the variables independently of which version of the model we use.

Second, all three shocks lead to an increase in private sector employment and output. At the same time, public sector employment and output decrease following the cut in government wages and vacancies, while the effect of the negative government consumption shock depends on whether the workers can move between the two sectors or not. The public sector employment responds negatively only when the share of searchers in the public sector is fixed. A cut in public sector wages and a cut in government consumption both lead to a decrease in total unemployment, while after a vacancy shock, unemployment falls only if the unemployed can move between the sectors.

Third, we find that consolidation via public wage or vacancy cuts leads to a lower private sector wage after the first period. On impact however, the response is positive due to a higher firm surplus that is affected by the positive wealth effect and consequently higher intermediate goods prices. A negative government spending shock leads to a different response of private sector wages. Wages decrease sharply on impact and return to the steady state in a few periods.

Fourth, lower wages translate into lower prices of home goods and lead to higher terms of trade and an increase in exports. The dynamics with which exports increase is similar following the negative shocks in public wages and vacancies. There is no effect on impact but exports start to increase quickly, reach a peak at about 5-10 quarters and revert slowly to the steady state thereafter. A negative government spending shock leads to a positive but much less persistent response of exports with a sharp increase on impact.

Finally, when changing the degree of trade openness for the case of the negative wage and vacancy shocks, we find that in a more open economy the positive effect on exports is smaller due to a smaller response of terms of trade. On the other hand, in a more open economy the CPI-PPI ratio reacts more to the cut in public sector wages or vacancies. This leads to lower imports which together with the reaction of exports yields a higher net export effect for a more open economy.

The rest of the paper is organized as follows. Section 2.2 estimates of the effects of the government wage and employment shocks on the main variables of interest. Section 2.3 presents the theoretical model. Parametrization is described in Section 2.4. Section 2.5 contains the simulations from the theoretical model. Section 2.6 presents the analysis of how the openness of the economy affects the results. Section 2.7 concludes.

2.2 Empirical evidence

In order to investigate the effects of a negative shock in government sector wages and government employment, we estimate a structural panel VAR, where we pool quarterly data on three small open economies, Australia, Canada and United Kingdom, for which we could get relatively long time series for the variables needed. The sample runs from 1991:1-2006:2, whereby the cut-off data is due to the cut-off of some of the Australian series.[3]

The empirical model includes the following endogenous variables: a labour market variable (to be specified below) x_t, log real per capita GDP y_t, the GDP deflator inflation rate π_t, the short term risk free interest rate i_t, the unemployment rate ur_t, net exports as share of GDP nx_t and log CPI based real effective exchange rate$reer_t$. The latter

[3]The data sources are listed in the Appendix.

is constructed in the original series such that an increase means that the products in domestic country become more expensive, i.e. that the domestic country appreciates vis-a-vis other countries. As the labour market variable, we include interchangeably the log number of government sector employees and the log of real compensation per employee in the government sector. Since there are no official series for the latter, we calculate it by dividing the real total compensation of government employees with the number of employees in this sector. All variables, except for the nominal interest rate, are seasonally adjusted.

We estimate the VAR by OLS, where we include country dummies and a country specific trend. Pooling the data in such way is expected to increase efficiency of the estimates. At the same time, panel estimation can be subject to the inconsistency of the estimates due to endogeneity stemming from combining lagged variables and fixed effects estimation (Nickell [1981] bias). Since the time series dimension (62 observations) is relatively large, we are probably safe form these concerns. The model includes 2 lags of the vector of endogenous variables.

After estimating the reduced form of the model, we identify the government wage and employment shocks using Cholesky decomposition of the variance-covariance matrix. The identification relies on the ordering of the shocks. We order the government labour market variables first, since the policy shocks such as cutting government sector wages or employment usually take some time before discussed and implemented. Therefore it is safe to assume that these variables fail to react to changes in the rest of our endogenous variables within a quarter. At the same time, changes in the government labour market variables are assumed to have an effect on the rest of the variables contemporaneously. The ordering of the rest of the variables follows the previous empirical literature on fiscal policy shocks. Similar to Perotti [2004] we order output after the government shocks, followed by inflation and the interest rate. The unemployment rate is included afterwards, as in Monacelli, Perotti, and Trigari [2010]. Finally, following Ravn, Schmitt-Grohé, and Uribe [2007] we order the net exports after GDP and before the real exchange rate.

[Figure 13 about here.]

[Figure 14 about here.]

In Figure 3.13 we present results for the negative government wage shock and in Figure 3.14 for the negative government employment shock. After a negative government wage shock, we observe a gradual increase in the GDP that becomes significant after about 10 quarters. Unemployment rate decreases with a negative effect lasting for more than 20 quarters. As the same time we observe an increase in net exports on impact and an increase in the real exchange rate, which means a loss in competitiveness. After a negative government emplyoment shock, the dynamics of the variables is very similar. GDP decreases on impact but quickly increases and remains above the zero line for many quarters. The response of the unemployment rate is a mirror image of the output response. The response of the exchange rate is poisitive but insignificant. The response of net exports is insignificant for about 10 periods, when the negative effect becomes significant.

2.3 The model

We analyze the shock in public wages in a small open economy DSGE model. We follow Faia and Monacelli [2008], where the world consists of two countries, Home and Foreign and the relative size of Home is approaching to zero. In this setting the dynamics in Foreign are viewed as exogeneous from the standpoint of Home. In both economies, there is a representative infinitely lived household, consisting of a continuum of individuals of size 1 that either work or are unemployed and searching for work. Like in Merz [1995], the income is shared between the members of the household, such that in the end they all consume the same. The workers can work or search for work in two sectors, private and public (government) sector, similar to the models by Quadrini and Trigari [2008], Gomes [2011] and Bermperoglou, Pappa, and Vella [2013]. In the baseline case, we depart from these papers and fix the share of individuals searching in the public sector. In the second version of the model, this share is instead chosen in the process of household's optimization and varies over time. We model the labour market in each of the sectors with search and matching frictions based on Mortensen and Pissarides [1994] and Pissarides [2000]. In the private sector wages are determined based on the Nash bargaining, while in the public sector they are determined by the government. Also the number of posted vacancies is determined exogenously by the government. In order to keep analytical tractability, we separate the hiring and pricing decisions in the private sector, as in Trigari [2009]. There are two types of firms, intermediate producers and final retailers. The intermediate firms produce a homogeneous good, are perfectly competitive and hire workers subject to search and matching frictions. The final goods firms are monopolistic competitive and repackage the intermediate goods into differentiated varieties and sell them with a mark-up to the final consumers. They set the prices following the standard Calvo pricing [Calvo, 1983]. Time is discrete.

2.3.1 Open economy model with fixed labour supply

Households

In both countries, there is a representative household with a continuum of members, that can be employed or unemployed. The members pool their income together and maximize the life-time utility of the representative household as a whole. This set-up follows the "representative family construct" as in Merz [1995] which is often used in the models with search and matching frictions [see e.g. Gertler, Sala, and Trigari, 2008, Trigari, 2009] in order to avoid the need for tracking individual employment histories. The households choose consumption of the composite index of goods c_t, government services y_t^g and a portfolio of one-period state-contingent securities b_{t+1},[4] in order to maximize the following expression:

$$E_t \sum_{j=0}^{\infty} \beta^j u\left(c_{t+j}, y_{t+j}^g\right) \quad s.t. \tag{2.1}$$

$$p_t^g y_t^g + p_t c_t + E_t\left[\Lambda_{t,t+1} b_{t+1}\right] = b_t + p_t w_t^p n_t^p + p_t w_t^g n_t^g + p_t b^u\left(1 - n_t^p - n_t^g\right) + \Gamma_t - T_t \tag{2.2}$$

In the budget constraint, b^u are real unemployment benefits, w_t^g and w_t^p real wages in government and private sector, $\Lambda_{t,t+1}$ is the stochastic discount factor for one-period ahead nominal payoffs. Γ_t are the nominal profits of the monopolistic firms and T_t the nominal lump-sum taxes. y_t^g are government services, produced in the public sector, and p_t^g the prices of these goods.[5]

Optimization gives the following optimality conditions:

$$\lambda_t p_t = u_c'(.) \tag{2.3}$$

$$\lambda_t p_t^g = u_g'(.) \tag{2.4}$$

$$\Lambda_{t,t+1} = \beta \frac{\lambda_{t+1}}{\lambda_t} \tag{2.5}$$

$\Lambda_{t,t+1}$ is the stochastic discount factor based on the households' marginal utility of consumption. Note that we can define the nominal interest rate (or return on the corresponding riskless one-period bond) by taking conditional expectations of equation (2.5)

[4]We assume existence of complete markets for state-contingent securities within and across the countries.

[5]Both Gomes [2011] and Bermperoglou, Pappa, and Vella [2013] include government services in the utility function, but the households do not optimize over y_t^g. In Gomes [2011] they take the amount of public services and unemployment as given, while in Bermperoglou, Pappa, and Vella [2013] the households choose unemployment and labour in private and government sectors, while still not optimizing over the public services.

and rearranging as:

$$R_t = (1 + r_t) = E_t \left[\Lambda_{t,t+1}\right]^{-1} = \left[\beta E_t \left(\frac{u'_{c,t+1}(.)}{u'_{c,t}(.)} \frac{p_t}{p_{t+1}}\right)\right]^{-1} \tag{2.6}$$

The utility function takes the following form:

$$u\left(c_t, y_t^g\right) = \frac{\left(c_t + \zeta_g y_t^g\right)^{1-\psi}}{1-\psi} \tag{2.7}$$

which yields the following expression for the marginal utility of consuming the composite index of goods: $u'_{c,t}(.) = (c_t + \zeta_g y_t^g)^{-\psi}$. The marginal utility of consuming government services is instead $u'_{y^g,t}(.) = \zeta_g \left(c_t + \zeta_g y_t^g\right)^{-\psi}$. From this and using (2.3) and (2.3), we can see that the ratio between government services prices and the price level $\frac{p_t^g}{p_t}$ in this set up equals ζ_g and is therefore a constant.

In addition to the intertemporal optimization, the households also optimize over different varieties of goods produced in Home and Foreign. As in Faia and Monacelli [2008] the households at Home consume a composite index of domestic and foreign bundles of goods c_t:

$$c_t = \left[(1-\gamma)^{\frac{1}{\eta}} c_{H,t}^{\frac{\eta-1}{\eta}} + \gamma^{\frac{1}{\eta}} c_{F,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{2.8}$$

where $\gamma = (1-n)\alpha$ denotes the weight of the foreign imported goods in the domestic consumption basket with n being the relative size of the Home country. We model Home as small open economy by letting $n \to 0$. α denotes the degree of trade openness of the Home economy. As in Faia and Monacelli [2008], we assume home bias in trade, which requires $\alpha < 1$. $\eta > 0$ denotes the elasticity of substitution between domestic and foreign goods. The consumption preferences in Foreign are described by a similar composite index of goods c_t^*:

$$c_t^* = \left[(1-\gamma^*)^{\frac{1}{\eta}} c_{H,t}^{*\frac{\eta-1}{\eta}} + (\gamma^*)^{\frac{1}{\eta}} c_{F,t}^{*\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{2.9}$$

where $\gamma^* = n\alpha^*$.

The consumption bundles $c_{H,t}$ and $c_{F,t}$ in the Home economy are aggregates of a continuum of varieties produced at Home and Foreign and are defined as:

$$c_{H,t} = \left(\frac{1}{n}\right)^{\frac{1}{\epsilon}} \left[\int_0^n c_{H,t}(i)^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon}{\epsilon-1}} \tag{2.10}$$

$$c_{F,t} = \left(\frac{1}{1-n}\right)^{\frac{1}{\epsilon}} \left[\int_n^1 c_{F,t}(i)^{\frac{\epsilon-1}{\epsilon}} di\right]^{\frac{\epsilon}{\epsilon-1}} \tag{2.11}$$

where ϵ is elasticity of substitution between different varieties. Analogous expressions hold in Foreign. The domestic household's demand for different varieties and for the Home and Foreign bundle are as follows:

$$c_{H,t}(i) = \frac{1}{n}\left(\frac{p_{H,t}(i)}{p_{H,t}}\right)^{-\epsilon} c_{H,t} \tag{2.12}$$

$$c_{F,t}(i) = \frac{1}{1-n}\left(\frac{p_{F,t}(i)}{p_{F,t}}\right)^{-\epsilon} c_{F,t} \tag{2.13}$$

$$c_{H,t} = (1-\gamma)\left(\frac{p_{H,t}}{p_t}\right)^{-\eta} c_t \tag{2.14}$$

$$c_{F,t} = \gamma\left(\frac{p_{F,t}}{p_t}\right)^{-\eta} c_t \tag{2.15}$$

where p_t is a domestic CPI index:

$$p_t = \left[(1-\gamma)\, p_{H,t}^{1-\eta} + \gamma p_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{2.16}$$

Again, we use analogous expressions for the demand for different varieties and CPI in the Foreign country.

Labour market

In each economy, there is private and public sector labour market, with a fixed share of individuals working and searching in each of the sectors. In what follows we specify the equations for the Home economy but analogous expressions are used for modelling the labour market in the Foreign economy. In the baseline model, the individuals cannot move between the sectors. In the private sector, wages are determined by means of Nash bargaining and public wages are determined by the government. Apart from search and matching frictions there are no other frictions in the labour market. We denote private sector variables with p and the public sector ones with g. Total labour force is equal to the size of the representative household,fixed and normalized to 1.

The timing of the events follows the set-up in Gertler, Sala, and Trigari [2008] and Monacelli, Perotti, and Trigari [2010], where the workers searching for a job in each of the sectors u_t^i for $i = g, p$ are those that were unemployed at the end of the previous period $t-1$:

$$u_t = 1 - n_{t-1}^p - n_{t-1}^g, \tag{2.17}$$

whereby the share of individuals searching in the government sector is determined by a fixed parameter $s < 1$:[6]

$$u_t^p = (1-s)u_t \tag{2.18}$$

$$u_t^g = su_t, \tag{2.19}$$

New matches m_t^i for $i = g, p$ between job seekers and vacancies are established and they become productive immediately. Additional workers get unemployed in each sector due to exogenous separation at rate ρ^i. The separated workers can only start searching for a new job next period and are thus excluded from the search-matching process within the current period. The law of motion for employment in each sector is therefore:

$$n_t^i = m_t^i + \left(1-\rho^i\right) n_{t-1}^i \tag{2.20}$$

Such timing according to Gertler, Sala, and Trigari [2008] yields more realistic cyclical behaviour, since it produces fluctuations due to cyclical variation in hiring and not in separations.[7] The matching is based on the standard Cobb-Douglas matching function:

$$m_t^i = \sigma_{m,i} \left(u_t^i\right)^{1-\alpha^i} \left(v_t^i\right)^{\alpha^i}, \ i = g, p \tag{2.21}$$

where α^i represents the elasticity of matches with respect to vacancies v_t^i.The probability of filling a vacancy in sector i is then $q_t^i = \frac{m_t^i}{v_t^i}$, while we define the probability of finding a job in sector i as $x_t^i = \frac{m_t^i}{u_t^i}$. Market tightness is defined as $\theta_t^i = \frac{v_t^i}{u_t^i}$.

Workers

The flow value of being employed in sector i is the real wage w_t^i. The continuation value of being employed depends on the next period values of being employed and unemployed and an exogenous probability of separation from the job ρ^i. The value of being employed at time t is the sum of flow and continuation values:

$$W_t^i = w_t^i + E_t \Lambda_{t,t+1} \Pi_{t+1} \left[\left(1-\rho^i\right) W_{t+1}^i + \rho^i U_{t+1}^i\right], \ i = p, g \tag{2.22}$$

where $\Pi_{t+1} = \frac{p_{t+1}}{p_t}$. Along similar lines, the value of being unemployed and searching in sector i is defined as follows:

$$U_t^i = b^u + E_t \Lambda_{t,t+1} \Pi_{t+1} \left[x_{t+1}^i W_{t+1}^i + \left(1-x_{t+1}^i\right) U_{t+1}^i\right], \ i = p, g \tag{2.23}$$

where the unemployment benefit b^u is the flow value of being unemployed. The continuation value depends on the probability of finding a job next period, x_{t+1}^i. The value of being

[6]This parameter will be endogenised later, see Section 2.3.2.
[7]See also Hall [2005a,b] and Shimer [2005].

employed rather than unemployed, or the household surplus is defined as $H_t^i = W_t^i - U_t^i$, for each sector i.

$$H_t^i = w_t^i - b^u + E_t\left[\Lambda_{t,t+1}\Pi_{t+1}H_{t+1}^i\left(1-\rho^i - x_{t+1}^i\right)\right],\ i = p, g. \tag{2.24}$$

Firms

There are two types of firms, intermediate goods producers and final goods firms. The intermediate firms are perfectly competitive and are producing a homogeneous good. They are the ones using labour input and thus subject to search and matching frictions. The final goods firms repackage the intermediate goods and sell them. They are monopolistic competitive and are able to set prices above the marginal costs, thus earning a mark-up. Prices are sticky and set according to the Calvo pricing Calvo [1983]. The separation of the price setting problem and the search and matching frictions follows Trigari [2009] and is used for analytical convenience.

Intermediate goods producers and the value of a filled vacancy

The intermediate goods firms produce the intermediate good and hire workers subject to search and matching frictions. Their production function is $y_t^I = a_t n_t^p - \kappa^p v_t^p$, where $\kappa^p v_t^p$ is the cost of posting a vacancy and a_t is the technology, that follows an AR(1) process. The firms choose vacancies v_t^p such that they maximize the stream of profits:

$$E_t\sum_{j=0}^{\infty}\Lambda_{t,t+j}\Pi_{t+1}\left[\frac{p_{t+j}^I}{p_{t+j}}\left(a_{t+j}n_{t+j}^p - \kappa^p v_{t+j}^p\right) - w_{t+j}^p n_{t+j}^p\right], \tag{2.25}$$

subject to the law of motion for employment in the private sector, i.e. equation (2.20) for $i = p$. Optimization gives us the following optimality condition:

$$\mu_t^\nu = \frac{\kappa^p}{q_t^p}\frac{p_t^I}{p_t} \tag{2.26}$$

where μ_t^ν is the Lagrange multiplier pertaining to equation (2.20) and presents the value of a worker for a firm. Maximizing the firms profits with respect to n_t^p gives us another optimality condition:

$$\mu_t^\nu = \frac{p_t^I}{p_t}a_t - w_t^p + E_t\left[\Lambda_{t,t+1}\Pi_{t+1}\mu_{t+1}^\nu\left(1-\rho^p\right)\right] \tag{2.27}$$

We get the vacancy posting condition by merging (2.26) and (2.27):

$$\frac{\kappa^p}{q_t^p}\frac{p_t^I}{p_t} = a_t\frac{p_t^I}{p_t} - w_t^p + E_t\left[\Lambda_{t,t+1}\Pi_{t+1}\frac{\kappa^p}{q_{t+1}^p}\frac{p_{t+1}^I}{p_{t+1}}(1-\rho^p)\right]. \tag{2.28}$$

We would get the same optimality condition if we merged the value function of having a job filled J_t with the value of a vacancy opening V_t

$$J_t = a_t\frac{p_t^I}{p_t} - w_t^p + E_t\left[\Lambda_{t,t+1}\Pi_{t+1}\left((1-\rho^p)J_{t+1} + \rho^p V_{t+1}\right)\right] \tag{2.29}$$

$$V_t = -\kappa^p + q_t^p J_t + E_t\left[\Lambda_{t,t+1}\Pi_{t+1}\left(1-q_t^P\right)V_{t+1}\right] \tag{2.30}$$

and applied the free entry condition ($V_t = 0$, $\forall\ t$). From the second equation we also get the definition of the firm surplus: $J_t = \frac{\kappa^p}{q_t^p}\frac{p_t^I}{p_t}$.

Wage bargaining

After the match is made, the optimal wage for all private sector workers is determined each period via the standard Nash bargaining, such that the total surplus is optimally split between a worker and a firm. This is done by choosing the optimal wage w^{p*} such that the weighted product of the firm and household's surplus is maximized:

$$\left[W_t^p(w_t^p) - U_t\right]^{\eta^N} J_t^p(w_t^p)^{1-\eta^N} \tag{2.31}$$

where η^N is the bargaining power of the worker. The first order condition when maximizing with respect to w^p is:

$$\eta^N J_t^p(w_t^{p*}) = \left(1-\eta^N\right) H_t^p(w_t^{p*}) \tag{2.32}$$

and the optimal wage can be then obtained by plugging (2.24) and (2.28) in the expression above and rearranging.

$$w_t^p = \eta^N\frac{p_t^I}{p_t}a_t + \left(1-\eta^N\right)b^u + \eta^N E_t\left[\Lambda_{t,t+1}\Pi_{t+1}\kappa^p\frac{p_{t+1}^I}{p_{t+1}}\theta_{t+1}\right]. \tag{2.33}$$

Final goods firms

There exists a continuum of monopolistically competitive final goods producers (retailers) denoted by i that buy the homogeneous intermediate good, differentiate it and sell the different varieties of the final good to the households, the government and abroad. The households consume amount $c_{H,t}$, the government amount $c_{H,t}^g$ and the consumers in

Foreign amount $c^*_{H,t}$ of the home produced goods index:

$$y_{H,t} = \left[\int_0^n y_{H,t}(i)^{\frac{\epsilon-1}{\epsilon}} dj\right]^{\frac{\epsilon}{\epsilon-1}} \tag{2.34}$$

with the corresponding aggregate price index:

$$p_{H,t} = \left[\int_0^n p_{H,t}(i)^{1-\epsilon} di\right]^{\frac{1}{1-\epsilon}}. \tag{2.35}$$

The aggregate demand curve for each of the i differentiated goods produced in Home economy includes the demand from Home and Foreign (households and governments) and has the following form:

$$y_{H,t}(i) = \left(\frac{p_{H,t}(i)}{p_{H,t}}\right)^{-\epsilon} y_{H,t} \tag{2.36}$$

where $y_{H,t}$ is the world aggregate demand for a bundle of goods produced in Home economy.

The retailers charge a mark-up over the marginal cost of the goods they resell. Following Calvo [1983] we assume that in each period the retailing firms are able to reset the price of their differentiated goods with probability $(1-\xi)$. The price level of domestic goods then evolves according to the following expression:

$$p_{H,t} = \left[\xi p_{H,t-1}^{1-\epsilon} + (1-\xi)\, \tilde{p}_{H,t}^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}. \tag{2.37}$$

where $\tilde{p}_{H,t}$ is the price determined by the retailers that are able to reset the price. They choose the optimal price $\tilde{p}_{H,t}(i)$ such that they maximize the expected discounted future profits given the demand for good i (eq. 2.36) and the probability ξ that they will not be able to change the price in the next period (in nominal terms):

$$\max E_t \sum_{j=0}^{\infty} \xi^j \Lambda_{t,t+j} \left(\tilde{p}_{H,t}(i) - mc^N_{t+j}\right) y_{H,t+j}(i). \tag{2.38}$$

The resulting optimality condition reads:

$$\tilde{p}_{H,t}(i) = \frac{\epsilon}{\epsilon-1} \frac{E_t \sum_{j=0}^{\infty} \Lambda_{t,t+j} \xi^j mc^N_{t+j} y_{H,t+j}(i)}{E_t \sum_{j=0}^{\infty} \Lambda_{t,t+j} \xi^j y_{H,t+j}(i)} \tag{2.39}$$

where $\frac{\epsilon}{\epsilon-1}$ represents the mark-up the retailers would charge in the case of flexible prices and mc^N_{t+j} the nominal marginal cost. Since the retailing firm buys goods from the intermediate good producers and differentiates them, the nominal marginal cost is the relative price of the intermediate good p_t^I. Since the relevant price level for home producers is $p_{H,t}$, we then define the real marginal cost as $p_t^I/p_{H,t}$ that can be derived from equation (2.28):

$$\frac{p_t^I}{p_{H,t}} = \left(a_t - \frac{\kappa^p}{q_t^p}\right)^{-1} \left[w_t^p \frac{p_t}{p_{H,t}} - E_t \left(\Lambda_{t,t+j} \frac{p_{H,t+j}}{p_{H,t}} \frac{\kappa^p}{q_{t+1}^p} \frac{p_{t+1}^I}{p_{H,t+1}} (1-\rho^p)\right)\right]. \tag{2.40}$$

Government

The government collects lump-sum taxes (net of lump-sum transfers) and gives unemployment benefits to the unemployed. In addition, government spends resources on goods produced in Home country $c_{H,t}^g$ (this consumption is pure waste) and on government sector wage bill. Government services are produced according to $y_t^g = a_t n_t^g - \kappa^g v_t^g$, where in addition to the wages, the government has to pay for the cost of posting vacancies. The government budget gets balanced every period via the lump-sum taxes and there is no government debt. The intertemporal government budget constraint is thus as follows:

$$p_t w_t^g n_t^g + p_{H,t} c_t^g + p_t b^u (1 - n_t^g - n_t^p) = T_t + p_t^g y_t^g \tag{2.41}$$

whereby the government vacancies v_t^g, wages w_t^g and consumption spending c_t^g are determined by the government according to the following processes:

$$log\left(w_t^g\right) = \left(1 - \rho^{w^g}\right) log\left(\bar{w}^g\right) + \rho^{w^g} log\left(w_{t-1}^g\right) + \epsilon_t^{wg} \tag{2.42}$$

$$log\left(v_t^g\right) = \left(1 - \rho^{v^g}\right) log\left(\bar{v}^g\right) + \rho^{v^g} log\left(v_{t-1}^g\right) + \epsilon_t^{vg} \tag{2.43}$$

$$log\left(c_t^g\right) = \left(1 - \rho^{c^g}\right) log\left(\bar{c}^g\right) + \rho^{c^g} log\left(c_{t-1}^g\right) + \epsilon_t^{cg} \tag{2.44}$$

Monetary policy

The monetary authority adjusts one period nominal interest rate in response to deviations of inflation from the steady state and to output growth following a Taylor rule:

$$\frac{R_t}{R^{ss}} = \left(\frac{R_{t-1}}{R^{ss}}\right)^{\rho_r} \left(\frac{\Pi_t}{\Pi^{ss}}\right)^{(1-\rho_r)\phi_\pi} \left(\frac{y_t}{y_{t-1}}\right)^{(1-\rho_r)\phi_y} \epsilon_t^r \tag{2.45}$$

where $R_t = 1 + r_t$ and $\Pi_t = 1 + \pi_t = p_t/p_{t-1}$. The rule includes also some degree of persistence in the process for the nominal interest rate.

Risk sharing

In this part we follow Faia and Monacelli [2008]. Foreign household optimizes along the same lines as Home household, with the optimality condition for bond holdings in Foreign:

$$\beta \frac{p_t^* \mathcal{E}_t}{p_{t+1}^* \mathcal{E}_{t+1}} \frac{u_{c,t+1}^{'*}(.)}{u_{c,t}^{'*}(.)} = \Lambda_{t,t+1} \tag{2.46}$$

where $\mathcal{E}_t$ is the nominal exchange rate in the form of foreign currency expressed in units of home currency. Taking conditional expectations, we can define the Foreign nominal interest rate as:

$$R_t^* = (1 + r_t^*) = E_t \left[\Lambda_{t,t+1} \frac{\mathcal{E}_{t+1}}{\mathcal{E}_t} \right]^{-1} = \left[\beta E_t \left(\frac{u_{c,t+1}^{'*}(.)}{u_{c,t}^{'*}(.)} \frac{p_t^*}{p_{t+1}^*} \right) \right]^{-1} \tag{2.47}$$

Risk sharing implies that $R_t = R_t^*$. Taking this into account and iterating the expression gives us the condition linking the marginal utilities of consumption across countries like in Faia and Monacelli [2008]:

$$\varkappa \frac{u_{c,t}^{'*}(.)}{u_{c,t}^{'}(.)} = \frac{\mathcal{E}_t p_t^*}{p_t} \equiv Q_t = q(S_t) \tag{2.48}$$

where $\varkappa$ is a ratio of starting values of marginal utilities in both countries, that can be normalized to 1 assuming an appropriate initial distribution of wealth. Q_t is the real exchange rate and S_t denotes the terms of trade ($S_t = p_{F,t}/p_{H,t}$).

As in Faia and Monacelli [2008], we specify the ratio between CPI and PPI at Home as a function of terms of trade:

$$\frac{p_t}{p_{H,t}} = \left[(1-\gamma) + \gamma S_t^{1-\eta} \right]^{\frac{1}{1-\eta}} \equiv g(S_t) \tag{2.49}$$

Similarly for the Foreign economy:

$$\frac{p_t^*}{p_{F,t}^*} = \left[(1-\gamma^*) + \gamma^* S_t^{\eta-1} \right]^{\frac{1}{1-\eta}} \equiv g^*(S_t). \tag{2.50}$$

The RER can be defined as

$$Q_t = S_t \frac{g^*(S_t)}{g(S_t)} \equiv q(S_t). \tag{2.51}$$

Foreign demand and the law of one price

We assume that the law of one price holds: $p_{F,t}(i) = \mathcal{E}_t p^*_{F,t}(i)$ for all i. Foreign demand for domestic variety i must therefore satisfy

$$c^*_{H,t}(i) = \frac{1}{n}\left(\frac{p^*_{H,t}(i)}{p^*_{H,t}}\right)^{-\epsilon} c^*_{H,t} \tag{2.52}$$

$$= \frac{1}{n}\left(\frac{p^*_{H,t}(i)}{p^*_{H,t}}\right)^{-\epsilon} \gamma^*\left(\frac{p^*_{H,t}}{p^*_t}\right)^{-\eta} c^*_t. \tag{2.53}$$

Market clearing

The production of the domestic variety i must equal the demand for this variety by the Home and Foreign households and government.

$$y_{H,t}(i) = n(c_{H,t}(i) + c^g_{H,t}(i)) + (1-n)\, c^*_{H,t}(i) = \tag{2.54}$$

$$= \left(\frac{p_{H,t}(i)}{p_{H,t}}\right)^{-\epsilon}\left[c^g_{H,t} + (1-\gamma)\left(\frac{p_{H,t}}{p_t}\right)^{-\eta} c_t + \frac{(1-n)}{n}\gamma^*\left(\frac{p^*_{H,t}}{p^*_t}\right)^{-\eta} c^*_t\right] \tag{2.55}$$

Small open economy

Following Faia and Monacelli [2008], we get a small economy version of the model by letting $n \to 0$. This implies $\gamma^* \to 0$ and $\gamma \to \alpha$. The composite indexes c_t and c^*_t become:

$$c_t = \left[(1-\alpha)^{\frac{1}{\eta}}\, c_{H,t}^{\frac{\eta-1}{\eta}} + \alpha^{\frac{1}{\eta}} c_{F,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \tag{2.56}$$

$$c^*_t = c^*_{F,t} \tag{2.57}$$

The demand functions of the households in the Home country change to

$$c_{H,t} = (1-\alpha)\left(\frac{p_{H,t}}{p_t}\right)^{-\eta} c_t \tag{2.58}$$

$$c_{F,t} = \alpha\left(\frac{p_{F,t}}{p_t}\right)^{-\eta} c_t \tag{2.59}$$

and the domestic CPI index p_t becomes

$$p_t = \left[(1-\alpha)\, p_{H,t}^{1-\eta} + \alpha p_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{2.60}$$

The ratios between terms of trade and CPI/PPI ratio in Home and Foreign change to

$$\frac{p_t}{p_{H,t}} = \left[(1-\alpha) + \alpha S_t^{1-\eta}\right]^{\frac{1}{1-\eta}} = g(S_t) \tag{2.61}$$

$$\frac{p_t^*}{p_{F,t}^*} = 1 \tag{2.62}$$

and the real exchange rate to $Q_t = S_t/g(S_t)$. If we let $n \to 0$, set $\alpha = \alpha^*$ and assume symmetric equilibrium (i.e. all firms that set the price set it to the same value and produce the same amount of differentiated goods), the market clearing condition simplifies into:

$$y_{H,t} = (1-\alpha)g(S_t)^{\eta}c_t + \alpha S_t^{\eta}c_t^* + c_t^g. \tag{2.63}$$

Closing the model

We can obtain the aggregate resource constraint by combining the household and government budget constraints and the definition of nominal profits of the final goods firms $\Gamma_t = p_t^H y_{H,t} - p_t^I(a_t^p n_t^p - \kappa^p v_t^p)$. The intermediate goods firms are perfectly competitive therefore their profits equal zero. Using this we can further simplify the profits of the retail firms to $\Gamma = p_t^H y_{H,t} - w_t^p n_t^p$. Finally, since the net exports (trade balance) have to correspond to the change in the country's net asset holdings, in our case the holdings of B_t, we can write the aggregate resource constraint as:

$$c_t^p p_t + c_t^g p_{H,t} + nx_t p_{H,t} = p_{H,t} y_{H,t} \tag{2.64}$$

Additionally, we spell out the expression for exports for further reference:

$$ex_t = \alpha c_t^* S_t^{\eta} \tag{2.65}$$

2.3.2 Model with endogenous movement across sectors

In this version of the model, we relax the assumption of having a fixed share of individuals searching in each of the sectors. This share is instead a part of the household optimization, as the unemployed at the end of the period choose the sector in which they want to search for a job.[8] In addition, we modify the utility function such that it includes a non-pecuniary benefit of being unemployed. The key differences between this version of the model and the baseline case lie in the set of equations characterising the labour market and the optimization of the household. The timing of the events remains the same.

[8]Previous literature using this approach includes Gomes [2011], Bermperoglou, Pappa, and Vella [2013] and Quadrini and Trigari [2008].

Like in the baseline model, the workers searching for a job in period t are those unemployed at the end of period $t-1$. They can now search in each of the two sectors:

$$u_t = 1 - n_{t-1}^p + n_{t-1}^g \tag{2.66}$$

$$u_t = u_t^g + u_t^p. \tag{2.67}$$

Differently from the previous setting, the share of individuals searching in the government sector is now varying:

$$u_t^g = s_t u_t. \tag{2.68}$$

New matches m_t^i between job seekers and vacancies are made in the same way as in the baseline model and the law of motion for employment in each sector remains the same.

The household optimization problem changes, since the households now optimize over consumption goods c_t, government services y_t^g, a portfolio of one-period state-contingent securities b_{t+1}, employment n_t^i and the number of household members searching in each of the sectors u_t^i and future unemployment u_t in order to maximize the following expression:

$$E_t \sum_{j=0}^{\infty} \beta^j \left[u\left(c_{t+j}, y_{t+j}^g\right) + \nu\left(u_{t+j}\right)\right] \quad s.t. \tag{2.69}$$

$$p_t^g y_t^g + p_t c_t + E_t\left[\Lambda_{t,t+1} b_{t+1}\right] = b_t + p_t w_t^p n_t^p + p_t w_t^g n_t^g + p_t b^u \left(1 - n_t^p - n_t^g\right) + \Gamma_t - T_t \tag{2.70}$$

and equations (2.66), (2.67) and (2.20). The utility function is now specified as:

$$u\left(c_t^p, y_t^g\right) = \frac{\left(c_t^p + z_g y_t^g\right)^{1-\psi}}{1-\psi} \tag{2.71}$$

$$\nu\left(n_t^p, n_t^g\right) = \chi u_{t+1} = \chi\left(1 - n_t^p - n_t^g\right) \tag{2.72}$$

with the first part being the same as in the baseline case and the second part including a positive non-pecuniary benefit of being unemployed. Household's optimization yields the following optimality conditions:

$$\lambda_t p_t = u_c'(.) \tag{2.73}$$

$$\lambda_t p_t^g = u_g'(.) \tag{2.74}$$

$$\Lambda_{t,t+1} = \beta \frac{\lambda_{t+1}}{\lambda_t} \tag{2.75}$$

$$\frac{\mu_t^i}{\lambda_t} = w_t^i - \frac{\xi_t}{\lambda_t} + \beta \frac{\lambda_{t+1}}{\lambda_t} \frac{p_{t+1}}{p_t} \frac{\mu_{t+1}^i}{\lambda_{t+1}} \left(1 - \rho^i\right) \tag{2.76}$$

$$\frac{\xi_t}{\lambda_t} = b + \frac{\nu_u'(.)}{\lambda_t} + \beta \frac{\lambda_{t+1}}{\lambda_t} \frac{p_{t+1}}{p_t} \frac{\mu_{t+1}^i x_{t+1}^i}{\lambda_{t+1}} \tag{2.77}$$

$$\mu_t^g x_t^g = \mu_t^p x_t^p \tag{2.78}$$

with conditions (2.73)-(2.75) being the same as in the baseline case. Combining optimality conditions (2.77) and (2.76), rearranging and denoting $\frac{\mu_t^i}{\lambda_t}$ as H_t^i yields the expression for the household surplus which differs only slightly from the analogue expression in the baseline case:

$$H_t^i = w_t^i - b^u - \frac{\nu_u'(.)}{\lambda_t} + E_t \Lambda_{t,t+1} \Pi_{t+1} \left[H_{t+1}^i \left(1 - \rho^i - x_{t+1}^i\right)\right], \; i = p, g. \tag{2.79}$$

Like before, this value function can be written in terms of the value of being employed in sector i, that depends on the wage that the employed worker receives today and the continuation value of the job:

$$W_t^i = w_t^i + E_t \Lambda_{t,t+1} \Pi_{t+1} \left[\left(1 - \rho^i\right) W_{t+1}^i + \rho^i U_{t+1}\right], \; i = p, g \tag{2.80}$$

Along similar lines, the value of being unemployed and searching in sector i is defined as follows:

$$U_t^i = b_t + \frac{\nu_u'(.)}{\lambda_t} + E_t \Lambda_{t,t+1} \Pi_{t+1} \left[x_{t+1}^i W_{t+1}^i + \left(1 - x_{t+1}^i\right) U_{t+1}\right], \; i = p, g \tag{2.81}$$

where the unemployment benefits b^u and the marginal utility of being unemployed (measured in terms of consumption marginal utility) are the flow value of being unemployed. The continuation value depends on the probability of finding a job next period, x_{t+1}.

Finally, the optimality condition (2.78) tells that there must be no gain from searching in one sector over another. A probability of finding a job times the value of working in that sector versus being unemployed must be equalized across the two sectors:

$$\begin{aligned} \mu_t^g x_t^g &= \mu_t^p x_t^p \\ H_t^g x_t^g &= H_t^p x_t^p \end{aligned} \tag{2.82}$$

This also means that the value of being unemployed in each of the sectors is the same, $U_t^g = U_t^p = U_t$.[9] From (2.82) we can derive another equality that implicitly determines the optimal share s_t of unemployed searching for a public sector job.

$$\begin{aligned} H_t^g x_t^g &= H_t^p x_t^p \\ \frac{H_t^g m_t^g}{u_t^g} &= \frac{H_t^p m_t^p}{u_t^p} \end{aligned}$$

[9]This condition is part of optimality conditions also in Quadrini and Trigari [2008] and Gomes [2011].

$$\frac{H_t^g m_t^g}{s_t} = \frac{H_t m_t^p}{1-s_t} \tag{2.83}$$

Finally, also the optimal wage expression changes due to the introduction of the non-pecuniary benefit of being unemployed in the utility function. The optimal wage in this case is then:

$$w_t^{p*} = \eta^N \left[a_t \frac{p_t^I}{p_t} + E_t \Lambda_{t,t+1} \Pi_{t+1} \kappa^p \theta_{t+1}^p \frac{p_{t+1}^I}{p_{t+1}} \right] + \left(1-\eta^N\right) \left[b_t + \frac{\nu_u'(.)}{\lambda_t} \right]. \tag{2.84}$$

The rest of the expressions in this version of the model are the same as in the baseline case.

2.4 Parametrization

The parameter values are set in line with the values used in the previous literature and are summarized in Table 3.13. The parametrization is the same for Home and Foreign economy and the model period is set to a quarter. The time discount factor (β) is set to 0.99 which corresponds to an annual interest rate of roughly 4%. We vary the value of the parameter governing the non-pecuniary benefits from being unemployed (χ) from 0 **to** 0.2. The utility individuals derive from being unemployed adds with the unemployment benefits to represent the flow value of being unemployed. We follow Gomes [2011] in determining the weight of government services in the utility function (z^g) that set the value of this parameter to 0.18, in order to obtain an optimal share of public employment close to 0.15.[10] We round this value up and set the parameter to 0.2. The coefficient of relative risk aversion (ψ) is set to 1, which falls in the range of values usually used in the literature, i.e. between 1 and 2.

The parameters characterizing the labour market section of the model are also chosen in line with the previous literature. The exogenous separation rate for private sector (ρ^p) is usually set to 0.06 [e.g. Gomes, 2011, Albertini, Kamber, and Kirker, 2012, Obstbaum, 2011, Christoffel, Kuester, and Linzert, 2009]. Higher values up to 0.105 were used by GST2008 and MPT2010[11], while Bermperoglou, Pappa, and Vella [2013] on the other hand set a much lower range between 0.02 and 0.03. Finally, when estimating his model using US quarterly data Gomes [2011] gets a posterior mean value for the parameter of only 0.016. In this paper we set the value to 0.045, in order to prevent the steady state unemployment to rise much above 10%. The exogenous separation rate for the government

[10] Gomes [2011] reports that this share varied between 0.13 to 0.19 in the United States in the last 60 years. In the recent decades it fluctuated close to 0.16.

[11] This is following Shimer [2005] and is in line with the assumption that on average jobs last two years and a half.

sector (ρ^g) ranges between one half and one third of the separation rate in the private sector according to Gomes [2011]. We fix it to 0.015 which combined with 0.045 in the private sector and other parameters leads to about 16% of all employed in the steady state working in the government sector. This is also a value Gomes [2011] and Bermperoglou, Pappa, and Vella [2013] use and corresponds to the US data. The matching elasticity with respect to vacancies in the private sector (α^p) is set to 0.5, which is well within the range usually used in the literature, i.e.between 0.4 and 0.72 [see Petrongolo and Pissarides, 2001]. For the public sector matching elasticity (α^g) we set a higher value 0.84, which is the posterior mean estimate of this parameter in Gomes [2011] using the US data.

[Table 10 about here.]

The labour matching efficiency for each of the sectors ($\sigma^{m,p}$ and $\sigma^{m,g}$) and the cost of posting vacancies (κ^p and κ^g) are set such that we get probability of filling a vacancy between 0.6 and 0.75 for the private sector and between 0.8 and 0.9 for the public sector, depending on the rest of the parameters. These probabilities are roughly in line with the previous literature.[12] The size of unemployment benefits is about one half of the private sector wage (like in Albertini, Kamber, and Kirker [2012]). The bargaining power η^N is distributed equally between workers and firms and by setting it equal to $1 - \alpha^p$ we also satisfy the Hosios [1990] efficiency condition.

We set the share of government consumption in total private output (ζ^{cg}) to 0.2, the ratio of public versus private sector wages (ζ^{wg}) at 1.1 and the ratio of public sector vacancies to private sector ones (ζ^{vg}) at 0.2.[13] The Calvo parameter (ξ) (probability of not changing the price) is set to 0.75 which implies that the prices on average stay unchanged for 4 quarters and is a standard assumption in the literature. We assume that the retailers are able to charge a 10% mark-up over their marginal costs, which leads to the value of price elasticity (ϵ) of 11. The Taylor rule coefficient on inflation (ϕ^π) is set to 1.2, the coefficient on output growth (ϕ^y) to 0.5 and the interest rate persistence parameter (ρ^r) is set to 0.9. The share of imports in the composite index of consumption goods (α) in Home economy is assumed to be 0.4 in the baseline case and implies that we have some degree of home bias. The price elasticity with respect to foreign goods (η) is assumed to be 2, which is within a range usually applied in the New Open Economy literature.

The persistence parameters for the processes and the standard deviation of the shocks are also listed in Table 3.13. For the productivity process, the values used are standard in the literature. The parameters defining the process for public wages are based on or

[12] See Christoffel, Kuester, and Linzert [2009].

[13] In the literature, the values between 1.02 [Gomes, 2011] and 1.16 [Bermperoglou, Pappa, and Vella, 2013] are used for the ratio of public to private sector wages.

equal to the estimates by Gomes [2011] using the US data. The persistence parameters for the government vacancies and government spending shock are determined in line with the parametrization in Bermperoglou, Pappa, and Vella [2013].[14]

2.5 Simulation results

In this section we analyze the effects of negative shocks to government wages, government vacancies and government consumption. The impulse responses are plotted in Figures 3.15-3.17 and are in percentage deviations from the steady state of the variable in question. Exceptions are the impulse response of exports in GDP and net exports in GDP that should be interpreted as deviation from the steady state GDP. In each panel, we plot the impulse responses for three versions of the model: (1) a version with fixed labour supply and fixed share of searchers in the public sector, s, (2) a version with endogenously determined share s and $\chi = 0$, and (3) a version with endogenously determined share s and $\chi = 0.2$.

Shock to government wages. The impulse resposes in Figure 3.15 show that when we fix the share of searchers in each of the sectors, most of the variables do not react to the public wage shock. The exception is the public sector worker's surplus (not plotted), that decreases as a consequence of lower wages. Comparing these results to the impulse responses of model versions (2) and (3) shows that endogenous movements of searchers between the two sectors are needed to observe any effect of the government wage shock on the rest of the variables.

Turning to the model versions with endogeneously determined share of unemployed searching in public sector, we first observe that the impulse responses are similar in shape but more muted in the case of lower χ. Further inspection shows that a cut in public wages decreases the share of people searching for a public sector job, u_t^g. At the same time, more unemployed start searching in the private sector (u_t^p increases) which increases the probability of filling a vacancy in the private sector and leads firms to post more vacancies. Higher number of private sector vacancies and more individuals searching for a private sector job leads to higher private sector employment, n_t^p, higher private sector output, y_t^p, and higher private consumption, c_t^p. In the public sector, we instead observe a gradual decrease in public sector employment and output. Total unemployment starts decreasing after the negative public wage shock due to the increase in the private sector employment.

[14]Also Gomes [2011] uses 0.8 for the persistence of the government vacancies shock in the baseline simulation, however when estimating the parameters of his model using US data, the prior mean of the persistence parameter for the government vacancies shock drops to 0.28, while the standard deviation is 0.44 which means that these shocks are extremely large. For presentation purposes we use a more persistent and smaller shock. The results of the alternative parametrization lead to very similar dynamics but more pointy impulse responses.

About seven quarters after the shock, it starts returning to the steady state.

Following the public wage cut, private sector wages increase on impact but then immediately decrease below the zero line before converging again to the steady state. There are two developments that explain such dynamics. First, the overall negative response after the intial period is due to the spill-over effects from the public to the private sector. Due to cut in public wages, the number of individuals searching in the private sector increases more than the private sector vacancies, which reduces the probability of finding a job and increases the probability of filling a vacancy for the firm. This decreases the firm surplus and affect the wages negatively. Second, the positive response of the private sector wages on impact is due to the increase in the ratio between intermediate prices and CPI index, that is a part of the firm surplus and drives the surplus up on impact.[15][16] Intermediate prices increase as demand for private goods is expected to increase in the future due to lower unemployment and positive wealth effect following the cut in public wages.[17] After the first period the spill-over effect prevails and overcomes the effect of higher intermediate prices.

[Figure 15 about here.]

The dynamics of the private sector wages has further effects on intermediate prices, PPI and CPI inflation and trade balance. These values follow the dynamics of the private sector wage by exhibiting a quick increase, then a drop below the steady state and finally a reversion to the steady state. Since the PPI inflation reacts more than the CPI inflation, the home goods become relatively cheaper. The terms of trade increase accordingly, which then translates into an increase in the real exchange rate (real depreciation) and higher net exports. Note that the latter is to a large extent driven by the increase in exports.

Shock to government vacancies. Consolidation packages often include lay-offs of public sector employees and to model that properly we would need to shock the separation rate in the public sector. A negative shock to government vacancies could be on the other hand interpreted as a freeze on hiring. In what follows, we analyse how the variables react to a negative shock in government vacancies (see Figure 3.16).

First we focus on the case where the share of searchers in the public sector stays fixed. We find that even in this case, in contrast to the public wage shock, a cut in vacancies

[15]Expression for the value of a filled vacancy or firm surplus is as follows: $J_t^p = \frac{\kappa^p}{q_t^p}\frac{p_t^I}{p_t}$.

[16]In order to verify the workings of this channel, we have also simulated the model by shutting down the movement in $\frac{p_t^I}{p_t}$ in the expression for optimal wages in the private sector (eq. 2.84) and we have found that following the public wage cut private wages fall already on impact.

[17]We find that the response of intermediate prices and their effect on the private wages depends on the value of Calvo parameter. For sufficiently low values of this parameter, the response of intermediate prices to the future increase in demand gets small enough not to affect the private sector wage. The latter then falls already on impact as the public wages are cut.

affects most of the variables, including the trade balance. A cut in government vacancies leads to a lower probability of getting a job in the public sector, lower public sector employment and consequently lower output of public services. In the private sector, we instead observe an increase in employment and output. This is a consequence of both, an increase in searchers for the private sector job and an increase in private sector vacancies due to higher probability of filling a vacancy.[18] Private sector wages are again affected by a higher demand that increases the intermediate prices and the firms surplus. After this initial positive effect subsides, the private sector wages decrease to below the steady state value. If we could exclude the effect of intermediate prices, the value of the firms surplus and the private sector wage would have decreased already on impact due to an increase in probability of filling a vacancy in the private sector.

[Figure 16 about here.]

Next, we look at the impulse responses from the versions of the model with a variable share of searchers in the public sector. We observe that some of the responses differ markedly from the case with fixed s, while variation in parameter χ affects the results only marginally. After the cut in government vacancies the probability of getting employed in the public sector decreases and more unemployed start searching in the private sector. Consequently, the probability of filling a vacancy in the private sector increases and the firms start posting more vacancies already on impact, whereby the effect is stronger than in the fixed s case. Like before, the private sector employment and output increase and the opposite happens in the public sector. Total unemployment decreases after a few quarters due to a strong increase in private hiring but increases again after about 20 quarters. The private sector wage dynamics can be again explained by the increase in the intermediate prices on impact and by higher probability of filling a vacancy in the following periods.

In both cases the movement in the private wages, home prices and CPI prices affect the terms of trade positively, with a stronger effect in the case of endogenous share of workers in the public sector. Overall, the result that emerges is that after a negative government vacancy shock exports and net exports increase. In the fixed share case, the terms of trade, the CPI-PPI ratio, RER and net exports have a small negative reaction to government vacancies shock on impact. No such effect can be noticed in the case of exports.

Government consumption shock. In the case of government consumption shock most of the variables react in the same or roughly the same way regardless of whether

[18] Despite having a fixed share of searchers in each sector, the number of searchers increases slightly in the first few periods in both sectors due to higher unemployment. Note also that on impact also vacancies in the private sector decrease slightly as a spill-over effect, however they start to increase soon after.

the unemployed are able to move between the two sectors while searching (see Figure 3.17). Major differences appear only in the responses of unemployed searching in the government sector, the household surplus in the public sector and the response of public sector employment and output.

[Figure 17 about here.]

After a cut in government purchases, we observe a typical wealth effect that leads to higher private consumption. Due to higher demand, the private sector vacancies and employment increase on impact. At the same time, higher vacancies on impact decrease the cost of firm and decrease the output of the private sector. Already in the next period this effect vanishes, as the effect of higher vacancies disappears and the output becomes driven only by higher private sector employment. The unemployment falls and there is a decrease in searchers in both sectors, if s is fixed, and in private sector only if s is variable. If the unemployed have a chance to move between sectors, they move away from the private sector. The reason for that is the fall in private sector wage which reflects the lower government demand and lower intermediate prices and firm surplus. Finally, we find that a cut in government consumption crowds in net exports, a result that is in line with the previous literature. Since the government consumption shock leads to lower home prices, the terms of trade and (net) exports increase.

2.6 Competitiveness channel

In this section we analyse how the effects of a government wage cut vary depending on the trade openness of the economy. We focus primarily on the exports and net exports as we are mostly interested in how the competitiveness of the country improves or worsens with the shock in public sector wages. In order to explore this matter, we plot impulse responses for the model variant (3), whereby we vary the value of α to get the results for different levels of trade openness (see Figure 3.18).

First, we find that the level of trade openness does not affect the magnitude of most of the labour market responses. Some differences are present in the household surplus in the private sector and consequently private sector wages, where we observe lower household surplus and lower wages for higher values of α. The differences are however very small and stem primarily from the different magnitudes of the private consumption response, that translate into different values of stochastic discount factors. Private consumption responds less to the negative government wage shock if the country is more open. A larger degree of trade openness means that Home can export more of its output and a smaller share of the output is consumed at home.

[Figure 18 about here.]

Second, we find that a slightly stronger wage response for higher values of α leads to a slightly stronger negative response of intermediate prices. This in turn leads to a smaller improvement in terms of trade S_t for a more open economy. At the same time higher α gives more weight to terms of trade in the calculation of the CPI-PPI ratio which therefore increases more in a more open economy. Terms of trade and the CPI-PPI ratio further influence the response of (net) exports to the government wage shock. Exports that depend on terms of trade and openness do not react at all if the economy is closed and react most in the case of a relatively closed economy. This follows directly from the stronger terms of trade reaction in the more closed case. At the same time, the net exports are directly affected by the CPI-PPI ratio (see eq. 2.65) that responds more intensively in a more open economy. This in turn translates into relatively more expensive Foreign products and lower imports.

Finally, simulation of the model for different degree of trade openness for the case of the government vacancies shock produces very similar results to the ones presented for the cut in government wages (see Figure 3.19 in Appendix).

2.7 Conclusion

In this paper the effects of fiscal consolidation via cuts in government wages and vacancies or employment. Our empirical findings that after a government wage or employment cut the output gradually increases and the unemployment rate decreases were replicated in a small open economy model with separate public and private sector labour markets. The model matched also the response of the net exports, while the results for the response of the real exchange rate were less consistent with the empirical results.

The theoretical model presented in this paper could be further developed in many ways. Some of them would be to include the labour-leisure choice, hand-to-mouth consumers or to analyse how the results change in the case of different financing possibilities for the government budget.

2.A Data sources

Our sample is based on data for Australia, Canada and the UK, for the period 1991:1-2006:2.

— *Number of employees in the government sector:* Australian Bureau of Statistics (A591164F), OECD Economic Outlook for Canada and the UK.

— *Compensation of government employees:* Australian Bureau of Statistics (A591404F), IMF International Financial Statistics (Canada), Eurostat for the UK.

— *GDP:* OECD Quarterly National Accounts. QNA.Q.(country).EXPGDP.CQRSA.S1

— *Risk-free interest rate:* As Australia had an incomplete series for their 13-week T-bill, we used an alternative short term rate: Dealer bill 90 day rate. ADBR090.

— *GDP deflator:* OECD Economic Outlook. OEO.Q.(country).PGDP.

— *Population:* Australian Bureau of Statistics, Statistics Canada, Eurostat for the UK.

— *Unemployment:* Australian Bureau of Statistics, Statistics Canada, Eurostat for the UK.

— *Imports and exports:* OECD Quarterly National Accounts. QNA.Q.(country). EXPIMP.CQRSA.S1; QNA.Q.(country). EXPEXP.CQRSA.S1.

— *CPI based real exchange rate:* OECD Main Economic indicators. MEI.Q.(country). CCRETT01.IXOB.

2.B Additional Figures

[Figure 19 about here.]

Chapter 3

An alternative method for identifying booms and busts in the euro area housing market

An alternative method for identifying booms and busts in the euro area housing market[1]

Dieter Gerdesmeier[2]

Andreja Lenarčič[3]

Barbara Roffia[4]

[1]The authors would like to thank M. Bordo, J. Duca, L. Gattini, M. Lozej, M. Tujula, T. Westermann, other participants of an internal ECB Seminar and an anonymous referee for useful comments and suggestions. The paper does not necessarily reflect the views of the European Central Bank, the Frankfurt School of Finance and Management and the Bank of Slovenia.

[2]European Cetral Bank. E-mail: dieter.gerdesmeier@ecb.europa.eu.

[3]Università Bocconi University (Milan, Italy) and Bank of Slovenia. E-mail: andreja.lenarcic@bsi.si.

[4]European Cetral Bank. E-mail: barbara.roffia@ecb.europa.eui.

Abstract

This paper develops a model-based method to detect booms and busts in the euro area housing market. An underlying model is constructed and tested, whereby the user cost rate, a demographic variable, unemployment rate, disposable income, debt-to-income ratio and housing stock are fundamental variables significantly explaining house price developments. Booms/busts are identified as episodes when the house price index exceeds the levels implied by those economic fundamentals. Furthermore, a cross-check with boom/bust episodes based on other methods is carried out to substantiate the results.

Keywords: house prices, booms, busts, quantile regressions

JEL Classification: E37, E44, E51

3.1 Introduction

Over the past decades, asset markets have played a growing role in macroeconomic dynamics. Policy-makers have become increasingly aware of the fact that sizeable changes and significant periodic corrections in asset prices may lead to financial and, ultimately, macroeconomic instability. For example, rapidly rising asset prices are often associated with an easing in credit conditions, increased spending on account of wealth increases and relaxation of credit constraints and, ultimately, inflationary pressures. By contrast, the bursting of an asset price bubble could imply significant financial losses by institutions and investors, and a sharp drop in aggregate demand, leading to deflationary risks via both direct wealth effects and instability in the financial sector. The existence of a zero lower bound on nominal interest rates, as well as heightened uncertainty with respect to the monetary transmission mechanism in times of turmoil, could then make it more difficult for central banks to maintain price stability. The developments in asset price indices, therefore, warrant close attention.

In principle, the analysis and the monitoring of developments in asset prices for policy purposes rest on three basic steps. The first step is to define and identify asset price boom and bust periods. The second step aims at finding indicator variables that can predict these periods. Finally, the third step consists in using the historical relationship between the indicator variables and the boom/bust periods to derive a likelihood of asset price boom/busts in real time.

In this paper, we contribute to the methodology used in the first step. We modify a model-based method previously used for detecting misalignments in stock prices to take into account the fundamental driving forces in the housing market. We then apply the method to the Euro area aggregate housing price index and check its robustness with respect to the various statistical/other methods that can be used for identifying booms and busts in the asset prices.

Identifying and quantifying asset price misalignments were always extremely difficult tasks, in particular from an ex-ante point of view. This observation is supported by the heterogeneity of studies based on different criteria, each involving some degree of arbitrariness, and the different results found in the recent literature on this topic. The methods that have been applied in order to select periods of asset price booms and busts can be divided into two broad categories. The first category contains purely univariate (or statistical) methods which identify particularly strong or weak asset price developments, while the second category consists of a multivariate (or model-based) analysis of the fundamental drivers of the developments in asset price indices. In either case, significant deviations from some norm, defined by historical experience in the first and the underlying model in the second case, would be considered booms or busts.

A few examples of statistical methodologies used include Bordo and Jeanne [2002] that define a bust as a period in which the three-year moving average of the growth rate of asset prices is smaller than a specific threshold. They define the threshold as the average growth rate less a multiple (1.3) of the standard deviation of the growth rates. In other studies applying a similar criterion, the threshold is defined either by choosing a different multiple of the standard deviation [e.g. Gerdesmeier, Reimers, and Roffia, 2010] or it is fixed at a constant value [e.g. **?**]. The duration of asset price misalignments is also sometimes taken into account, whereby excessive developments in asset prices are labeled as imbalances if they last for a protracted period, for instance if they deviate from their threshold for a certain number of consecutive quarters. All these criteria have been applied symmetrically to booms by considering the periods when the index overshoots a pre-defined threshold. Finally, the studies above also differ in terms of whether the boom/bust detection method is applied to the individual asset market price indices, such as stock and housing markets, or to a composite asset price index.

Differently from the statistical approaches, the model-based approach to detect excessive misalignments relies on economic theory. The basic idea is to compare the individual market indices with the levels which would be implied by economic fundamentals. One of the methods which can be used for this purpose is the so-called *quantile regression approach* applied to a reduced form model specifying the relation between the asset prices and the underlying fundamentals. This methodology for constructing indicators of misalignments in individual asset markets is based on the hypothesis that asset prices have a long-run relation with some macroeconomic fundamentals. When asset prices are close to the levels implied by such long-run relation, they can be considered *fair* or at a *normal* level, while any deviation from such a value would mean an emergence of misalignment. Booms and busts are then defined as periods when these misalignments are larger than a certain threshold implied by the conditional distribution.[5] In principle, confidence bounds of the model-based estimates of the long-run relationship between a price index and its fundamentals could serve as such a threshold. However, as the developments in the asset price indices are fairly non-linear, the use of quantile regressions is warranted. Machado and Sousa [2006] were the first to use this approach for boom/bust identification in the case of the stock price index. In this paper, we extend their approach to make it suitable for identifying misalignments in the housing market.

The novelty of the present paper is twofold. First, the quantile regression approach for detecting booms and busts is extended to the housing market. This, inter alia, requires the development of a plausible model of fundamental factors in the house price

[5] At a more theoretical level, one could argue that the univariate statistical models rely on the unconditional distribution, whereas the quantile approach relies on the conditional distribution.

index [6]. The underlying model includes the user cost rate, a demographic variable, the unemployment rate, disposable income, the debt-to-income ratio and the housing stock as fundamental variables that are found to significantly explain the house price developments. In addition, the effects of the fundamental variables on house prices are found to vary in some cases across quantiles. This suggests that conventional linear methods do not always fully summarize the existing disparities and that there is benefit in applying the quantile regression. Second, we compare the performance of the quantile method for the boom/bust identification in the housing prices with that of a number of alternative, statistical methods. A comparison across these methods suggests that the booms and busts based on the quantile methods are broadly consistent with the episodes resulting from the other methods.

The paper is structured as follows. Section 2 briefly describes the methodology of quantile regressions, their main advantages and reviews the papers using the quantile regressions in the context of asset and housing prices. Section 3 reviews some approaches in the literature on modeling housing prices developments. Section 4 contains the description of the data set, the selection and construction of the variables that are used in the estimations, and their properties. It also presents some simple reduced-form housing models estimated by dynamic OLS and discusses the estimates of the preferred specifications. Section 5 contains the results obtained by means of the quantile regression approach and the identified boom and bust periods for the euro area. Section 6 compares boom and bust periods identified by the means of quantile regression techniques with the results based on statistical methods. Section 7 concludes.

3.2 The quantile regression framework and selected empirical evidence

Linear regression estimates the mean value of the response variable for given levels of predictor variables. If, for instance, one is interested in the relationship between house prices and their fundamentals, the linear regression model provides an estimate of how the fundamentals affect house prices *on average*. Such methodology, however, cannot answer another important question, which is whether the disposable income or other fundamental variables influence the house prices differently at various segments of the distribution rather than on average. The latter question is clearly of relevance in the context of our study since house price boom/busts are well-known to be highly non-linear

[6] Kennedy and Andersen [1994] study developments in house prices and discuss the fundamental developments (based on simple models of house price dynamics) and speculative bubbles. Fundamentals and house price bubbles are also analysed in McCarthy and Peach [2002].

events. Against this background, a more comprehensive picture can be provided by the use of quantile regression techniques. Originally developed by Koenker and Bassett [1978], the quantile regression models the relationship between a set of predictor variables and specific percentiles (or quantiles) of the response variable. For instance, if one looks at the 50th percentile, a median regression is obtained, i.e. the changes in the median house prices as a function of the predictors. Similar regressions can be run for other quantiles. The size of the regression coefficients then quantifies the effect that the predictor variables have on a specified quantile of the response variable.

More generally, quantile regressions seek to model the conditional quantile functions, in which the quantiles of the conditional distribution of the dependent variable are expressed as functions of observed covariates.

The quantile estimator solves the following optimization problem [7]:

$$\min_{\beta} \sum_{t=1}^{T} \sigma_{\tau}(y_t - x_t^{'}\beta) \tag{3.1}$$

where y_i is the vector of the dependent variable, x_t is a matrix of independent regressors, β is the estimated vector of parameters and $\sigma_{\tau}(\cdot)$ is the absolute value function that yields the τ^{th} th sample quantile as its solution. In general, the linear model for the τ^{th} quantile $(0 < \tau < 1)$ solves:

$$\min_{\beta} \frac{1}{T} \left[\sum_{t:y_t \geq x_t^{'}\beta} \tau |y_t - x_t^{'}\beta| + \sum_{t:y_t < x_t^{'}\beta} (1-\tau)|y_t - x_t^{'}\beta| \right] \tag{3.2}$$

The resulting minimisation problem can be solved using linear programming methods. The coefficient for a regressor j can be interpreted as the marginal change in the τ^{th} conditional quantile of y due to a marginal change in j. As one keeps increasing τ from zero to one, one can trace the entire conditional distribution of the dependent variable.[8] In the particular case of this paper, the quantile regression allows us to trace the entire asset price distribution, conditional on the set of regressors, reflecting the set of fundamental variables.

The use of quantile regressions has a number of additional benefits. The median regression can be more efficient than mean regression estimators in the presence of heteroskedasticity. Quantile regressions are also robust with regard to outliers in the dependent variable. Finally, when the error term is non-normal, quantile regression estimators

[7]SeeCecchetti and Li [2008].

[8]Standard errors and confidence limits for the quantile regression coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results with the bootstrapping method often being seen as more practical [see Greene, 2003].

may be more efficient than least squares estimators.

The quantile methodology has been applied in a number of studies in several fields of empirical economics. In terms of the econometric approach, applications involve single-equation approaches [Machado and Sousa, 2006], panel vector autoregressions [Cecchetti and Li, 2008] as well time-varying cointegration approaches [Xiao, 2010]. As regards the subject of investigation, the quantile methodology has been applied inter alia to stock prices [Machado and Sousa, 2006, Barnes and Hughes, 2002, Saastamoinen, 2008, Allen, Kumar Singh, and Powell, 2009, Xiao, 2010] and to their implications for growth and inflation [Cecchetti and Li, 2008]. Similarly, applications for house prices can be found in Zietz, Zietz, and Sirmans [2008], McMillen [2008] and Liao and Wang [2010].

3.3 Modelling house prices

The quantile regression approach to identifying booms and busts implicitly rests on the assumption that there exists an underlying model for the variable to be explained. For example, Machado and Sousa [2006] use standard asset pricing theory to model the fundamental developments in stock prices. In the same vein, some authors [e.g. Kennedy and Andersen, 1994, McCarthy and Peach, 2004] rely on asset pricing theory as a basis for the valuation of house prices. It seems, however, that for modelling house prices the structural approach - based on demand and supply equations - is preferred in the literature.[9]

This notwithstanding, the models used in the literature on house prices are heterogeneous in many aspects.

First, the models used differ in terms of the exact specification of the dependent variable as well as in terms of the explanatory variables included. The main determinants of house prices on the demand side, that appear in the selected literature, are some measure of households' income, a demographic variable, a measure of the user cost of housing or cost of financing and existing stock of houses. On the supply side, construction costs, the price of land, costs of financing, home ownership levels or rates and existing stock of houses are most often included as explanatory variables. The household income is usually proxied by personal consumption, consumption of non-durables and services or households' real disposable income. Additionally, the households' financial wealth, real GDP and unemployment rate are used in some studies to proxy disposable income. Among the demographic variables, the number of households or the share of the 15 to 64-year-old cohort over total population are usually used. A time trend often serves as a proxy for the existing stock of dwellings. Other variables often used in the literature

[9]For an overview of early studies, [see Fair, 1972] Other early studies modelling housing market include Alberts [1962], Kearl [1979] and Poterba [1984].

as explanatory variables are the household debt-to-income ratio and the real stock of mortgage. The user cost of housing is usually calculated following Poterba [1984] as the mortgage interest cost after adjusting for inflation or expected average growth in house prices, and the tax treatment of the mortgage interest. Additionally the cost of depreciation is sometimes taken into account. As an alternative, some authors proxy the user cost with the real or nominal mortgage rate.

Second, while several papers model the demand and supply side of the housing market separately, a number of studies simply include supply and demand determinants in a single equation framework or estimate the two sides of the equilibrium jointly. Some examples from the first group are DiPasquale and Wheaton [1994], McCarthy and Peach [2002, 2004] and Antipa and Lecat [2009], while Kasparova and White [2001], Kaufmann and Mühleisen [2003], Tsatsaronis and Zhu [2004], Ganoulis and Giuliodori [2010] and Gattini and Hiebert [2010] build models that would pertain to the second group.[10]

Third, some studies focus on the fundamental long-run developments and use the instrumental variable estimation techniques [e.g. Antipa and Lecat, 2009], whereas others analyse the long-run developments and short-run dynamics in a combined setting by estimating an error correction model [e.g. Antipa and Lecat, 2009, McCarthy and Peach, 2002, 2004, Gattini and Hiebert, 2010]. **Table 3.14-3.15** reports some details on the variables used in a selected set of models.

[Table 11 about here.]

[Table 12 about here.]

3.4 Model selection and the data

The crucial step in applying the quantile method for boom/bust detection is to choose a simple model that captures the relation between the asset prices and underlying fundamentals reasonably well. The model used in this study can be summarised in the following general form:

$$Asset\ Prices = \beta_1 + \beta_2(Fundamentals) \tag{3.3}$$

where *Asset Prices* represent the (log of) the house prices and *Fundamentals* denote a vector of fundamental determinants of the market. The latter are selected following the literature reviewed in Section 3 and includesome measure of income, a demographic

[10]Some papers focus only on demand equation as the supply is seen as being relatively static in the short run and sometimes even in the long run Kennedy and Andersen [1994].

factor and a measure of user cost. In addition, we base our choice of variables on the data availability and their time series properties.

Our interest consists in developing a simple linear model which specifies a long-run relation between housing prices and some fundamental variables and which can - in a subsequent step - serve as a basis for applying the quantile regression approach. Notwithstanding the fact that cointegration can be regarded as an attempt to model the conditional mean, whereas the quantile methodology is about modelling the conditional distribution, it has to be emphasised that the quantile approach is only valid insofar as it can be proven to represent a long-run economic relationship between housing prices and various demand and supply determinants suggested by the literature (see Section 4.2 below).

We consider a number of variables that represent fundamental determinants of house prices (PH) as suggested by the literature. The data availability for the euro area limits the selection to the following list of potential regressors: disposable income (DISPI), disposable income per capita (DISPIPC), the user cost rate (UCR), the unemployment rate (UR), the housing stock (HS), the housing stock per capita (HSPC), the number of households (NHH), the share of the 15 to 64-year olds in total population (WAPOP), the share of the labour force in total population (LFPOP) and the debt-to-income ratio (D2I).[11] Some of the variables can only be included interchangeably as we suspect them being highly collinear in nature. For instance, we use either disposable income or disposable income per capita, housing stock or housing stock per capita and either a number of households or the share of working age population or labour force in population.

3.4.1 The dataset

This study focuses on the identification of boom and bust cycles in the euro area housing market. While there can be no doubt that the euro area housing market is heterogeneous by its very nature, this is an issue of less of concern from a monetary policy perspective. The latter claim is due to the fact that the policy debate, that is often labelled in terms of a *leaning against the wind* centres around the idea of a pre-emptive policy/ interest rate move when the emergence of a potentially harmful boom-bust-cycle becomes obvious. Moreover, since the Members of the ECB's Governing Council are asked to take decisions from a *euro area perspective*, this seems to justify a focus at the aggregate housing market. Against this background, it seems justified to carry out such an analysis for the housing market of the euro area as a whole.

The data for the euro area are quarterly and the sample period runs from 1983 Q1 to 2011 Q4. All the variables are in real terms and, when needed, transformed from the

[11]Due to the data limitations for the euro area, we could not include two variables affecting the supply side that are often used in the literature: the number of housing permits and the construction costs.

nominal values using the private consumption deflator. House prices, GDP, household disposable income and the private consumption deflator are seasonally adjusted. All per capita variables are obtained by dividing the variable in question with total population. Except for the long-term interest rate and mortgage rate, the unemployment rate, the user cost rate, house price inflation and the household debt-to-income ratio, the variables are measured in logarithms. For some of the variables, only the annual data are available and in those cases we interpolate the series using the cubic-spline method to transform the data into the quarterly frequency. Such interpolations were necessary for the following variables: the housing stock, the number of households and the population between 15 and 64 years. The sources of the series are the Eurostat and the European Central Bank databases. [12]

Another variable needed to be constructed is the cost of using the housing services (UCR). Like most of the literature, we refer to the definition of this cost in Poterba [1984, 1992], where a one-period user cost of housing is defined as a sum of depreciation, repair or maintenance costs, after-tax mortgage interest payments and property taxes (which together form the opportunity cost of housing equity) less the capital gain from holding the residential structure. Poterba [1992] considers also a risk premium for housing investments. The subsequent literature uses variants of this approach, omitting one or several determinants of the cost that are believed to be relatively stable over time, namely the repair and maintenance costs, property taxes and the depreciation rate. [13] The papers also differ in whether the user cost is expressed in terms of the price of residential unit or as the percentage rate (and, therefore, called *user cost rate*). We use the latter format and consider several versions of the user cost, all based on the following expression:

$$ucr_t = i_t(1 - \tau_t) + \delta_t - E_t(\pi_{t+1}) \tag{3.4}$$

where ucr_t denotes the user cost rate, i_t the long-term interest rate or the mortgage rate, τ_t the average income tax rate, δ_t the depreciation of the residential capital and $E_t(\pi_{t+1})$ the expected future nominal capital gains from owning a residential property. We proxy the latter with either a four-quarter average of house price inflation or a four-quarter average of inflation derived from the private final consumption deflator. Given that we do not have data on the depreciation of the residential capital for the euro area, we assume that it is constant [14] and leave it out as it would only shift the level of the user

[12]More details about the data and their sources can be found in Gerdesmeier, Lenarčič, and Roffia [2012], where the Annex contains also details about the construction of the series that were not readily available, for instance, the debt to income ratio.

[13]See DiPasquale and Wheaton [1994], Kennedy and Andersen [1994], McCarthy and Peach [2004], Lecat and Mesonnier [2005] and Antipa and Lecat [2009].

[14]In ECB (2006), the depreciation rate of residential construction for the period 1981-2005 is estimated to be around 2% per year and fairly constant over the period.

cost rate, while not affecting its dynamics. In addition, due to the heterogeneity of the tax treatment of mortgage payments across euro area, we also omit the average income tax rate from the user cost rate calculation. Our approximate calculations of average income tax rate show that it is fairly stable over the period of interest (moving slowly between 11% and 15%).

In Figure 1 we plot four versions of the user cost rate, which differ in terms of what measures of the interest rate and of the expected capital gains are used. The figure shows that the choice of the interest rate affects the user cost rate only slightly (comparing the red line **v1** based on the long-term interest rates and dotted pink **v2** which has been constructed using the mortgage rate). Conversely, the choice of different proxies for the expected future capital gains changes the dynamics of the user cost rate considerably. In particular, the dynamics are very different when house price inflation (lines **v1** and **v2**) is used, compared to the user cost rate calculated using the consumer price inflation (see blue line **v3**) and the private final consumption inflation (green dashed line **v4**). In addition, the latter two user cost rates show very similar dynamics.

[Figure 20 about here.]

3.4.2 Unit root tests and testing for cointegration

The candidate variables for fundamental determinants of housing prices were tested for stationarity using three unit-root tests: the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS) (the results are available upon request). Most of the variables seem to be integrated of order one, with the few exceptions being (on the basis of some of the tests) the unemployment rate (UR), the share of working age population in total population (WAPOP) and two versions of the user cost rate (v3 and v4 of the UCR).

Based on these results, we proceed by analyzing the number of cointegrating relationships among the non-stationary dependent and explanatory variables, using the Johansen cointegration test (see **Table 3.20** in Annex **1**). [15] More precisely, the models used include the main three determinants of house prices (i.e. the user cost rate, the demographic variable and the disposable income), but differ in terms of what measures are used for these variables, and which additional explanatory variables are included. In most cases, evidence in favour of one co-integrating vector is found.

There is, however, a huge body of literature criticizing the robustness and efficiency of the long-run estimates for a single co-integrating vector derived on the basis of the

[15] The stationary variables, such as WAPOP and UR, are treated as variables exogenous to the cointegrating relation in the model.

standard cointegration approaches à la Engle and Granger (1987) and à la Johansen [1995]. Against this background, a number of alternative approaches have been suggested, among them the autoregressive distributed lag (ARDL, [see Pesaran and Shin, 1995, Pesaran, Shin, and Smith, 2001], the Fully Modified Ordinary Least Squares (FMOLS, see Philips and Hansen (1990) and the dynamic OLS (DOLS, Saikkonen [1992] and Stock and Watson [1993]. The latter involves augmenting the cointegrating regression with leads and lags of the changes in the right-hand variables, so that asymptotically more efficient estimates may be obtained. It would not only yield consistent estimates, but also remove potential simultaneity issues from the long-run relationship.

3.4.3 Results from the DOLS estimations and selection of the best models

In line with the above considerations, we proceed by narrowing down the set of equations based on the results of dynamic OLS regressions. More precisely, we drop all the specifications in which the sign of some coefficients is different from what the economic theory would indicate. For instance, it would be plausible to find a positive coefficient for disposable income since a higher disposable income should affect the demand for houses and, in light of the relatively fixed supply of housing stock in the short run, also increase the prices.

Table 3.16 and **Table 3.17** show the DOLS results for the selected set of specifications. More precisely, in **Table 3.16** we present the results of models where the working age population is employed to represent the demographic explanatory variable, while **Table 3.17** contains the results with the labour force in total population as demographic variable. All the specifications include the version v4 of the user cost rate. [16],[17]

In the selected specifications in **Table 3.16**, the signs and magnitude of the coefficients remain quite stable over different specifications. Also, almost all the variables enter the regression with the expected sign and turn out to be significant. As regards the coefficient of housing stock and housing stock per capita, one would expect it to be negative, in principle, given that a higher existing housing stock can be interpreted as higher supply which would lead to lower house prices, everything else equal. However, given the fact that the housing stock is measured in terms of its value and thus includes a price component, a positive sign could also be plausible with a predominantly demand-driven phenomenon,

[16]Among the other three versions, version v3 led to very similar results, while this does not hold for the other two versions v1 and v2, which deliver unsatisfactory results in terms of coefficients signs. It is also worth noting that in both tables, for space reasons, we omit the coefficients of the lags and leads of cointegrating variables.

[17]For the sake of consistency, we use only combinations of variables that are either all specified in absolute or in per capita terms.

i.e. if agents expect prices to follow an upward spiral this could trigger a self-fulfilling prophecy.

[Table 13 about here.]

All variables affect house prices significantly and with coefficients of the expected sign. The UCR affects the house prices negatively, as lower costs increase demand and thus prices. Positive demographic developments and more disposable income instead affect the demand and prices in a positive way.

The specifications with the share of labour force to total population as demographic variable (see **Table 3.17**) yield similar results in terms of sign and significance. The housing price index is affected negatively by the user cost rate and the unemployment rate, while it is affected positively by the demographic variable and disposable income or disposable income per capita. In most cases, the demographic variable turns out to be insignificant. Finally, specifications 6 and 7 that include the debt-to-income ratio of the households as an explanatory variable yield interesting results. In specification 6, the coefficient is not significant, while in specification 7 it is negative and significant, which is consistent with the idea that higher debt means that the households are more credit constrained and are consequently able to demand less housing.

[Table 14 about here.]

3.5 Quantile regression results and identifying boom-bust episodes

After having selected the models which explain house prices in terms of their main fundamentals, we further analyse these relationships by means of quantile regressions. Based on the values of predictors and the estimated regression coefficients, fitted values are derived for the quantiles of interest, smoothed by the HP-filter (with $\lambda = 1600$) and used for identifying the periods of booms and busts in the house price dynamics. [18] More precisely, booms/busts are represented by longer-lasting deviations from equilibrium, with observations falling outside the [20,80] interval (for busts and booms, respectively). In addition to the estimates for this set of percentiles, we report the results for the median. **Table 3.1** reports the results of quantile regressions using working age population as

[18] We follow the approach used by Machado and Sousa [2006], pp. 13-14. Note also, that results presented do not significantly differ from the ones based on alternative filtering techniques, such as the asymmetric Christiano-Fitzgerald filter.

demographic factor, while **Table 3.2-3.3** contains the results using the share of labour force in total population.[19]

The coefficients should be interpreted as follows. For instance, in the first specification, one percent increase in real housing stock per capita raises real house prices by 1.06 percent at the 20th percentile of the conditional distribution and by 0.52 percent at the 80th percentile. Generally speaking, we find that the results are broadly consistent with the earlier DOLS results in qualitative terms. There are, however, some differences in the coefficients across quantiles. This feature is also statistically confirmed by the Wald tests, reported in **Table 3.1** and **Table 3.2-3.3**, that reject the null hypothesis of equality of slope coefficients in all the specifications.

When focusing on the specifications with the working age population as demographic variable presented in **Table 3.1**, we can observe the following regularities. The coefficient estimates for the user cost rate tend to be fairly similar across the reported quantiles of the (conditional) distribution of house prices. The coefficient for the working population is mostly insignificant at the lowest reported quantile but tends to become larger and significant at higher quantiles. This suggests that the demographic factor mostly affects the upper part of the conditional distribution of house prices. In other words, there is more upward pressure from the demographic factor on the house prices when they are in the upper part of their distribution. Another interesting result arises in relation to the coefficients of disposable income and disposable income per capita. The effect of disposable income seems to have a significant positive effect only in the highest reported quantile of the distribution, indicating that the average effect (resulting from DOLS-estimations) does not properly pick up the fundamental relation. As could be expected, disposable income has a positive impact on house prices. Finally, housing stock and housing stock per capita seem to have a fairly similar effect on the house prices at different quantiles. The sign of the related coefficients remains the same across the distribution and specifications, while there are only some changes in the size of the coefficients, and in case of specification 2, significance of the coefficient related to the 80th percentile.

Turning to the specifications with labour force, we can observe the following. In almost all specifications, the disposable income and the disposable income per capita have a significant positive effect on all reported quantiles of the house price distribution (see **Table 3.2-3.3**). The labour force enters significantly at least for some quantiles in most of the specifications and whenever significant, it has a positive effect on house prices. The effect of the user cost rate is significant and negative, with a slightly lower coefficient in the lowest quantile. Interestingly, the unemployment rate (in specification

[19] As in previous tables, the coefficients pertaining to the additional lags and leads are not reported for the sake of brevity.

5) gives mixed results as it affects the upper part of the distribution negatively, while having a positive effect on lower quantiles of the house price distribution. The effect of the debt-to-income ratio is negative and significant in the higher quantiles in specification 7.

Given these results, we conclude that the conventional DOLS method does not always fully summarize the existing disparities and that there is benefit in cross-checking the results by means of quantile regression.

3.6 Identifying boom/bust episodes with quantile regression

The additional information provided about the distribution in house prices can be used as an alternative method to identify booms and busts in this type of asset prices. Using the estimated coefficients, we calculate fitted values for specific quantiles of the conditional distribution and plot them against the developments in real house prices. If house prices move into the highest (lowest) quantile, this can be dubbed as a boom (bust) period (see **Figure 3.21-3.27**). For instance, according to this line of reasoning, the specification 1 that is illustrated in graphical terms in **Figure 3.21-3.27** (corresponding to the first equation in **Table 3.1**) would detect a boom in 1983-1984, 1989-1993 and in the most recent period around 2005-2008. A bust instead would be detected in the years 1985-1987, 1997-1999 and in the last part of the sample from 2009 onwards. These results can be considered as core years of booms and busts, especially in the first half of the sample, and are also broadly confirmed by the other specifications. This notwithstanding, when looking at the years from 1995 onwards, half of the specifications used would point towards a longer-lasting bust period from the mid-1990 till early 2000, whereas for the same specifications, the bust at the end of the sample would only be detected in 2011. It, therefore, seems to be interesting to compare the results, obtained by using the quantile methodology with the ones obtained by other methods. The boom and bust periods for the selected models are presented in Annex **2** (see **Figure 3.28**).

[Figure 21 about here.]

[Figure 22 about here.]

[Figure 23 about here.]

[Figure 24 about here.]

[Figure 25 about here.]

[Figure 26 about here.]

[Figure 27 about here.]

3.7 A comparison of methods for identifying boom and bust periods in the housing market

In the literature, there is a variety of methodologies for identifying asset price booms and/or busts, some of which being more of a statistical nature and others (such as the quantile methodology) being more of a fundamental nature. In this section we compare the results (for the housing market) from the quantile regressions described above with those stemming out of three statistical methods which have been widely used in the literature. In particular, the methodologies which are adopted for the comparative analysis in this section identify booms and busts in the housing price markets in the following ways:

a) a boom (bust) is defined as a period in which the 3-year moving average of the annual growth rate of the index of house prices is bigger (smaller) than the average growth rate plus (minus) 1.3 times its standard deviation [see Bordo and Jeanne, 2002];

b) a boom is defined as a period in which the house price gap (i.e. the gap between the actual house price index and its trend calculated using the Christiano-Fitzgerald filter) is above its mean plus a factor of times its standard deviation, whereby both the mean and the standard deviation are calculated over a rolling period of 60 quarters [see Gerdesmeier, Reimers, and Roffia, 2011].[20] A bust event instead is defined as a situation in which – at the end of the rolling period of r=12 quarters – the house price index has declined below its mean minus a factor of times the standard deviation in the period from 1 to with respect to its maximum reached in the same period [see Gerdesmeier, Reimers, and Roffia, 2010];

c) a boom (bust) is a period when the 4-quarter trailing moving average of the annual growth rate of the real house price index rises (falls) above (below) its mean plus (minus) 1.3 times its standard deviation (modified from 5% in the original paper by the **?** due to heterogeneity among euro area countries);

d) and, the quantile regression technique adopted in the previous section, where booms/busts are represented by longer-lasting deviations from equilibrium, with observations falling outside the [20,80] interval (for booms and busts, respectively), using the model specification illustrated in the previous section in **Table 3.1** and **Table 3.2-3.3**. The results of the comparative exercise for house prices across the four methodologies

[20] [see Borio and Drehmann, 2009]. The criterion applied to derive a boom episode is different from the one applied for detecting bust episodes, as the cumulated increase in the indicator over the boom periods is usually much slower and smoother than the corresponding decrease in times of busts.

are reported in **Table 3.18-3.19**.[21] The following observations are worth noting. First, the two periods when booms are detected by most of the methods are those related to the early 1990s and mid-2000s. As regards the 1980s, while the quantile model detects a boom in 1983, two other methods point to a boom in the late 1980s. Second, looking at busts, the two periods selected by most methods are those in the mid-1980s and around 2008-2010. In particular, the last episode related to the recent financial crisis represents a typical episode, whereby a bust occurred in the aftermath of the boom and is characterised by a more synchronised house price developments across euro area countries, while previous episodes experienced a large dispersion across euro area countries in general. Overall, this comparative analysis suggests that a comprehensive approach which takes into account both statistical and more fundamental methods for boom/bust identification is warranted.

[Table 15 about here.]

[Table 16 about here.]

Finally, some remarks should be made regarding this comparative analysis and, especially, on the results obtained with the three statistical methods. First, it is possible that, by construction, the statistical methods encounter some difficulties in detecting the boom and/or bust at the beginning of the sample due to a starting-point problem. Second, the statistical methods used in the analysis do not imply a certain duration of the boom/bust periods as a criterion for their identification, which may be reflected by the fact that some episodes consist only in one quarter of over/undershooting of the housing prices. Finally, as regards the quantile methodology, given the fact that the standard deviation adapts slowly to modest increases/decreases and thus only sharp and abrupt changes easily cross the boundaries, this could lead to a slightly delayed detection of misalignments.

3.8 Conclusions

It is a well-known fact that asset markets have been playing an increasingly important role in many economies, and the large swings in asset prices have become a relevant issue for policy-makers. Monetary policy has been cited as both a possible cause of asset price booms and a tool for defusing those booms before they can cause macroeconomic instability. Consequently, economists and policy-makers have focused on how monetary

[21] For this comparative analysis, the quantile regressions were run to cover a sample up to 2009 in order to include the most recent bust into the data. Due to missing observations in 2009 for two variables, the respective forecasts were taken into account. Overall, the quantile regressions were found to be robust to this sample expansion.

policy might cause an asset price boom or turn a boom caused by real phenomena into a bubble, which may burst unexpectedly rendering damage to the economy. This paper adds to the literature in many respects. First, the quantile regression approach advocated by Machado and Sousa [2006] is applied to the housing market to detect booms and busts. This, inter alia, requires the development of a model for the house price index. Second, when developing and estimating such a model, the following fundamental variables are found to explain house price developments: demographic variables, the unemployment rate, the disposable income, the housing stock, the debt-to-income ratio and a user cost measure. Third, in many cases, these effects seem to be non-linear, as they vary across specific quantiles. Fourth, the additional information provided on the distribution in house prices can be used as an alternative method to identify booms and busts in this type of asset prices class. Finally, the outcome of the identification of boom/bust episodes based on these quantile regressions seems to be in line with other statistical and fundamental methods usually used for this purpose, and thus can be regarded as complementary tool for identifying those episodes.

Table 3.1: Quantile regression results for euro area real house prices - working age population

Explanatory variables		1			2	
	0.20	0.50	0.80	0.20	0.50	0.80
User cost rate	-1.09**	-1.22***	-1.18***	-0.95**	-1.3***	-0.99***
	(0.43)	(0.32)	(0.34)	(0.38)	(0.35)	(0.36)
Working population	2.89	5.02**	4.75***	2.44	5.63**	4.19**
	(3.43)	(2.1)	(1.57)	(3.42)	(2.29)	(1.63)
Disposable income				0.34	-0.12	1.27**
				(0.4)	(0.26)	(0.57)
Disposable income per capita	0.26	0.1	1.21**			
	(0.39)	(0.27)	(0.52)			
Housing stock per capita	1.06***	1.13***	0.52**			
	(0.21)	(0.15)	(0.25)			
Housing stock				0.79***	1.04***	0.18
			(0.25)	(0.16)	(0.33)	
Unemployment rate						
Constant	8.54**	6.34***	11.41***	-14.7***	-14.77***	-18.83***
	(3.95)	(2.12)	(2.96)	(1.25)	(1.63)	(2.49)
No. of leads and lags	2	2	2	2	2	2
PseudoR^2	0.88	0.85	0.87	0.88	0.85	0.86
Wald slope equality test		0.000			0.000	

Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

Table 3.2: Quantile regression results for euro area real house prices - share of labour force in total population - Panel A

Explanatory variables		3			4			5	
	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80
User cost rate	-0.69**	-0.8***	-0.65**	-0.38*	-0.83***	-0.52**	-0.6***	-0.61***	-0.69***
	(0.31)	(0.25)	(0.25)	(0.21)	(0.24)	(0.2)	(0.2)	(0.22)	(0.26)
Labour force in total population	4.38	0.63	4.07	-1.97	1.47	6.69***	5.33***	-0.34	-1.03
	(3.9)	(1.62)	(2.93)	(1.58)	(1.56)	(1.91)	(1.93)	(1.8)	(2.77)
Disposable income				1.78***	1.33***	0.61**			
				(0.22)	(0.22)	(0.29)			
Disposable income per capita	1.21	2.02***	1.37**				1.03***	2.21***	2.37***
	(0.73)	(0.31)	(0.61)				(0.37)	(0.36)	(0.56)
Housing stock per capita									
Housing stock									
Unemployment rate							1.93***	-0.81	-1.56***
							(0.00)	(0.00)	(0.00)
Debt-to income ratio									
Constant	8.28	17.19***	9.95	-18.52***	-15.31***	-9.95***	6.14	19.43***	21.23***
	(8.24)	(3.51)	(6.74)	(1.69)	(1.68)	(2.24)	(4.15)	(4.01)	(6.23)
No. of leads and lags	1	1	1	1	1	1	1	1	1
PseudoR^2	0.84	0.83	0.83	0.86	0.83	0.83	0.85	0.83	0.84
Wald slope equality test		0.000			0.000			0.000	

Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

Table 3.3: Quantile regression results for euro area real house prices - share of labour force in total population- Panel B

Explanatory variables		6			7	
	0.20	0.50	0.80	0.20	0.50	0.80
User cost rate	-0.2	-0.78**	-0.92***	-0.47*	-0.92***	-0.95***
	(0.29)	(0.31)	(0.19)	(0.26)	(0.26)	(0.18)
Labour force in total population	-2.88	0.38	2.06	-0.54	1.55	4.93**
	(2.24)	(1.87)	(2.6)	(1.5)	(1.64)	(2.29)
Disposable income				1.69***	1.69***	1.55***
				(0.23)	(0.24)	(0.31)
Disposable income per capita	2.21***	2.12***	2.09***			
	(0.35)	(0.33)	(0.44)			
Housing stock per capita						
Housing stock						
Unemployment rate						
Debt-to income ratio	0.002	-0.0002	-0.001	-0.001	-0.002**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	20.31	18.19***	17.32***	20.31	18.19***	17.32***
	(3.88)	(3.56)	(4.85)	(3.88)	(3.56)	(4.85)
No. of leads and lags	1	1	1	1	1	1
PseudoR^2	0.85	0.83	0.84	0.86	0.84	0.85
Wald slope equality test		0.000			0.000	

Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

3.A Annex 1

[Table 17 about here.]

3.B Annex 2

[Figure 28 about here.]

Bibliography

Afonso, A., J. Baxa, and M. Slavík (2011): "Fiscal Developments and Financial Stress: A Threshold VAR Analysis," Working Paper 1319, ECB.

Albertini, J., G. Kamber, and M. Kirker (2012): "Estimated Small Open Economy Model with Frictional Unemployment," *Pacific Economic Review*, 17(2), 326–353.

Alberts, W. W. (1962): "Business Cycles, Residential Construction Cycles, and the Mortgage Market," *Journal of Political Economy*, 70, 263.

Alesina, A., C. Favero, and F. Giavazzi (2012): "The Output Effect of Fiscal Consolidations," Working Paper 18336, NBER.

Alesina, A., and R. Perotti (1996a): "Fiscal Expansions and Fiscal Adjustments in OECD Countries," Working Paper 5214, NBER.

——— (1996b): "FiscalAdjustments in OECD Countries: Composition and Macroeconomic Effects," Working Paper 5730, NBER.

Allen, D., A. Kumar Singh, and R. Powell (2009): "Asset pricing, the Fama-French factor model and the implications of quantile regression analysis," Working Paper 0911, School of Accounting, Finance and Economics & FEMARC.

Altissimo, F., and V. Corradi (2002): "Bounds for Inference with Nuisance Parameters Present Only Under the Alternative," *Econometrics Journal*, 5(2), 494–519.

Andrews, D. W. K., and W. Ploberger (1994): "Optimal tests when a nuisance parameter is present only under the alternative," *Econometrica*, 62(6), 1383–1414.

Antipa, P., and R. Lecat (2009): "The 'Housing bubble' and financial factors: Insights from a structural model of the French and Spanish residential markets," Working paper 267, Banque de France.

Ardagna, S. (2007): "Fiscal policy in unionized labor markets," *Journal of Economic Dynamics and Control*, 31(5), 1498–1534.

Artis, M., A. B. Galvão, and M. Marcellino (2007): “The Transmission Mechanism in a Changing World,” *Journal of Applied Econometrics*, 22(1), 39–61.

Auerbach, A., and Y. Gorodnichenko (2010): “Measuring the Output Response to Fiscal Policy,” mimeo.

——— (2011): “Fiscal Multipliers in Recession and Expansion,” mimeo.

Barnes, M., and A. Hughes (2002): “A quantile regression analysis of the cross section of stock market returns,” Working paper 02-2, Federal Reserve Bank of Boston.

Barro, R. J., and C. J. Redlick (2011): “Macroeconomic Effects from Government Purchases and Taxes,” 126(1), 51–102.

Batini, N., G. Callegari, and G. Melina (2012): “Successful Austerity in the United States, Europe and Japan,” Working Paper WP/12/190, IMF.

Baum, A., and G. B. Koester (2011): “The impact of fiscal policy on economic activity over the business cycle — evidence from a threshold VAR analysis,” Discussion Paper: Economic Studies 03/2011, Deutsche Bundesbank.

Bermperoglou, D., E. Pappa, and E. Vella (2013): “Spending-based austerity measures and their effects on output and unemployment,” Discussion paper.

Bi, H. (2010): “Sovereign Default Risk Premia, Fiscal Limits, and Fiscal Policy,” mimeo.

Bilbiie, F., T. Monacelli, and R. Perotti (2012): “Tax Cuts vs. Spending Increases: Welfare and the Zero Lower Bound,” .

Blanchard, O., and R. Perotti (2002): “An Empirical Characterization Of The Dynamic Effects Of Changes In Government Spending And Taxes On Output,” 117(4), 1329–1368.

Blanchard, O. J. (1990): “Suggestions for a New Set of Fiscal Indicators,” OECD Economics Department Working Papers 79, OECD.

Bohn, H. (1998): “The Behavior Of U.S. Public Debt And Deficits,” *The Quarterly Journal of Economics*, 113(3), 949–963.

Bordo, M., and O. Jeanne (2002): “Boom-busts in asset prices, economic instability and monetary policy,” Working Paper 8966, NBER.

Borio, C., and M. Drehmann (2009): “Towards an Operational Framework for Financial Stability: "Fuzzy" Measurement and its Consequences,” Working Papers Central Bank of Chile 544, Central Bank of Chile.

Burriel, P., F. de Castro, D. Garrote, J. Gordo, Esther Paredes, and J. J. Prez (2009): "Fiscal Policy Shocks in the Euro Area and the US," Working Paper 1133, ECB.

Caldara, D. (2011): "The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers," mimeo.

Caldara, D., and C. Kamps (2008): "What are the effects of fiscal policy shocks? A VAR-based comparative analysis," Working Paper 877, ECB.

——— (2012): "The Analytics of SVARs: A Unified Framework to Measure Fiscal Multipliers," Finance and Economics Discussion Series 2012-20, Borad of Governors of the Federal Reserve System.

Callen, T., M. Terrones, X. Debrun, J. Daniel, and C. Allard (2003): "Public debt in Emerging markets: Is it too high?," in *World Economic Outlook*, pp. 113–152. International Monetary Fund.

Calvo, G. A. (1983): "Staggered prices in a utility-maximizing framework," *Journal of Monetary Economics*, 12(3), 383–398.

Canzoneri, M., F. Collard, H. Dellas, and B. Diba (2011): "Fiscal Multipliers in Recessions," mimeo.

Cecchetti, S., and L. Li (2008): "Measuring the impact of asset price booms using quantile vector autoregressions," $http : //www.nber.org/public_html/confer/2008/si2008/EFWW/li.pdf$.

Chahrour, R., S. Schmitt-Grohé, and M. Uribe (2010): "A model-based evaluation of the debate on the size of the tax multiplier," Working Paper 16169, NBER.

Choi, W. G., and M. B. Devereux (2005): "Asymmetric Effects of Government Spending: Does the Level of Real Interest Rates Matter?," Working Paper WP/05/7, IMF.

Christiano, L., M. Eichenbaum, and S. Rebelo (2011): "When Is the Government Spending Multiplier Large?," *Journal of Political Economy*, 119(1), 78 – 121.

Christoffel, K., K. Kuester, and T. Linzert (2009): "The role of labor markets for euro area monetary policy," *European Economic Review*, 53(8), 908–936.

Chung, H., and E. M. Leeper (2007): "What Has Financed Government Debt?," Working Paper 13425, NBER.

Coenen, G., R. Straub, and M. Trabandt (2012): "Fiscal Policy and the Great Recession in the Euro Area," 102(3), 71–76.

Cogan, J. F., T. Cwik, J. B. Taylor, and V. Wieland (2010): "New Keynesian versus old Keynesian government spending multipliers," *Journal of Economic Dynamics and Control*, 34(3), 281–295.

Corsetti, G., A. Meier, and G. J. Müller (2009): "Fiscal Stimulus with Spending Reversals," Discussion Paper 7302, CEPR.

——— (2010): "What determines government spending multipliers?," mimeo.

DiPasquale, D., and W. Wheaton (1994): "Housing market dynamics and the future of housing prices," *Journal of Urban Economics*, 35, 1–27.

ECB (2011): "Ensuring Fiscal Sustainability," *ECB Monthly Bulletin*, April, 61–77.

Eggertsson, G. B. (2011): "What Fiscal Policy is Effective at Zero Interest Rates?," in *NBER Macroeconomics Annual 2010, Volume 25*, NBER Chapters, pp. 59–112. National Bureau of Economic Research, Inc.

Faia, E., and T. Monacelli (2008): "Optimal Monetary Policy in a Small Open Economy with Home Bias," *Journal of Money, Credit and Banking*, 40(4), 721–750.

Fair, R. (1972): "Disequilibrium in housing models," *The Journal of Finance*, 27(2), 207–221.

Favero, C., and F. Giavazzi (2007): "Debt and the Effects of Fiscal Policy," Working Paper 317, IGIER.

Fazzari, S. M., J. C. Morley, and I. Panovska (2012): "State-Dependent Effects of Fiscal Policy," Research Paper 2012-27, UNSW Australian School of Business.

Fund, I. M. (2009): "Lessons for monetary policy from asset price fluctuations," Discussion Paper Chapter 3.

Galí, J., J. D. López-Salido, and J. Vallés (2007): "Understanding the Effects of Government Spending on Consumption," *Journal of the European Economic Association*, 5(1), 227–270.

Galvão, A. B. (2006): "Structural Break Threshold VARs for Predicting US Recessions Using the Spread," *Journal of Applied Econometrics*, 21(4), 463–487.

Galvão, A. B., and M. Marcellino (2010): "Endogenous Monetary Policy Regimes and the Great Moderation," mimeo.

Ganoulis, I., and M. Giuliodori (2010): "Financial liberalization and house price dynamics in Europe," *Applied Economics*, pp. 1–18.

Gattini, L., and P. Hiebert (2010): "Forecasting and assessing euro area house prices through the lens of key fundamentals," Working Papers Series 1249, ECB.

Gerdesmeier, D., A. Lenarčič, and B. Roffia (2012): "An alternative method for identifying booms and busts in the euro area housing market," Working Paper Series 1493, ECB.

Gerdesmeier, D., H.-E. Reimers, and B. Roffia (2010): "Asset price misalignments and the role of money and credit," *International Finance, Wiley Blackwell*, 13(3), 377–407.

——— (2011): "Early Warning Indicators for Asset Price Booms," *Review of Economics and Finance*, 3, 1–20.

Gertler, M., L. Sala, and A. Trigari (2008): "An Estimated Monetary DSGE Model with Unemployment and Staggered Nominal Wage Bargaining," *Journal of Money, Credit and Banking*, 40(8), 1713–1764.

Ghosh, A. R., J. I. Kim, E. G. Mendoza, J. D. Ostry, and M. S. Qureshi (2011): "Fiscal Fatigue, Fiscal Space and Debt Sustainability in Advanced Economies," Working Paper 16782, NBER.

Giavazzi, F., T. Jappelli, and M. Pagano (2000): "Searching for non-linear effects of fiscal policy: Evidence from industrial and developing countries," Working Paper 7460, NBER.

Giavazzi, F., T. Jappelli, M. Pagano, and M. Benedetti (2005): "Searching for Non-Monotonic Effects of Fiscal Policy: New Evidence," Working Paper 11593, NBER.

Giavazzi, F., and M. Pagano (1990): "Can Severe Fiscal Contractions Be Expansionary? Tales of Two Small European Countries," Working Paper 3372, NBER.

——— (1995): "Non-Keynesian Effects of Fiscal Policy Changes: International Evidence and the Swedish Experience," Working Paper 5332, NBER.

Gomes, P. (2011): "Fiscal policy and the labour market: the effects of public sector employment and wage," Economic Papers 439, European Commission.

Gonzalo, J., and J.-Y. Pitarakis (2002): "Estimation and model selection based inference in single and multiple threshold models," *Journal of Econometrics*, 110(2), 319–352.

Greene, W. (2003): *Econometric analysis*. Prentice Hall, NJ., 5th edition edn.

Hall, R. (2005a): "Employment Efficiency and Sticky Wages: Evidence from Flows in the Labor Market," *Review of Economics and Statistics*, 87(3), 397–407.

——— (2005b): "Job Loss, Job Finding, and Unemployment in the U.S. Economy over the Past Fifty Years," in *NBER Macroeconomics Annual*, ed. by M. Gertler, and K. Rogoff, pp. 101–137. MIT Press.

Hansen, B. E. (1996): "Inference When a Nuisance Parameter Is Not Identified under the Null Hypothesis," *Econometrica*, 64(2), 413–30.

——— (1999): "Testing for Linearity," *Journal of Economic Surveys*, 13(5), 551–576.

——— (2000): "Sample Splitting and Threshold Estimation," *Econometrica*, 68(3), 575–603.

Haugh, D., P. Ollivaud, and D. Turner (2009): "What drives sovereign risk premiums?," Economic Departments Working Papers 718, OECD.

Hosios, A. J. (1990): "On the Efficiency of Matching and Related Models of Search and Unemployment," *Review of Economic Studies*, 57(2), 279–98.

Ilzetzki, E., E. G. Mendoza, and C. A. Végh (2010): "How Big (Small?) are Fiscal Multipliers?," mimeo.

Johansen, S. (1995): *Likelihood-based inference in cointegrated vector autoregressive models*. Oxford University Press, Oxford.

Juessen, F., L. Linnemann, and A. Schabert (2011): "Understanding default risk premia on public debt," .

Kasparova, D., and M. White (2001): "The responsiveness of house prices to macroeconomic forces: a cross-country comparison," *European Journal of Housing Policy*, (3).

Kaufmann, M., and M. Mühleisen (2003): "Are house prices overvalued?," Country Report 03/245, IMF, Chapter 2.

Kearl, J. (1979): "Inflation, mortgages, and housing," *Journal of Political Economy*, 87, 1–29.

Kennedy, N., and P. Andersen (1994): "Household saving and real house prices: an international perspective," Working Papers 20, BIS.

Kirchner, M., J. Cimadomo, and S. Hauptmeier (2010): "Transmission of Government Spending Shocks in the Euro Area: Time Variation and Driving Forces," Working Paper 1219, ECB.

Koenker, R., and G. Bassett (1978): "Regression quantiles," *Econometrica*, 46, 33–50.

Lecat, R., and J.-S. Mesonnier (2005): "What role do financial factors play in house price dynamics?," 134, Banque de France.

Leeper, E. M., T. B. Walker, and S.-C. S. Yang (2009): "Fiscal Foresight and Information Flows," Working Paper 14630, NBER.

Liao, W.-C., and X. Wang (2010): "Hedonic house prices and spatial quantile regression," Working Paper Series 009, IRES.

Machado, J., and J. Sousa (2006): "Identifying asset price booms and busts with quantile regressions," Working Papers 8, Banco de Portugal.

McCarthy, J., and R. Peach (2002): "Monetary policy transmission to residential investment," *Economic Policy Review, Federal Reserve Bank of New York*, pp. 139–158.

——— (2004): "Are home prices the next "bubble"?," *Economic Policy Review, Federal Reserve Bank of New York*, pp. 1–17.

McMillen, D. (2008): "Changes in the distribution of house prices over time: structural characteristics, neighborhood, or coefficients?," *Journal of Urban Economics*, 64(3), 573–589.

Mertens, K., and M. O. Ravn (2010): "Fiscal Policy in an Expectations Driven Liquidity Trap," CEPR Discussion Papers 7931, C.E.P.R. Discussion Papers.

——— (2011): "A Reconciliation of SVAR and Narrative Estimates of Tax Multipliers," .

Merz, M. (1995): "Search in the labor market and the real business cycle," *Journal of Monetary Economics*, 36(2), 269–300.

Michaillat, P. (2012): "Fiscal Multipliers Over the Business Cycle," CEP Discussion Paper 1115.

MONACELLI, T., R. PEROTTI, AND A. TRIGARI (2010): "Unemployment fiscal multipliers," *Journal of Monetary Economics*, 57(5), 531–553.

MORTENSEN, D. T., AND C. A. PISSARIDES (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61(3), 397–415.

MOUNTFORD, A., AND H. UHLIG (2008): "What are the Effects of Fiscal Policy Shocks?," Working Paper 14551, NBER.

NICKEL, C., P. ROTHER, AND L. ZIMMERMANN (2010): "Major public debt reductions: Lessons from the past, lessons for the future," Working Paper 1241, ECB.

NICKELL, S. (1981): "Biases in Dynamic Models with Fixed Effects," *Econometrica*, 49, 1417–1426.

OBSTBAUM, M. (2011): "The role of labour markets in fiscal policy transmission," Research Discussion Papers 16/2011, Bank of Finland.

OH, H., AND R. REIS (2012): "Targeted Transfers and the Fiscal Response to the Great Recession," 59(S), S50–S64.

PAPPA, E. (2009): "The Effects Of Fiscal Shocks On Employment And The Real Wage," *International Economic Review*, 50(1), 217–244.

PEROTTI, R. (1999): "Fiscal Policy in Good Times and Bad," 114(4), 1399–1436.

——— (2004): "Estimating the effects of fiscal policy in OECD countries," Working Paper 276, IGIER.

——— (2011): "Expectations and Fiscal Policy: An Empirical Investigation," .

PESARAN, M., AND Y. SHIN (1995): "An autoregressive distributed lag modelling approach to cointegration analysis," *Centennial Volume of Ragnar Frisch*, Cambridge University Press, Cambridge.

PESARAN, M., Y. SHIN, AND R. SMITH (2001): "Bounds testing approaches to the analysis of level relationships," *Journal of Applied Econometrics*, 16, 289–326.

PETRONGOLO, B., AND C. PISSARIDES (2001): "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 39(2), 390–431.

PISSARIDES, C. A. (2000): *Equilibrium Unemployment Theory, 2nd Edition*, vol. 1 of *MIT Press Books*. The MIT Press.

Poterba, J. (1984): "Tax Subsidies to owner-occupied housing: an asset-market approach," *The Quarterly Journal of Economics*, 99(4), 729–752.

——— (1992): "Taxation and housing: old questions, new answers," *The American Economic Review, Papers and Proceedings of the Hundred and Fourth Annual Meeting of the American Economic Association*, 82(2), 237–242.

Quadrini, V., and A. Trigari (2008): "Public Employment and the Business Cycle," *Scandinavian Journal of Economics*, 109(4), 723–742.

Ramey, V. (2011): "Can Gocernment Purchases Stimulate the Economy?," *Journal of Economic Literature*, 49(3), 673–685.

Ramey, V. A. (2009): "Identifying Government Spending Shocks: It's All in the Timing," Working Paper 15464, NBER.

Ramey, V. A., and M. D. Shapiro (1998): "Costly capital reallocation and the effects of government spending," *Carnegie-Rochester Conference Series on Public Policy*, 48(1), 145–194.

Ravn, M. O., S. Schmitt-Grohé, and M. Uribe (2007): "Explaining the Effects of Government Spending Shocks on Consumption and the Real Exchange Rate," NBER Working Papers 13328, National Bureau of Economic Research, Inc.

Ravn, M. O., and S. Simonelli (2007): "Labor Market Dynamics and the Business Cycle: Structural Evidence for the United States," Economics Working Papers ECO2007/13, European University Institute.

Romer, C. D., and D. H. Romer (2009): "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks," mimeo.

Saastamoinen, J. (2008): "Quantile regression analysis of dispersion of stock returns - evidence of herding?," *Keskustelualoitteita 57, Joensuun yliopisto, Taloustieteet.*

Saikkonen, P. (1992): "Estimation and testing of cointegrated systems by an autoregressive approximation," *Econometric Theory*, 8, 1–27.

Shimer, R. (2005): "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 95(1), 25–49.

Stock, J. H., and M. Watson (1993): "A simple estimator of cointegrating vectors in higher order integrated systems," *Econometrica*, 61, 783–820.

Sutherland, A. (1997): “Fiscal crises and aggregate demand: can high public debt reverse the effects of fiscal policy?,” *Journal of Public Economics*, 65, 147–162.

Teräsvirta, T. (1998): “Modelling Economic Relationships with Smooth Transition Regressions,” in *Handbook of Applied Economic Statistics*, ed. by A. Ullah, and D. E. A. Giles, pp. 507–552. Marcel Dekker.

Trigari, A. (2009): “Equilibrium Unemployment, Job Flows, and Inflation Dynamics,” *Journal of Money, Credit and Banking*, 41(1), 1–33.

Tsatsaronis, K., and H. Zhu (2004): “What drives housing price dynamics: cross-country evidence,” Quarterly review, BIS.

Tsay, R. S. (1998): “Testing and Modelling Multivariate Threshold Models,” *Journal of the American Statistical Association*, 93(443), 1188–1202.

Xiao, Z. (2010): “Quantile Cointegrating Regression,” *Journal of Econometrics*, 150(2), 248–260.

Zietz, J., E. Zietz, and G. Sirmans (2008): “Determinants of house prices: a quantile regression approach,” *The Journal of Real Estate Finance and Economics, Springer*, 37(4), 317–333.

Table 3.4: Candidate threshold variables

Related to	Variable
Financing the debt	real short-run rate
	real long-run rate
	real cost of financing the debt
Stationarity of debt	real short-run rate over GDP growth rate
	real long-run rate over GDP growth rate
	real cost of financing debt over GDP growth rate
Deficit	quarterly primary deficit-to-GDP ratio
	annual primary deficit-to-GDP ratio
	worse of the last two periods' quarterly deficit-to-GDP ratio
Debt stock	debt-to-GDP ratio
	quarterly change in the debt-to-GDP ratio
	year-on-year change in the debt-to-GDP ratio
Ability to repay	net interest payments-to-receipts ratio
	net interest payments-to-GDP ratio
	sensitivity of real short-run rate to debt-to-GDP ratio
	sensitivity of real long-run rate to debt-to-GDP ratio
	sensitivity of real cost of financing debt to debt-to-GDP ratio

Note: The real short term rate is computed using the 3-month T-bill rate. The real long term rate is computed using the 10-year government bond rate. The real cost of financing the debt is computed using the nominal cost of financing the debt. Real rates are computed using the GDP deflator inflation. For the definition of the nominal cost of financing the debt and the GDP deflator see the Appendix.

Table 3.5: Elasticity values

	α_{gy}	$\alpha_{g\Delta p}$	α_{gi}	α_{ty}	$\alpha_{t\Delta p}$	α_{ti}
Linear model	0	-0.5	0	1.864	1.622	0
Good times	0	-0.5	0	1.860	1.618	0
Bad times	0	-0.5	0	1.892	1.666	0

Table 3.6: Value of the information criteria for the different nonlinear models

Threshold Variable	**AIC**	**SC**	**HQC**
Financing the debt			
real short-run rate	-36.16	-34.56	-35.37
real long-run rate	-36.15	-34.62	-35.36
real cost of financing the debt	-36.10	-34.83	-35.48
Stationarity of debt			
real short-run rate over GDP growth rate	-36.10	-34.83	-35.48
real long-run rate over GDP growth rate	-35.74	-34.45	-35.07
real cost of financing debt over GDP growth rate	-36.28	-34.66	-35.58
Deficit			
quarterly primary deficit-to-GDP ratio	-36.17	-34.64	-35.38
annual primary deficit-to-GDP ratio	-36.18	-34.61	-35.43
worse of the last two periods' quarterly deficit-to-GDP ratio	-36.31	-34.66	-35.50
Debt stock			
debt-to-GDP ratio	**-36.53**	**-35.22**	**-35.87**
cyclical component of real, per capita debt	-35.88	-34.74	-35.35
quarterly change in the debt-to-GDP ratio	-36.17	-34.57	-35.43
year-on-year change in the debt-to-GDP ratio	-35.98	-34.54	-35.23
Ability to repay			
net interest payments-to-receipts ratio	-36.29	-34.77	-35.50
net interest payments-to-GDP ratio	-36.25	-34.75	-35.44
sensitivity of real short-run rate to debt-to-GDP ratio	-35.89	-34.28	-35.15
sensitivity of real long-run rate to debt-to-GDP ratio	-35.74	-34.28	-34.98
sensitivity of real cost of financing debt to debt-to-GDP ratio	-35.70	-34.38	-34.99

Table 3.7: Nonlinearity test results

	Variable addition test				**Tsay's predictive residuals test**			
Delay	$d = 1$	$d = 2$	$d = 3$	$d = 4$	$d = 1$	$d = 2$	$d = 3$	$d = 4$
Test statistics	103.5**	108.7**	125.8**	131.4**	146.3**	142.7**	145.7**	151.0**

Note: The test statistics of the variable addition and the predictive residuals tests both have a chi-squared distribution with 35 and 40 degrees of freedom, respectively. Two asterisks denote values significant at 1 percent.

Table 3.8: Feedback from the debt-to-GDP ratio

Lag	**Model**	$\boldsymbol{g_t}$	$\boldsymbol{t_t}$	$\boldsymbol{y_t}$	$\boldsymbol{\Delta p_t}$	$\boldsymbol{i_t}$
$\boldsymbol{d_{t-1}}$	Linear	0.53	-1.60	-0.53	-0.00	-0.26
		(0.95)	(2.08)	(2.33)	(0.03)	(4.32)
	Non linear, good times	0.39	-1.92	-0.47	0.06	-0.33
		(0.55)	(1.90)	(1.62)	(0.58)	(4.25)
	Non linear, bad times	-0.38	0.49	-0.36	-0.15	-0.05
		(0.60)	(0.73)	(1.35)	(2.72)	(0.93)
$\boldsymbol{d_{t-2}}$	Linear	-0.57	1.64	0.53	-0.01	0.26
		(-1.00)	(2.12)	(2.33)	(-0.18)	(4.37)
	Non linear, good times	-0.49	1.92	0.48	-0.08	0.34
		(0.68)	(1.89)	(1.66)	(0.81)	(4.31)
	Non linear, bad times	0.33	-0.49	0.37	0.15	0.06
		(0.52)	(0.70)	(1.33)	(2.67)	(1.03)

Note: The table shows the coefficients from the matrices $\mathbf{\Gamma}$ and $\mathbf{\Gamma}^{(j)}$ in equations (1.1) and (1.2), respectively. T-statistics are reported in the brackets.

Table 3.9: The reduced form equivalents of the structural shocks

Structural shock	$\boldsymbol{e_g}$	$\boldsymbol{e_t}$	$\boldsymbol{e_y}$	$\boldsymbol{e_{\Delta p}}$	$\boldsymbol{e_i}$
		Expenditure shock			
Good times ($u_g^{(1)}$)	1.01	−0.16	0.03	−0.01	−0.02
Bad times ($u_g^{(2)}$)	0.99	−0.02	0.12	0.02	−0.01
		Revenue shock			
Good times ($u_t^{(1)}$)	0.01	−0.92	0.06	−0.02	−0.00
Bad times ($u_t^{(2)}$)	−0.01	−0.87	0.05	0.02	−0.00

Note: Each row contains the reduced form equivalent of a one standard deviation structural shock.

Table 3.10: The fiscal multiplier as a function of the size and the sign of the shock

Size of the shock (% of GDP)	**Linear model**			**Good times**			**Bad times**		
	6	**12**	**20**	**6**	**12**	**20**	**6**	**12**	**20**
				quarters after impact					
Expenditure multipliers									
5.0	0.76	1.17	1.43	1.01	1.33	1.34	0.47	0.51	0.60
1.0				1.12	1.52	1.58	0.49	0.56	0.67
0.2				1.14	1.54	1.62	0.50	0.58	0.71
-0.2				1.14	1.55	1.64	0.50	0.59	0.72
-1.0				1.15	1.56	1.66	0.50	0.60	0.72
-5.0				1.17	1.60	1.73	0.52	0.63	0.80
Revenue multipliers									
-5.0	0.82	1.20	1.50	0.99	1.22	1.23	-0.24	-0.43	0.68
-1.0				1.00	1.30	1.37	-0.18	-0.17	0.90
-0.2				1.00	1.31	1.41	-0.14	-0.07	0.85
0.2				1.00	1.32	1.42	-0.13	0.01	0.90
1.0				1.00	1.33	1.45	-0.09	0.10	0.95
5.0				0.99	1.39	1.57	0.06	0.84	1.17

Note: The table shows the expansionary effect of the expenditure and revenues shocks with different size and sign. Expenditure multipliers are computed as the response of output divided by the size of the shock $\left(\frac{y}{g}\frac{\Delta g}{\Delta y}\right)$. Revenue multipliers are computed as the response of output divided by the size of the shock multiplied by minus one $\left(-\frac{y}{t}\frac{\Delta t}{\Delta y}\right)$ in order to express their expansionary effect and to facilitate comparison with expenditure multipliers.

Table 3.11: The US stimulus package shocks used in our simulation (percent of GDP)

Period	**2009Q2**	**2009Q3**	**2009Q4**	**2010Q1**	**2010Q2**	**2010Q3**	**2010Q4**
Expenditure	0.28	0.42	0.56	0.67	0.73	0.67	0.52
Revenue	0.36	0.43	0.40	0.32	0.19	0.12	0.12

Table 3.12: Values of the information criteria for structural break models

Model	**AIC**	**SC**	**HQC**
ET-VAR with debt-to-GDP ratio	**-36.75**	**-35.26**	**-36.05**
SB-VAR	-36.17	-34.65	-35.40
ESB-VAR	-36.17	-34.78	-35.51

Table 3.13: BaselineParametrization

Structural parameters		**Value**
Time discount factor	β	0.99
Utility from being unemployed	χ	0.2
Utility from gov. services	z^g	0.2
Risk aversion	ψ	1
Exogeneous separation rate (private sector)	ρ^p	0.045
Exogeneous separation rate (gov. sector)	ρ^g	0.015
Efficiency of matching (private sector)	$\sigma^{m,p}$	0.5
Efficiency of matching (gov. sector)	$\sigma^{m,g}$	0.6
Matching elasticity wrt vacancies (private sector)	α^p	0.5
Matching elasticity wrt vacancies (gov. sector)	α^g	0.84
Unemployment benefits	b^u	0.4
Cost of posting vacancy (private sector)	κ^p	0.7
Cost of posting vacancy (gov. sector)	κ^g	0.2
Bargaining power	η^N	0.5
Share of gov. consumption in total private output	ζ^{cg}	0.2
Ratio of gov. wages versus private sector wages	ζ^{wg}	1.1
Ratio of public sector vacancies to private sector ones	ζ^{vg}	0.2
Probability of not changing the price - Calvo parameter	ξ	0.75
Price elasticity	ϵ	11
Home bias	α	0.4
Price elasticity wrt foreign goods	η	2
Interest rate persistence	ρ^r	0.9
Taylor rule coefficient - response to inflation	ϕ^π	1.2
Taylor rule coefficient - response to output growth	ϕ^y	0.5
Autoregressive parameters		
Productivity	ρ^a	0.95
Gov. vacancies	ρ^{vg}	0.8
Gov. wages	ρ^{wg}	0.95
Gov. consumption	ρ^{cg}	0.8
Standard deviations		
Productivity	σ^a	0.007
Gov. vacancies	σ^{vg}	0.01
Gov. wages	σ^{wg}	0.011
Gov. consumption	σ^{cg}	0.01

Table 3.14: House price determinants in a selected set of models

Paper:	Demand side variables	Supply side variables	Estimation technique
Kennedy and Andersen (1994)	household real disposable income (HRDI), unemployment rate (UR), user cost of housing (UCH), time trend (as a proxy for existing stock of dwellings), share of the 15-64-year-old cohort over total population, lagged household debt-to-income ratio (HDIR), an autoregressive term	-	OLS
DiPasquale and Wheaton (1994)	rents, stock of houses per household, permanent income of households (PIH), expected home-ownership rate and UCH	house prices (HP), existing stock of houses (HS), short-term construction financing, construction costs (CC), land prices	
McCarthy and Peach (2002, 2004)	PIH, UCH, HS	investment rate, CC	supply and demand relations estimated separately in an EC framework
Antipa and Lecat (2009)	HS, UCH, PIH, additionally also the number of households and UR.	real house prices, CC, number of housing permits and starts.	long-term demand and supply equations in the first step (2SLS) and ECM to capture the short-term dynamics in the second step
Klyuev (2008)	changes in real disposable income per capita (RDIPC), UR, RMR	real CC, average household size	OLS (demand and supply equations); ECM (with real house price index, the real interest rate and real rents forming a cointegrating relationship)

Table 3.15: House price determinants in a selected set of models - continued

Paper:	Demand and supply side variables	Estimation technique
Kasparova and White (2001)	real GDP, RMR, housing permits.	ECM
Ganoulis and Giuliodori (2010)	RDIPC, RMR, real stock of mortgage debt per capita, total population older than 24 years, CC, residential HS, real stock market index	
Tsatsaronis and Zhu (2004)	House price growth, GDP growth, inflation rate, real short-term interest rate, term spread between a long-maturity, government bond yield and the short rate and the growth rate in inflation-adjusted bank credit.	Structural VAR
Gattini and Hiebert (2010)	Real housing prices, real housing investment, RDIPC, mixed maturity measure of the real interest rate.	VECM

Table 3.16: DOLS regression results for euro area real house prices - working age population

Explanatory variables	1	2
User cost rate	-1.156***	-1.216***
	(0.294)	(0.305)
Working population	3.150*	3.695**
	(1.727)	1.780
Disposable income per capita	0.597**	
	0.263	
Disposable income		0.463*
		0.273
Housing stock per capita	0.835***	
	0.142	
Housing stock		0.668***
		0.169
Unemployment rate		
Constant	9.594***	-15.41***
	2.098	1.019
No. of leads and lags	2	2
No. of observations	111	111
R^2	0.98	0.96

Note: Standard errors are reported below the respective coefficients and are heteroskedasticity-consistent. ***, ** and * indicate significance at the p<0.01, ** p<0.05, * p<0.1 significance levels.

Table 3.17: DOLS regression results for euro area real house prices - share of labour force to total population

Explanatory variables	3	4	5	6	7
User cost rate	-0.646***	-0.634***	-0.616***	-0.645***	-0.820***
	(0.189)	(0.176)	(0.196)	(0.203)	(0.196)
Labour force in total population	3.084	2.766*	2.691	2.476	2.129
	(1.886)	(1.613)	(1.999)	(2.025)	(1.637)
Disposable income per capita	1.514***		1.583***	1.511***	
	(0.369)		(0.387)	(0.376)	
Disposable income		1.143***			1.515***
		(0.228)			(0.280)
Unemployment rate			-0.268***		
			(0.440)		
Debt-to-income ratio				0.001	-0.002**
				(0.001)	(0.001)
Constant	11.61***	-13.86***	11.61***	11.83***	-17.44***
	(4.119)	(1.713)	(4.119)	(4.189)	(2.338)
No. of leads and lags	1	1	1	1	1
No. of observations	113	113	113	113	113
R^2	0.97	0.97	0.97	0.97	0.97

Note: Standard errors are reported below the respective coefficients and are heteroskedasticity-consistent. ***, ** and * indicate significance at the p<0.01, ** p<0.05, * p<0.1 significance levels.

Table 3.18: House price determinants in a selected set of models: BOOMS

Gerdesmeier-Lenarcic-Roffia (2012)	IMF (2009)	Gerdesmeier-Lenarcic-Roffia (2009)	Bordo and Jeanne (2002)
Quantile methodology (>80th percentile)	4 qtr. M.A. of the y-o-y growth rate> mean + 1.3*stdev	house price gap > mean + 1.75 *stdev (calculated over 60 qtrs)	3-year M.A. of the y.o.y. growth rate > mean + 1.3*stdev
1983			
	1987-1988	1986-1988	
1990-1993	1989-1991		1990-1992
2005-2008		2005	2005-2007

Note: The results of the quantile methodology shown refer to the episodes selected by the two best specifications presented in Table 3 and Table 4 (namely equations 1 and 6).

Table 3.19: House price determinants in a selected set of models: BUSTS

Gerdesmeier-Lenarcic-Roffia (2012)	IMF (2009)	Gerdesmeier-Lenarcic-Roffia (2009)	Bordo and Jeanne (2002)
Quantile methodology (<20th percentile)	4 qtr. M.A. of the y-o-y growth rate< mean - 1.3*stdev	house price gap < mean - 1.5 *stdev (calculated over 60 qtrs)	3-year M.A. of the y.o.y. growth rate < mean - 1.3*stdev
	1982-1983	1981-1982	
1985-1987	1985		1984-1986
1997-1999			
2000-2003			
2009-2010	2009	2008-2009	
2011		2011-2012	

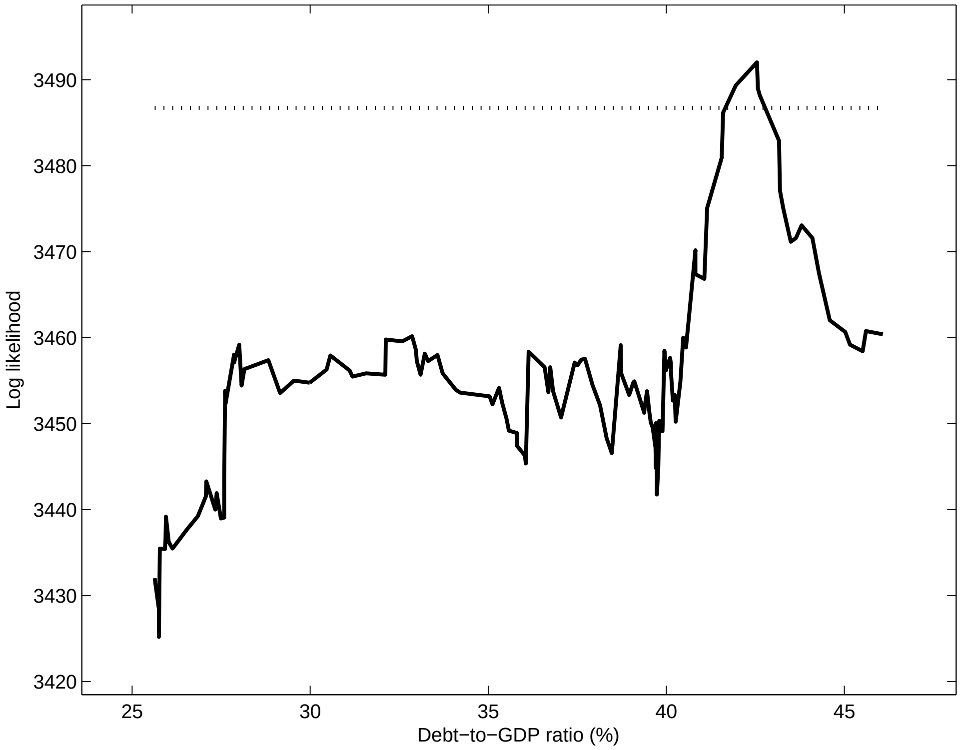
Note: The results of the quantile methodology shown refer to the episodes selected by the two best specifications presented in Table 3 and Table 4 (namely equations 1 and 6).

Table 3.20: Cointegration tests results for house prices in the euro area

		Suggested lags			2 lags in levels	
Specification	Cointegrating vector	External*	AIC	SC	HQ	1 lag
1	ph,dispipc,hspc	ucr, wapop	3	2	3	0/1
2	ph, dispi, hs	ucr, wapop	3	2	3	0/1
3	ph, dispipc, lfpop	ucr	3	2	3	1
4	ph, dispi, lfpop	ucr	3	2	3	1
5	ph, dispipc, lfpop	ucr,ur	3	2	3	1
6	ph, dispipc, lfpop, d2i	ucr	12	2	3	1
7	ph, dispi, lfpop, d2i	ucr	12	2	3	3/1

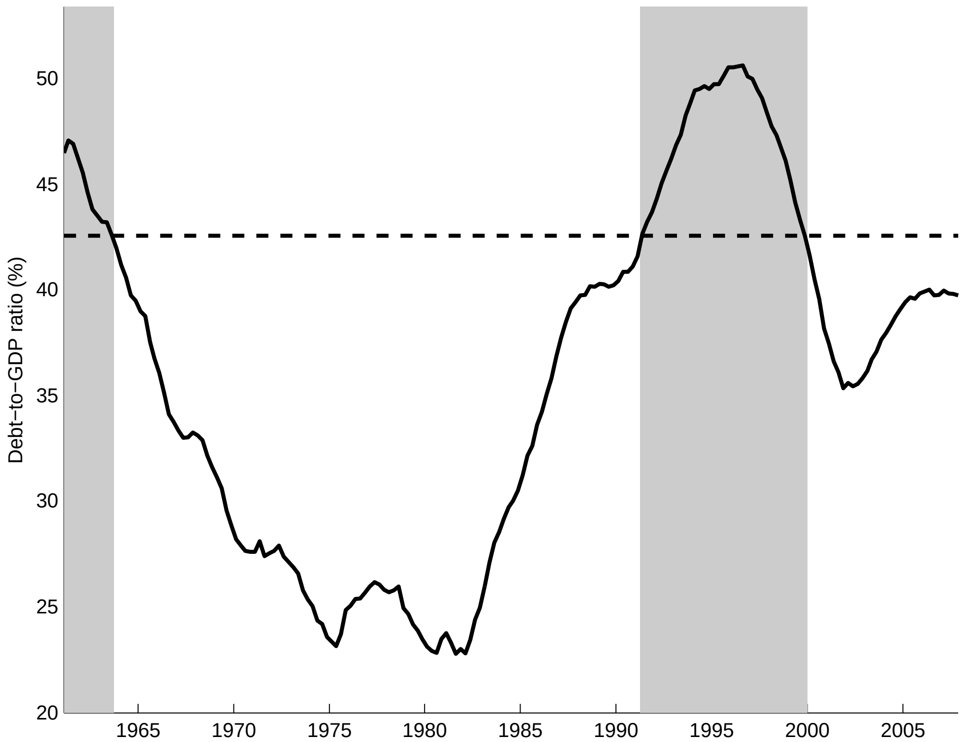
Notes: *ph* denotes real house prices, *dspi* denotes disposable income (while *dspipc* is the respective per capita measure), *hs* is housing stock (while *hspc* is the respective per capita measure), *d2i* denotes debt-to-income ratio, *lfpop* is the labour force, *ucr* is the user cost rate, *ur* denotes the unemployment rate and *wapop* is the working population. In all the models, the variables which are stationary are added as *external* regressors and are not included in the cointegrating vector. Tests reported include a constant in the cointegrating relationship and assume no trend in the data. The cells marked in yellow denote the relevant lag length selected by the HQ and SC criteria.

Figure 3.1: The log likelihood as a function of the threshold value



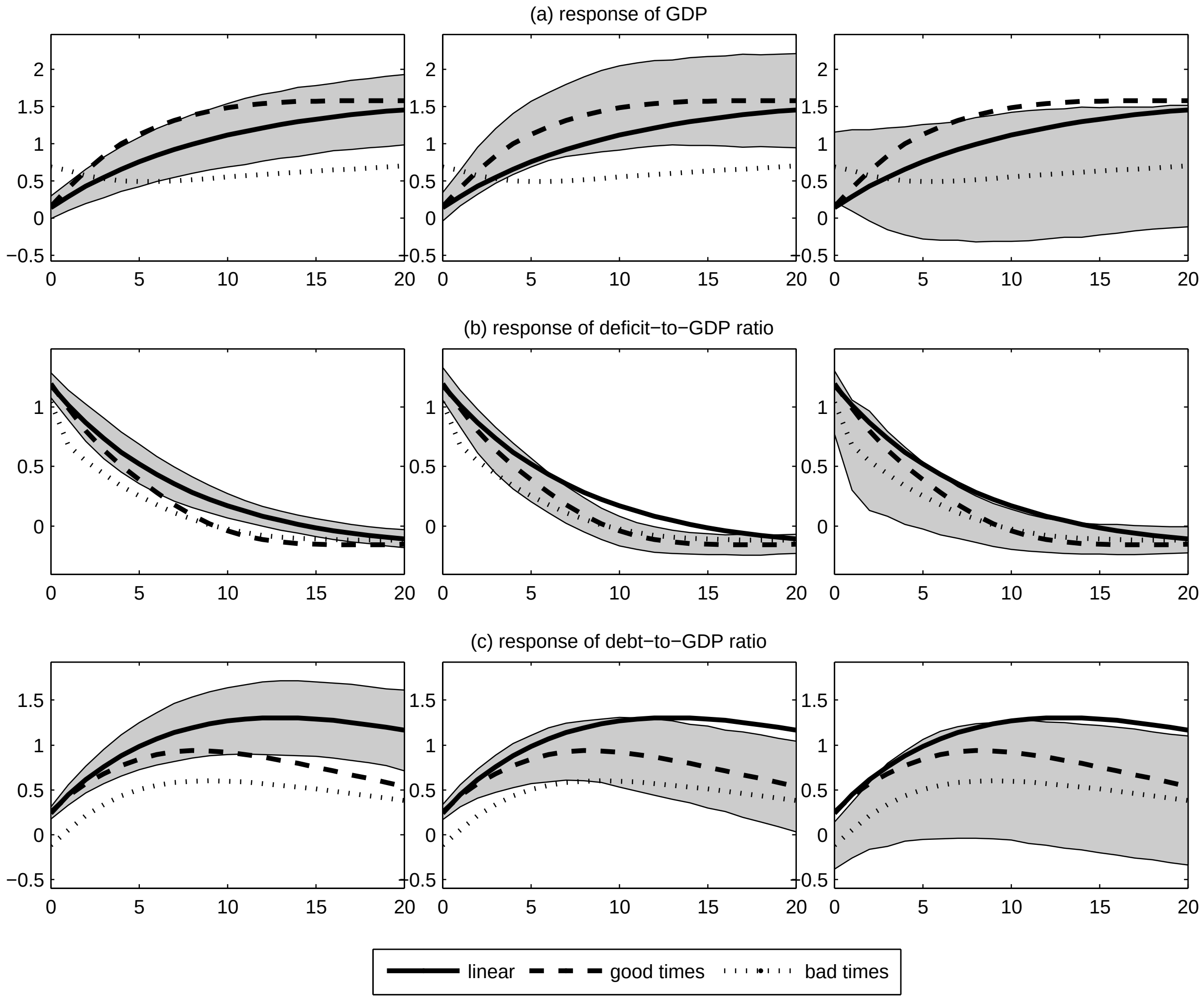
Note: The intersections of the dotted horizontal line with the log likelihood function form the 10 percent confidence interval around the estimated threshold value based on the LR-statistics approach of Hansen [2000].

Figure 3.2: The history of regimes



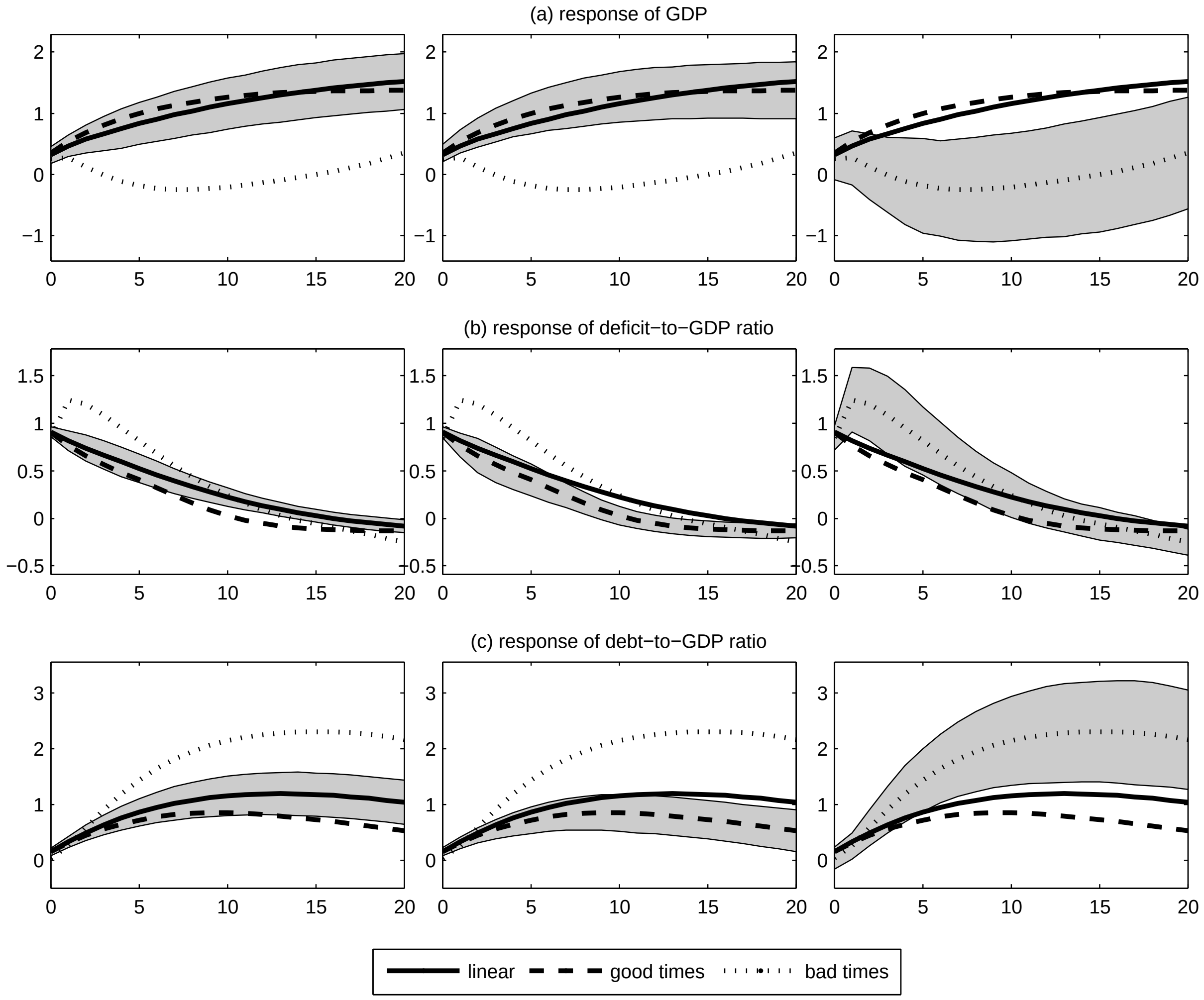
Notes: The dashed horizontal line represents the estimated threshold value. The shaded periods belong to the regime with high debt-to-GDP ratio.

Figure 3.3: The impulse responses to an expenditure shock



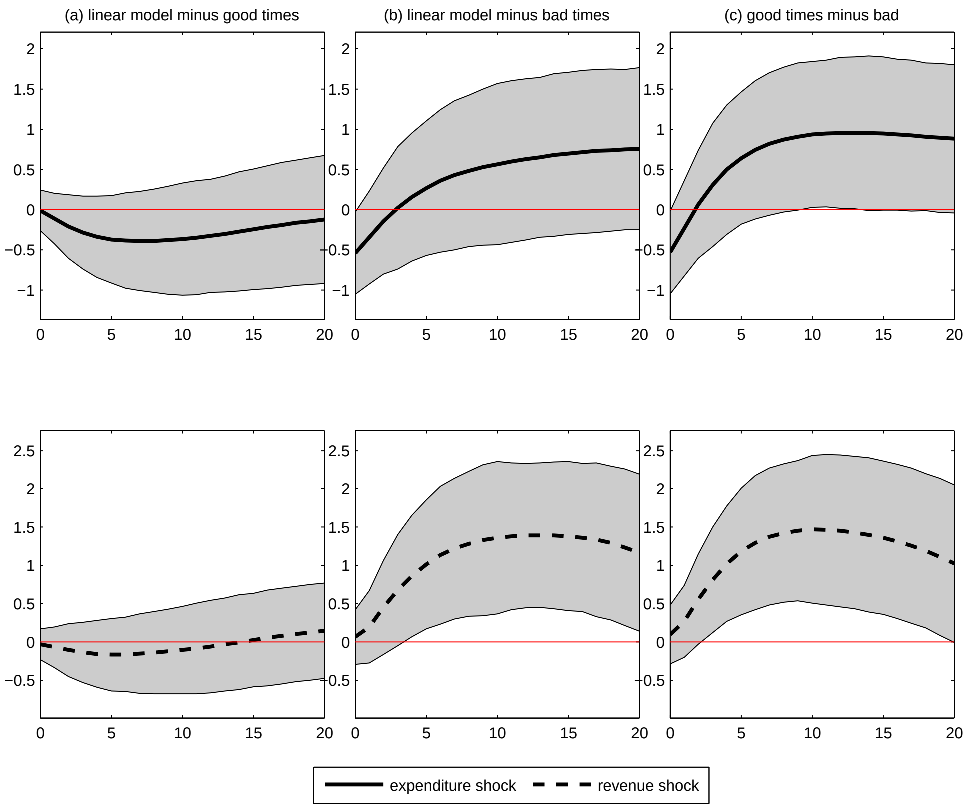
Notes: Following Blanchard and Perotti [2002] we use a structural shock equivalent to 1 percent of GDP during our simulations. The shaded area represents a one standard deviation confidence band for the impulse responses of the linear model, good times and bad times in the first, second and third columns respectively.

Figure 3.4: The impulse responses to a revenue shock



Notes: Following Blanchard and Perotti [2002] we use a structural shock equivalent to 1 percent of GDP during our simulations. The shaded area represents a one standard deviation confidence band for the impulse responses of the linear model, good times and bad times in the first, second and third columns respectively.

Figure 3.5: Pairwise differences of the output multipliers between models and regimes



Notes: Following Blanchard and Perotti [2002] we use a structural shock equivalent to 1 percent of GDP during our simulations. The shaded area represents a one standard deviation confidence band.

Figure 3.6: The simulated deficit in the baseline scenarios

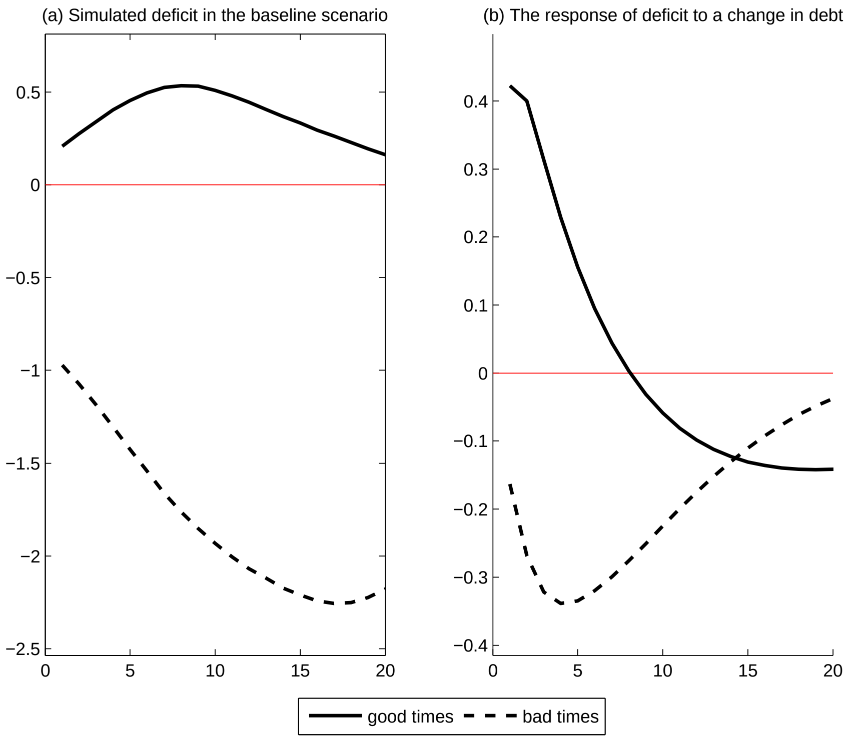
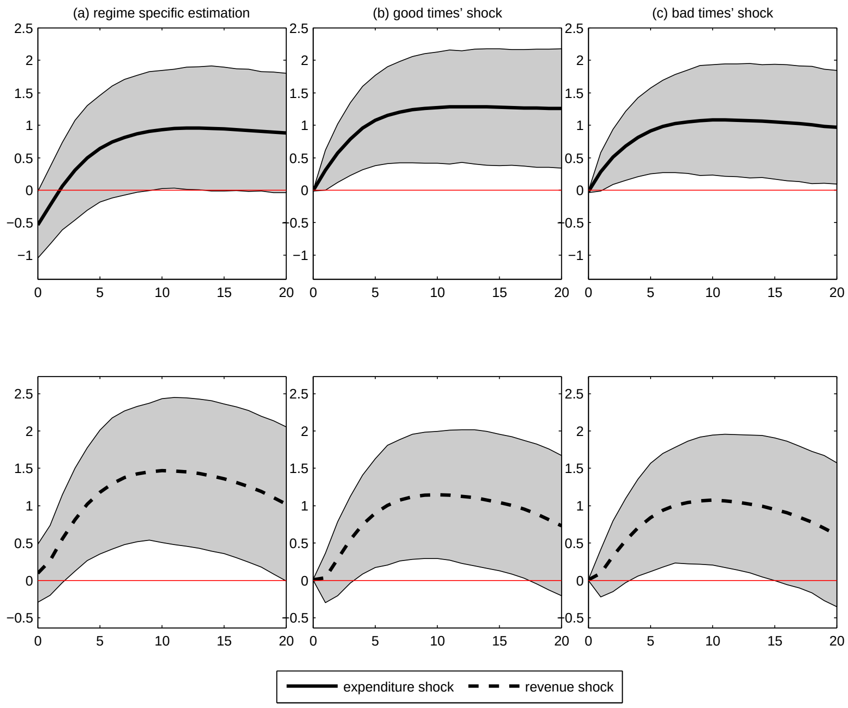
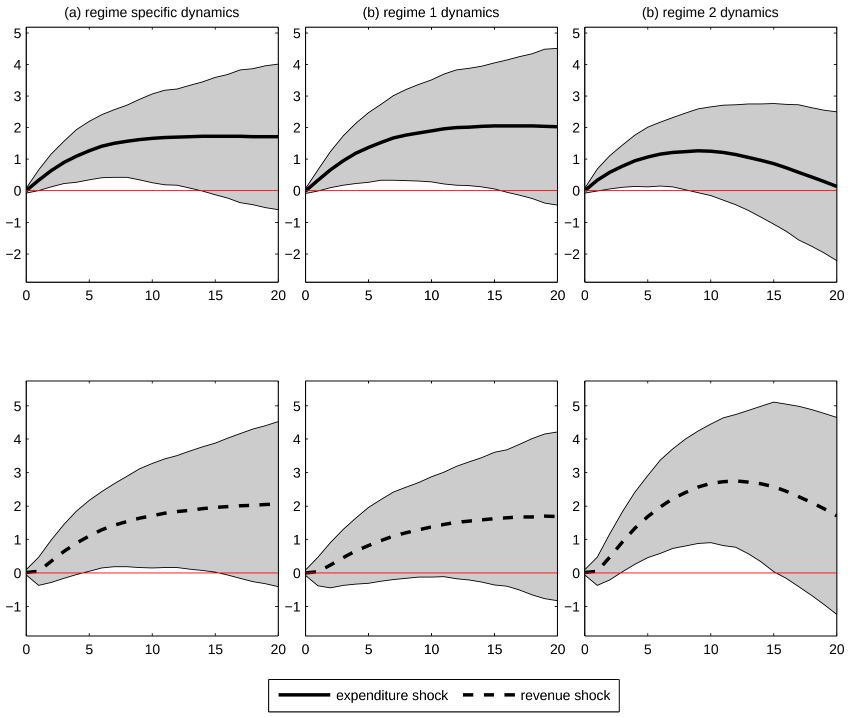


Figure 3.7: Pairwise differences of the output multipliers between regimes



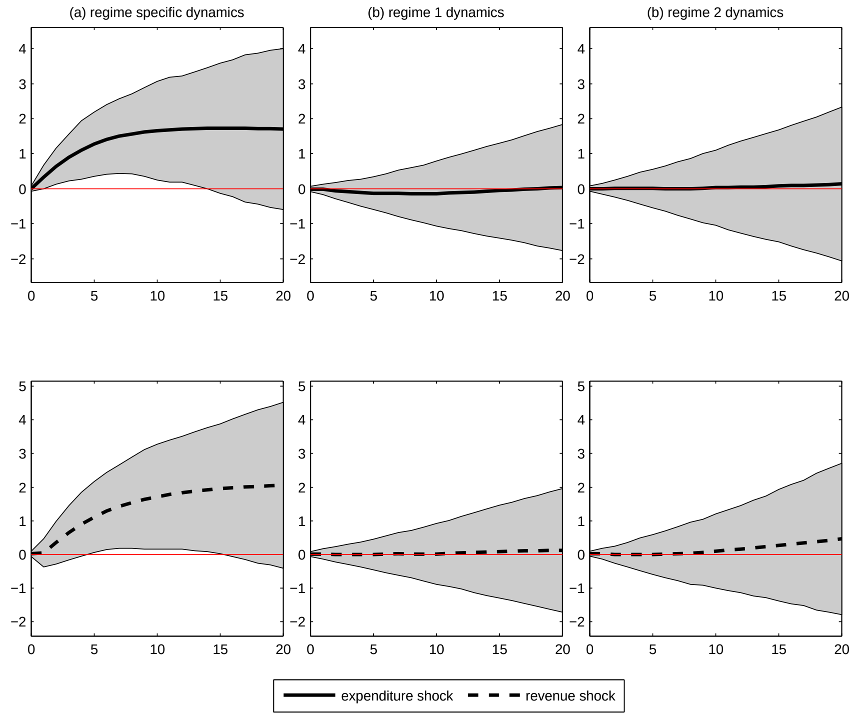
Notes: Following Blanchard and Perotti [2002] we use a structural shock equivalent to 1 percent of GDP during our simulations. The shaded area represents a one standard deviation confidence band. The panels in the left column are based on simulations that use the identified shocks from our regime specific identification. The second and third columns are based on simulations where we use the same identified shocks in both regimes; the identified good and bad times' shocks in the second and third columns, respectively.

Figure 3.8: Pairwise differences of the output multipliers between regimes of the counterfactual impulse responses.



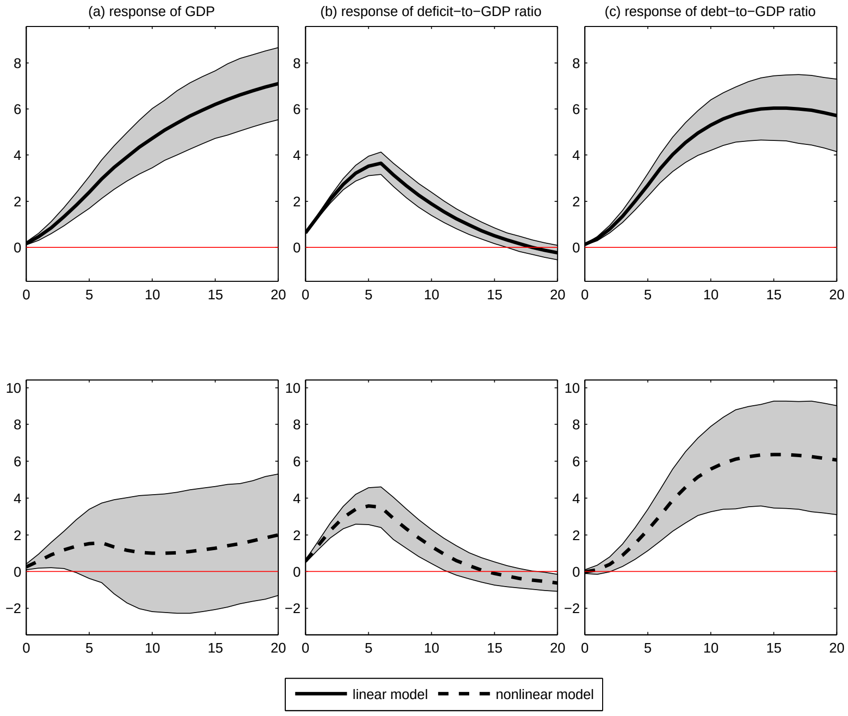
Notes: The shaded area represents a one standard deviation confidence band. The panels in the left column are based on simulations from the benchmark model with identical structural shocks in both regimes. The second and third columns are based on simulations from a counterfactual exercise where we use the same fiscal rules in both regimes; the estimated fiscal rules from good and bad times' in the second and third columns, respectively.

Figure 3.9: Pairwise differences of the output multipliers between regimes of the counterfactual impulse responses.



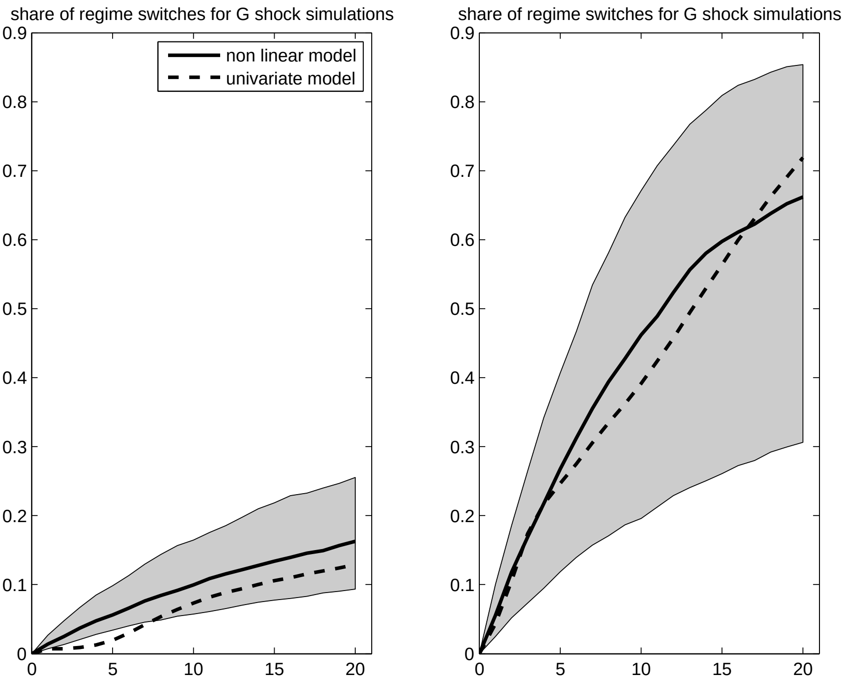
Notes: The shaded area represents a one standard deviation confidence band. The panels in the left column are based on simulations from the benchmark model with identical structural shocks in both regimes. The second and third columns are based on simulations from a counterfactual exercise where we use the same estimated coefficients in all but the interest rate equation in both regimes; the estimated coefficients from good and bad times' in the second and third columns, respectively.

Figure 3.10: Impulse responses to the US stimulus package in the linear and the nonlinear models.



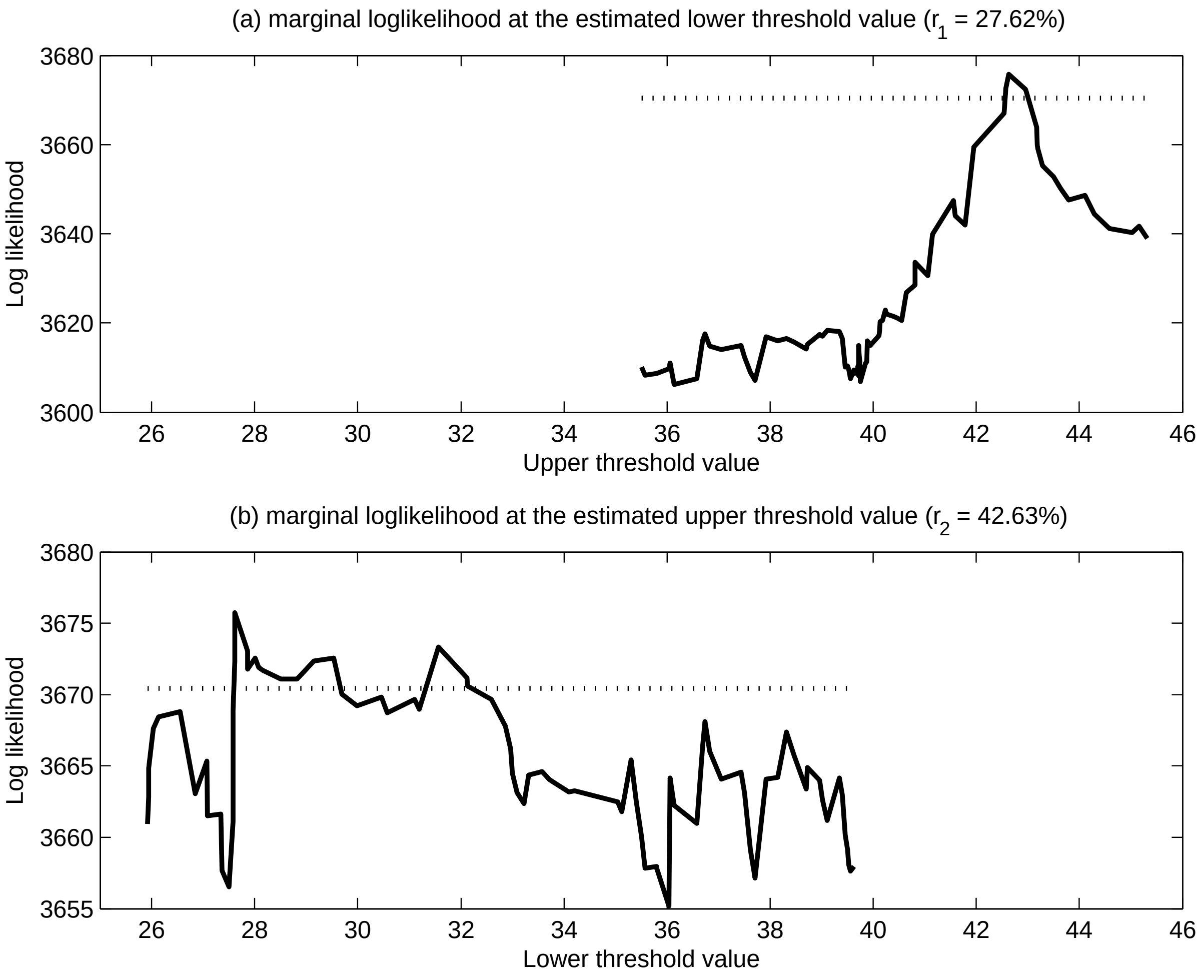
Notes: The shaded area represents a one standard deviation confidence band for the impulse responses.

Figure 3.11: Regime switching probabilities



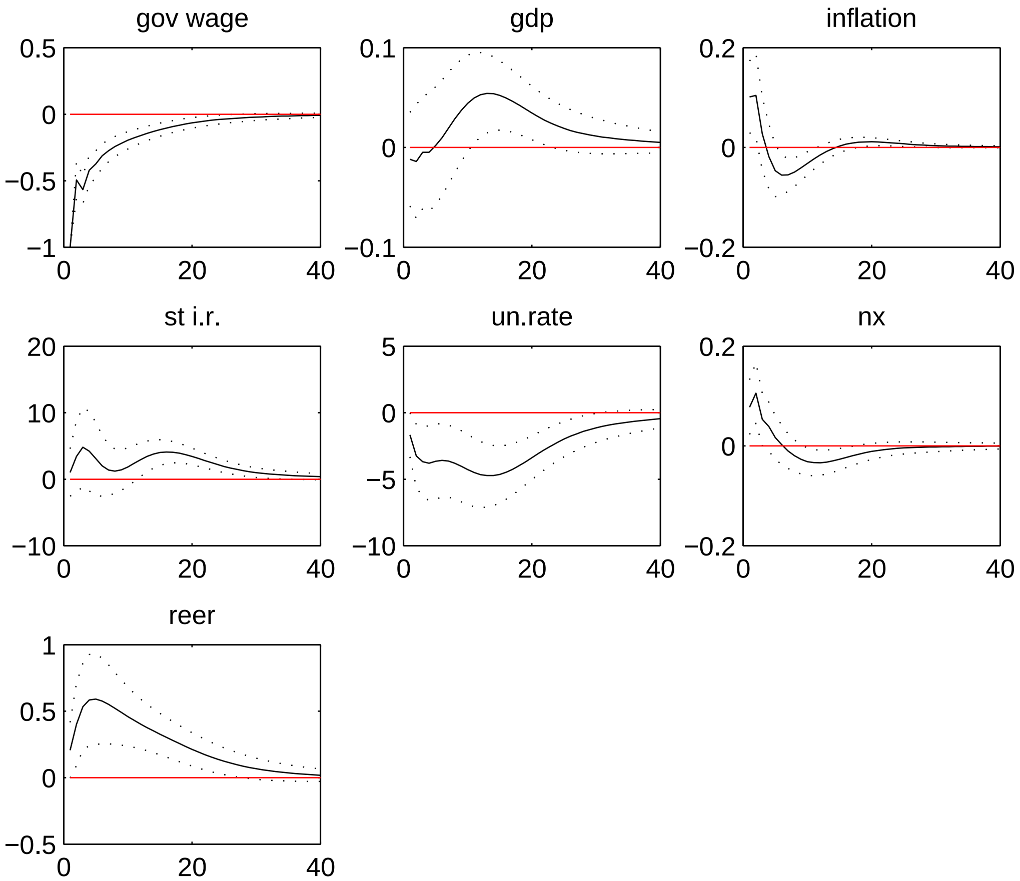
Notes: Regime switching probabilities in our benchmark nonlinear model and in a univariate model of the threshold variable. The shaded area represents a one standard deviation confidence band. The left panel plots the regime switching probabilities at each horizon for simulations starting in good times approximated by the fraction of the simulations being in bad times. The right panel plots the probabilities for bad times computed in a similar way.

Figure 3.12: The marginal log likelihood as a function of the threshold value



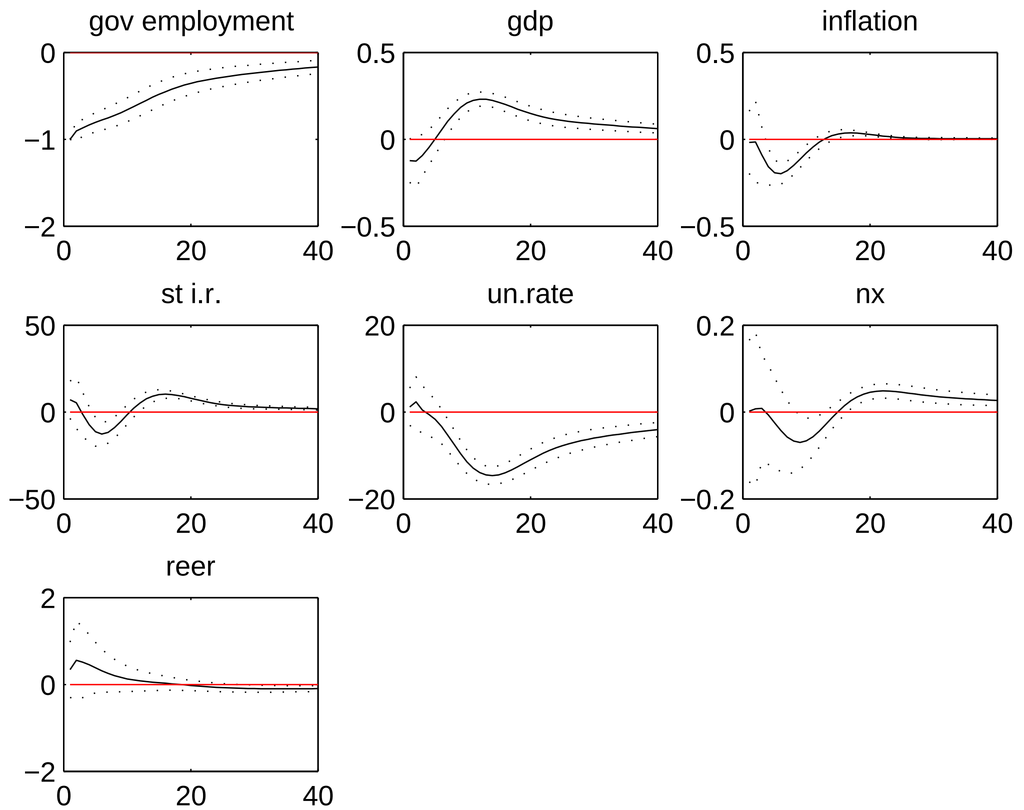
*Notes:*The top panel plots the cross-section of the log likelihood function $\mathscr{L}(r_1, r_2)$ with the lower threshold value (r_1) fixed at its point estimate. The bottom panel plots the cross-section of the log likelihood function with the upper threshold value (r_2) fixed at its point estimate.

Figure 3.13: The empirical impulse responses to a negative shock in average government wage



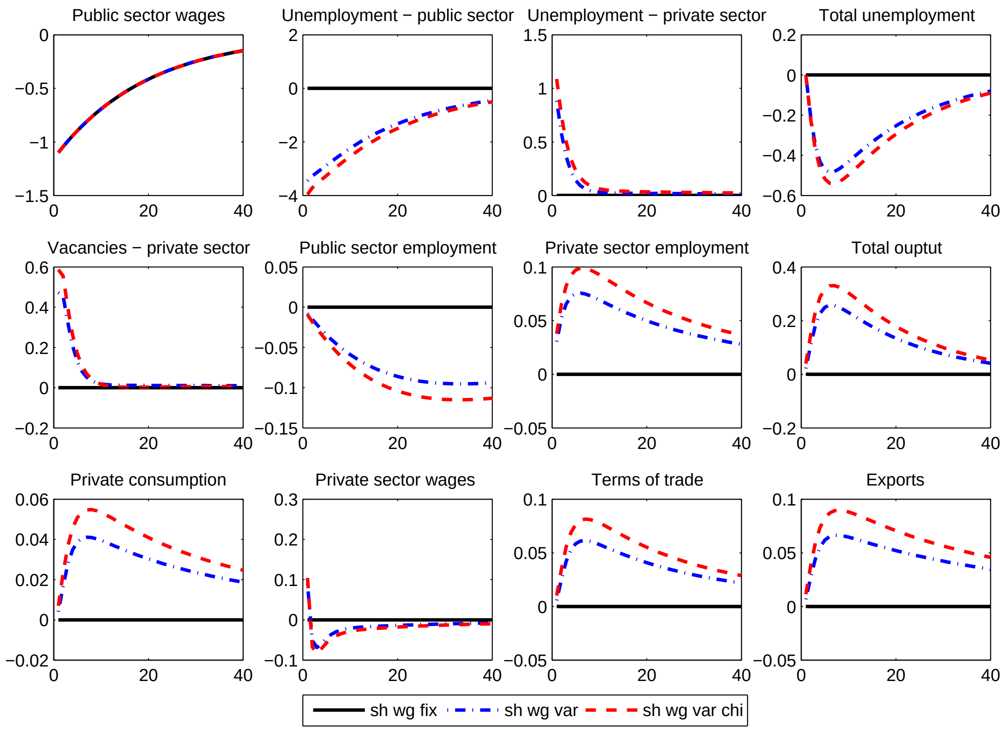
Notes: The responses are plotted with bootstrapped 95% confidence intervals. Periods are quarters.

Figure 3.14: The empirical impulse responses to a negative shock in average government wage



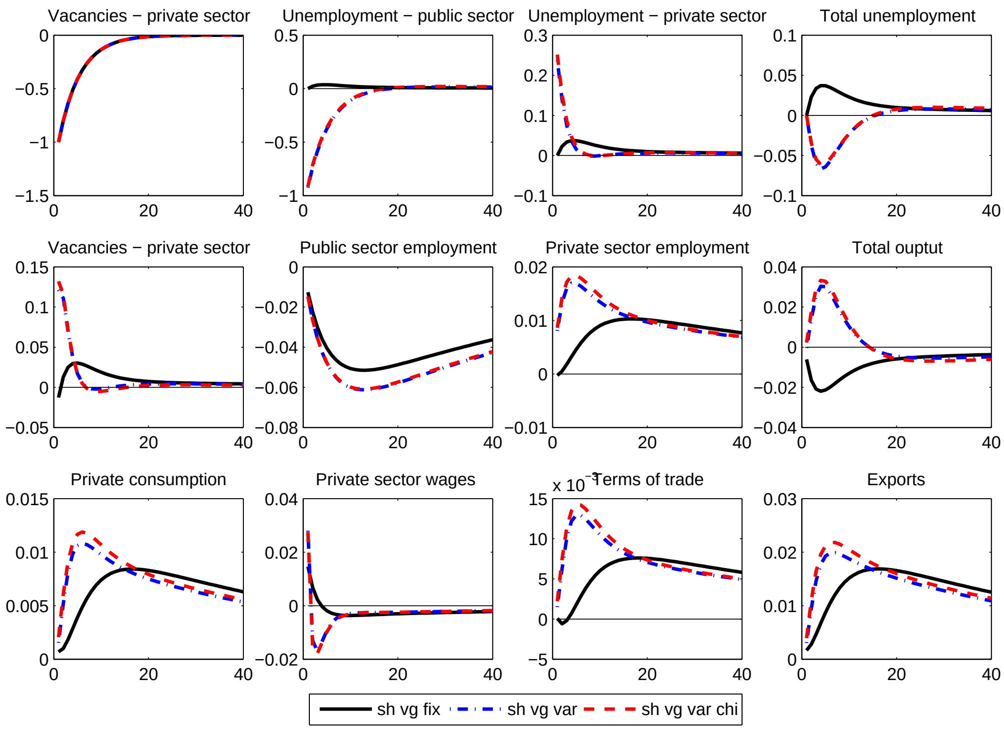
Notes: The responses are plotted with bootstrapped 95% confidence intervals. Periods are quarters.

Figure 3.15: The impulse responses to a negative public wage level shock



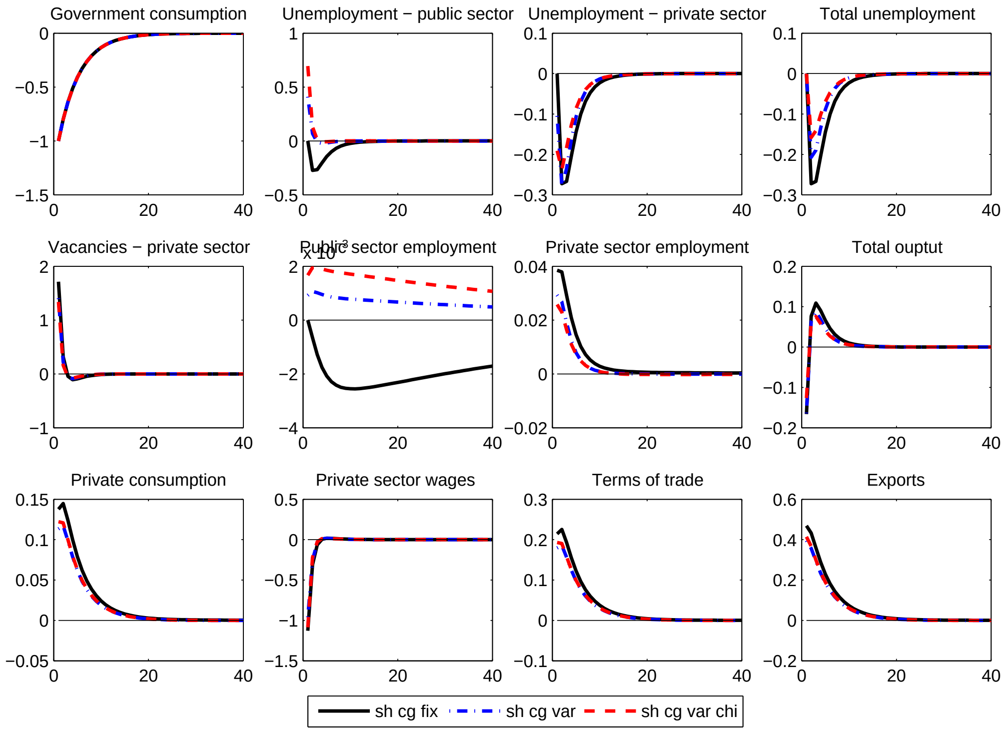
Notes: Black full line - model with fixed s, blue dash-dot line - model with endogenous s, red dash line - model with endogenous s and $\chi = 0.2$.

Figure 3.16: The impulse responses to a negative public vacancies shock



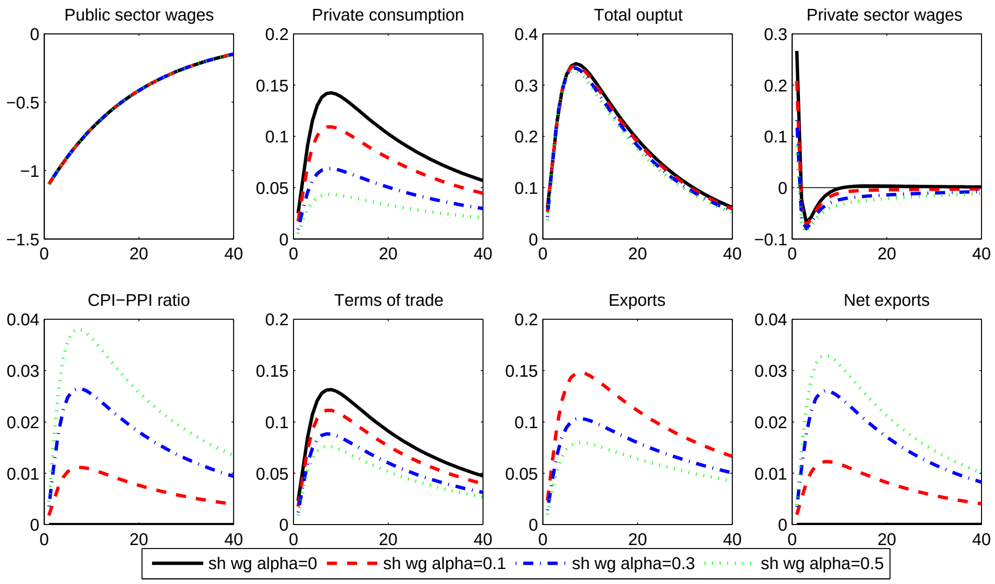
Notes: Black full line - model with fixed s, blue dash-dot line - model with endogenous s, red dash line - model with endogenous s and $\chi = 0.2$.

Figure 3.17: The impulse responses to a negative government consumption shock



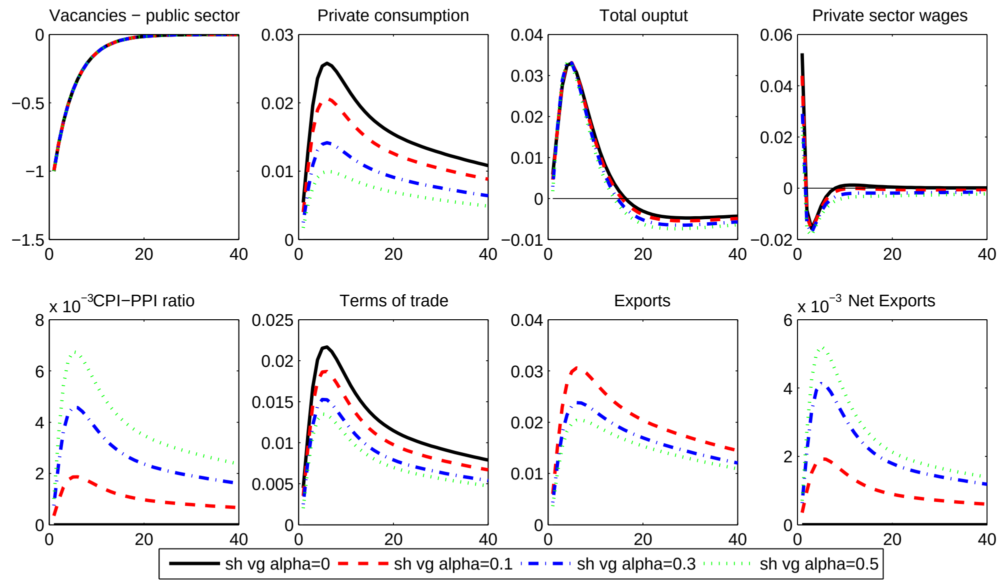
Notes: Black full line - model with fixed s, blue dash-dot line - model with endogenous s, red dash line - model with endogenous s and $\chi = 0.2$.

Figure 3.18: The impulse responses to a negative public wage shock depending on trade openness



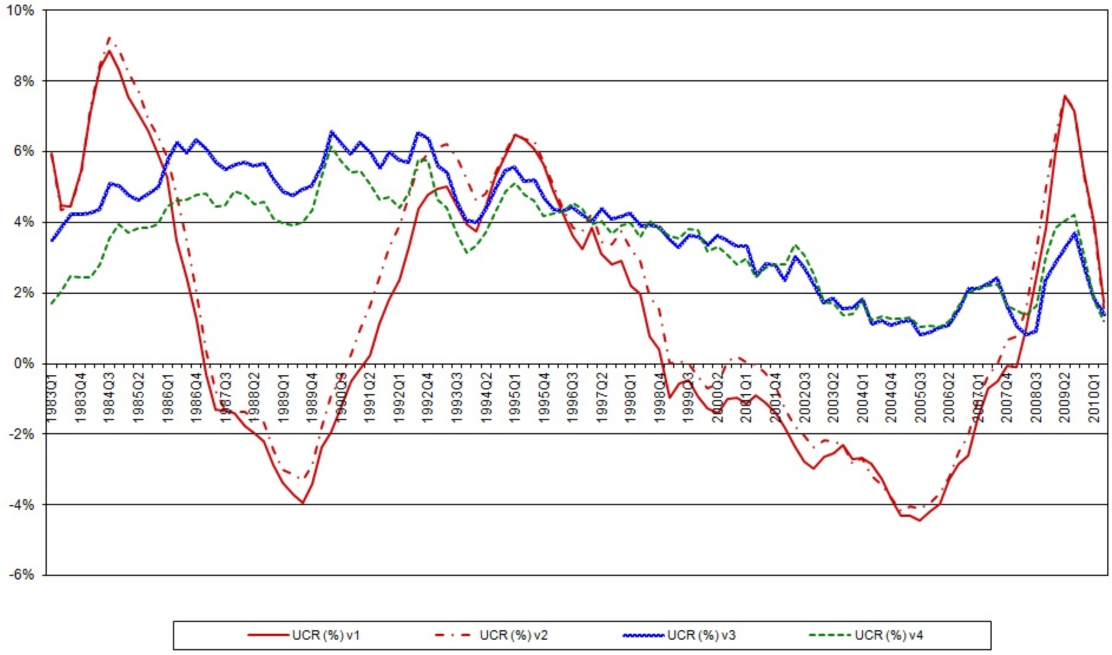
Notes:The depicted impulse responses are from the same version of the model but using a different value of α, that defines the openness of the economy.

Figure 3.19: The impulse responses to a negative public vacancy shock depending on trade openness



Notes:The depicted impulse responses are from the same version of the model but using a different value of α, that defines the openness of the economy.

Figure 3.20: User cost rates fot the euro area



Source: Own calculations.

Figure 3.21: Specification 1

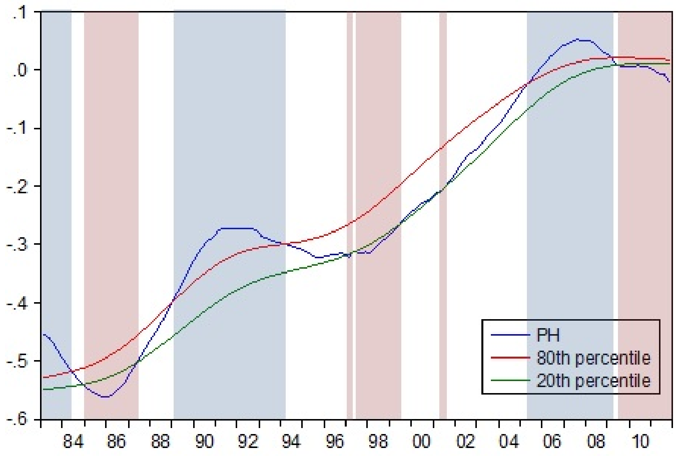


Figure 3.22: Specification 2

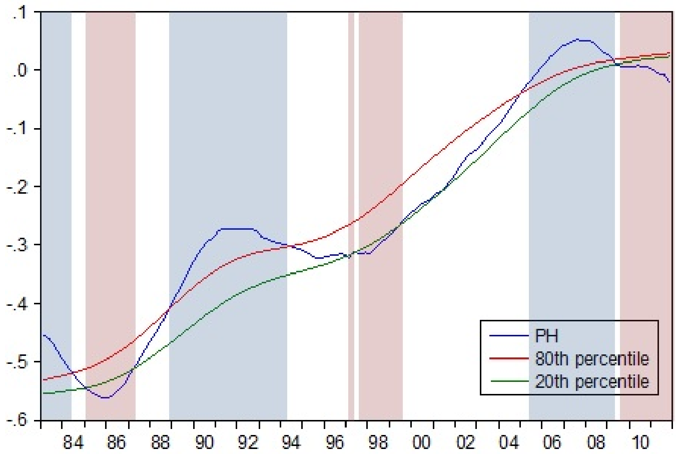


Figure 3.23: Specification 3

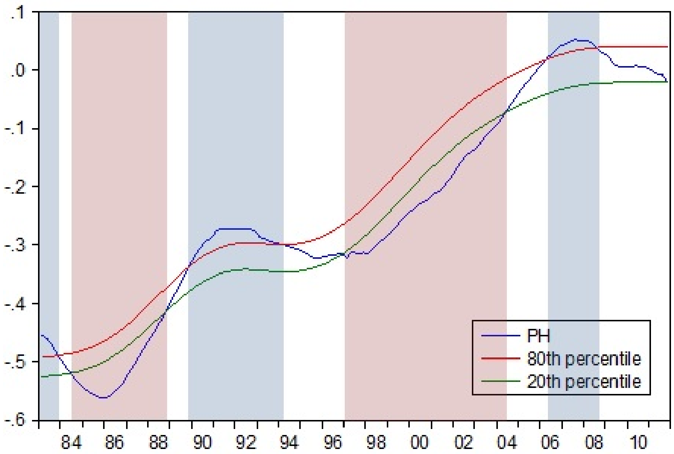


Figure 3.24: Specification 4

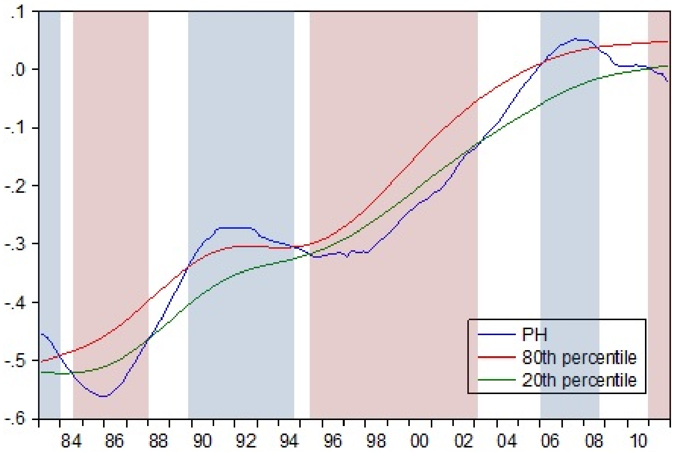


Figure 3.25: Specification 5

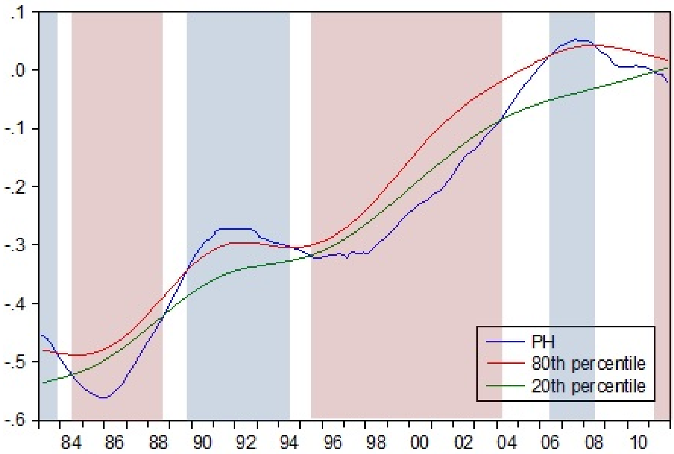


Figure 3.26: Specification 6

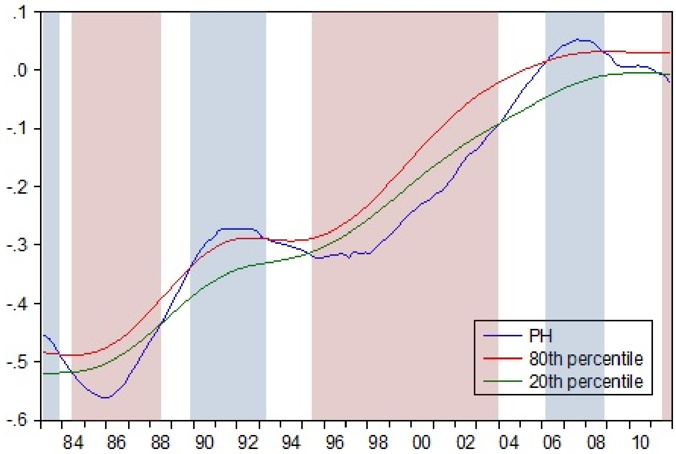


Figure 3.27: Specification 7

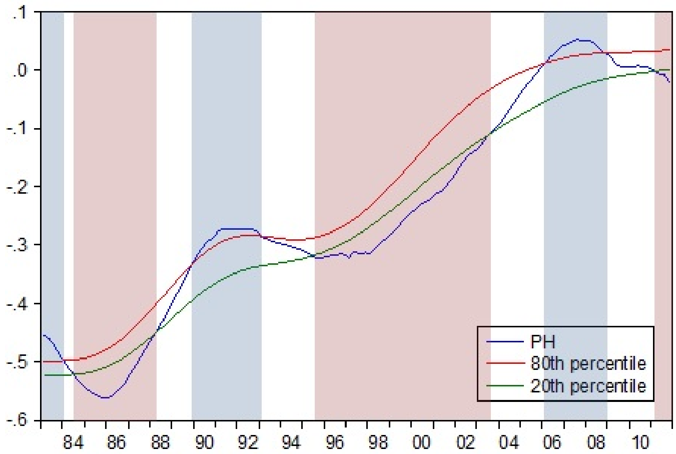


Figure 3.28: Boom-bust periods based on quantile regressions for house prices in the euro area

Note: the yellow (blue) area denotes booms (busts).