Department of Economics

On the Dynamic Effects of Government Stimulus Measures in a Changing Economy

Klemens Hauzenberger

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

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To Hermine and Walter

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Preface

When I think back at the time when I have started working on fiscal stimulus issues, something lay in the air, yet it was hard to read the signs of a mayor crisis being on the way. This was in August 2008, just a few weeks before Lehman Brothers went bankrupt and the severe global recession began to take its course. The origin of my thesis in the wake of the longest and deepest economic downturn since the Great Depression was, to be frank, more luck than great foresight. If someone gets the credit for a good "forecast" then it should go to my supervisor Massimiliano Marcellino. He was the one who gave me the hint about the revival of fiscal policy in the academic debate.

In 2008 and 2009 the U.S. Congress passed bills worth 902 billion dollars to prevent the economy from deteriorating any further and to facilitate the recovery. The situation and ways to deal with the crisis were not much different in many other countries. All this has certainly stimulated the huge recent literature about the effectiveness of fiscal measures since the days of August 2008. Many economists from both sides of the Keynesian-Classical debate are now actively contributing toward a better understanding on how a trillion of dollars, or so, and other "government stimulus" measures affect the economy. My thesis is a small step in that direction: it empirically characterizes the dynamic effects within the broad class of vector time series models and pays particular attention to the econometric challenges of an ever-changing economic environment.

My special thanks go to Massimiliano Marcellino and Jessica Spataro. Without them the number of pages after the Preface would be a very round one, meaning zero. Their empathy, encouragement and help was essential in a time when certain circumstances brought me close to giving up on the whole thesis project. I am also grateful to Helmut Lütkepohl, Robert Stehrer and Leo Michelis for their professional advices. I will never forget, in a positive way, Leo's "15 hours 7 days a week" speeches about the exact amount of time a well-trained PhD student should spend over her or his research.

The Austrian Federal Ministry for Science and Research and the European University Institute provided the necessary financial support. The Deutsche Bundesbank, in particular Hermann-Josef Hansen and Johannes Hoffmann, gave me the time and infrastructure

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during the final preparation of the thesis.

My friends Michael Bradtke, Max Drack, Chris Mason and Kurt Schmidsberger always lent me an ear for any non-academic problems concerning my studies. I am grateful to them for the refreshing changes as well as the one or two cold beverages. Most of all, I would like to thank my loving parents, for taking care of everything at home while I was miles away. Without their support none of this would have been possible.

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Abstract

The massive fiscal stimulus measures we have seen in the recent years have brought questions about the effectiveness of certain government actions back to the fore. My focus here is on the dynamic effects of changes in government spending, taxes and the distribution between profits and labor income. The econometric procedures explicitly take into account structural breaks, regime-dependency and time-varying parameters.

The first chapter addresses the question of functional income redistribution for the postwar economies of the U.S. and Canada within a structural VECM with up to two breaks of unknown timing. Cointegrating rank and break dates are estimated jointly. In the U.S. the short-run spending effect on output, set in motion by higher labor income, is strong enough to make such a redistribution an attractive, maybe provocative, policy alternative. Across the border in Canada, however, the negative medium-run capacity effect, brought about by diminished profits, dominates the picture more or less from the beginning and output slumps considerably. The result actually suggests a, maybe even more provocative, redistribution toward profits. I discuss several possible explanations like the formation of expectations and the different exposure to international trade.

In the second chapter I provide a novel way to assess the impact of a government spending stimulus on U.S. activity. The novelty lies in the combination of flexible projections and regime switches between recessions and expansions. This combined approach has numerous advantages: it captures asymmetries over the business cycle; it can approximate other important smooth nonlinearities in the DGP; it is more robust to misspecification; and estimation can be simply done by least squares. I find a stimulus to be considerably more effective in recessions with a prolonged period of high spending, steadily increasing output, surging federal debts, and a well working multiplier effect which, over time, drives debt levels back to trend. During expansions, or in a symmetric model without regime switches, there is only a short lived positive effect on output, too short for the multiplier to kick in. Constraint in its capacity to increase taxes the government systematically cuts spending below trend to control the level of federal debts.

The last chapter studies the dynamic effects of changes in government spending or

taxes by means of a time-varying parameter structural VAR. The smooth and gradual changes of the parameters in the VAR make this model the perfect choice to study the evolution of the effectiveness of fiscal policy, as opposed to the different effects in recessions and expansions. My results accord well with the notion of important changes in the transmission of fiscal policy in the U.S.: the effectiveness in stabilizing the economy has decreased, more or less so for tax shocks and de facto with respect to spending. I also find evidence, through counterfactual policy simulations, for positive long-run effects on output when the government actively reduces the level of debts by cutting spending. A passive debt reduction in the form of faster tax adjustments in response to past expenditures has adverse effects on output.

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Chapter 1

An Empirical Characterization of Redistribution Shocks and Output Dynamics

(joint with Robert Stehrer)

What are the economic effects of redistributing one dollar from profits to labor income? We address this question for the post-World War II economies of the United States and Canada within a structural VECM procedure allowing for up to two breaks of unknown timing. In the United States the short-run spending effect on growth, set in motion by higher labor income, is strong enough to make such a redistribution an attractive, maybe provocative, policy alternative. Across the border in Canada, however, the negative medium-run capacity effect, brought about by diminished profits, dominates the picture more or less from the beginning and output slumps considerably. The result actually suggests a, maybe even more provocative, redistribution toward profits. We discuss several possible explanations like the formation of expectations and the different exposure to international trade. Methodologically, we provide a novel procedure to estimate cointegrating rank and break dates jointly. (JEL C32, C53, E12, E25)

Keywords: labor income/profit redistribution; structural VECM; joint estimation of cointegrating rank and multiple break dates

1.1 Introduction

In the last two decades numerous authors and research groups have put in huge efforts and ingenuity to correctly disentangle and characterize the economic effects of shocks to technology and monetary policy. Issues on the economic effects of a "redistribution shock" or, say, transferring money between labor income and profits, although having a long tradition in macroeconomics, fell into disfavor in the main economic debate.[1] In light of the 2009 economic crisis and discussion on potential economic stimulus programs other than government spending and low interest rate policies, we address the question on how such a redistribution shock will affect output.

From a theoretical perspective the debate might be characterized by focusing on two channels which affect aggregate demand: a short-run spending effect on the one and a medium-run capacity effect on the other hand. The spending argument rests on the post-Keynesian perspective of differing marginal propensities to spend out of labor income and profits.[2] Workers will spend more of an additional dollar than firms and, therefore, a redistribution toward labor income will increase output. The capacity argument positively links investment with realized and expected profits. As a consequence, a distributional shift toward profits (equivalently, away from labor income) might have a positive effect on investment, resulting in higher output growth over the medium-run.[3]

In view of the trade-off between these two channels, our purpose in this paper is to characterize the dynamic effects of a redistribution between labor income and profits on output in the United States and Canada during the post-World War II period. We do so using a small 3-dimensional structural vector time series model of quarterly labor income, profits and output. Identifying a redistribution shock is intricate, inasmuch as any output effect generated by the redistribution has, in turn, an immediate effect back on profits and labor income. Profits may move with output under existing markup rates, and labor income changes as firms and workers try to adjust employment and wage rates. But exactly

[1] See European Commission (2007, Chap. 5) for a recent overview of the debate.

[2] Though not going into detail, a view linked to economists related to the Keynesian and post-Keynesian tradition such as John Maynard Keynes himself, Richard Goodwin, Nicholas Kaldor, Michael Kalecki and Joan Robinson to name a few.

[3] From a more general perspective, this debate centers around the notion of wage-led versus profit-led economic expansion; see Bhaduri and Marglin (1990) for a model which can accommodate both views and Stockhammer, Onaran and Ederer (2009) for an empirical application thereof.

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these "automatic" responses of labor income and profits render the identification problem to be non-recursive and standard procedures such as a simple Choleski decomposition are not applicable. Therefore, to achieve identification, we opt for a structural VECM approach and exploit its inherent long-run restrictions to obtain estimates of the automatic responses, and, by implication, identification of temporary and permanent shocks. The distinction between the types of shocks and our clear focus on redistribution as a possible aggregate demand instrument lead us to design a redistribution shock as a combination of transitory shocks to labor income and profits. We design it such that there is a one-for-one redistribution between labor income and profits. Having defined and identified the redistribution shock we can trace its dynamic effects on output. This is, in a nutshell, what we aim at in this paper.

Structural vector time series approaches, in general, have been widely used to assess the effects of technology shocks, monetary policy, and fiscal policy (see, in particular, King et al. 1991, Bernanke and Mihov 1998, Blanchard and Perotti 2002). We argue that such an approach is equally well suited to study the effects of a redistribution between labor income and profits for two reasons. First, movements in labor income and profits can be treated as exogenous with respect to output because stabilization motives, in contrast to monetary policy, are rarely the predominant driving force behind fluctuations in the distribution. A redistribution shock is therefore exogenous with respect to output. Second, and similar to fiscal policy, decision and implementation lags rule out—at least within a quarter—most of the discretionary response of labor income and profits to unexpected contemporaneous changes in output. What is left then are the automatic responses of unexpected movements in output on labor income and profits for which we account for in our identification strategy to obtain a proper representation of a redistribution shock.

The long time span of the post-World War II period contains, most probably, structural breaks. We therefore allow for up to two level breaks of unknown timing in our structural VECM. We do so by combining an "older" approach on how to estimate the break dates with recent advances in testing for the cointegrating rank when breaks are present. The older approach goes back to the unit root test of Zivot and Andrews (1992) and its numerous successors. The goal is to pick the two break dates such that most weight is given to the stationary alternative. Gregory and Hansen (1996) extend these unit root tests to residual-based cointegration analysis in which the weight is then always on the alternative hypothesis of the next higher cointegrating rank. We take up this testing strategy but perform the cointegration tests with two level breaks within the framework of Saikkonen and Lütkepohl (2000*a*, 2000b), and Lütkepohl, Saikkonen and Trenkler (2004). This yields a two-step system-based framework. In the first step one removes the deterministic components by a feasible generalized least squares procedure. Then, in the second step, we apply the commonly used Johansen (1995) likelihood ratio test to the adjusted series. The prior adjustment is convenient because it results in an asymptotic null distribution of the cointegration rank test statistic which does not depend on the timing of the level breaks.

Besides the empirical question addressed and the issues related to identification, the "joint nature" of our estimation of the cointegrating rank and the two break dates, is the methodological contribution of this paper. Other approaches typically estimate the break dates before the cointegration analysis, either on the basis of an—with respect to the cointegrating rank—unrestricted model (see, e.g., Lütkepohl, Saikkonen and Trenkler 2004, Saikkonen, Lütkepohl and Trenkler 2006) or on the basis of unit root tests (see, e.g., Koukouritakis and Michelis 2009) Our joint estimation procedure removes an additional layer of uncertainty from the analysis, as it avoids the pre-test bias introduced by using different models for choosing cointegrating rank and break dates. The paper also provides Monte Carlo evidence showing the basic consistency of our joint estimation procedure.

Our main results underline the trade-off between the two transmission channels mentioned above. In the United States the short-run spending effect is strong enough to make a one-dollar redistribution from profits toward labor income successful in terms of output growth: output is above trend for two years, with a multiplier of 0.51 dollars, before the negative capacity effect eventually takes over. In Canada, however, this negative capacity effect dominates the picture more or less from the beginning. After initially increasing by 0.47 dollars, output slumps by notable 1.73 dollars within the first two years and reverts to trend only slowly thereafter. Thus, it is a redistribution toward labor income that has a positive short-run effect on output in the United States, whereas in Canada one will need to shift sources in the opposite direction to generate a positive effect. We discuss several issues in turn why the transmission of a redistribution shock differs in the two countries.

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Prominent candidates among them are differences in the formation of expectations, perhaps explained by the growing gap in unionization and collective bargaining power, and differences in the exposure to international trade.

1.2 Identification and Theoretical Background

Throughout the paper we will use a small 3-dimensional VECM with two level breaks including labor income, profits and output for the United States and Canada. The identification of more, possibly non-zero, contemporaneous relations—including the automatic responses—than the $k(k+1)/2$ distinct elements of the covariance matrix actually offer in a k-dimensional system is at the center of our methodology. Accordingly, we want to impose less than $k(k-1)/2$ restrictions on the contemporaneous relations. The parsimonious setup of the model ignores potentially important macroeconomic variables hiding a detailed analysis of the transmission channel, e.g. through consumption or investment. Higher dimensional systems with possible cross-country linkages would require a different framework to study the effects of a redistribution in more detail. An option, for instance, could be the global error-correcting model of Pesaran, Schuermann and Weiner (2004) or the global VAR of Dees et al. (2007). Because of difficulties with identification, cointegration and breaks we stick to our small three variable model, which shall be sufficient to characterize the most relevant features of redistributing between labor income and profits.

Our strategy to achieve identification makes use of the endeavors of John Hicks and Paul Samuelson to absorb Keynes thoughts into neoclassical economics. The result, as Blanchard (1997) forcefully argues, is the core of usable macroeconomics. Two propositions build the basis for what we nowadays know as the neoclassical synthesis: first, in the short-run aggregate demand dominates movements in economic activity and, second, the economy tends to return to a steady-state growth path. A redistribution shock changes aggregate demand and, therefore, these two propositions characterize the long-run effects of such a shock, after all the complex short- and medium-run effects have worked out. Essentially, this characterization suggests a stable steady-state relation of labor income and profits with output, giving the notion of two cointegration relations in the data. Cointegration puts restrictions on the permanent impact matrix, thus reducing the number of restrictions we need to impose on the contemporaneous relations. From a methodological

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point of view this type of identification follows the VECM approach of King et al. (1991).

Suppose the observed sample is $\{y_t\}_{t=1}^T$ in which y_t is a 3-dimensional vector containing the logarithm of quarterly real macroeconomic time series on labor income (inc_t), profits (π_t), and output (gdp_t). Without loss of generality we can write a structural model linking the reduced-form residuals $\{u_t\}_{t=1}^T$ of the vector time series model with the mutually uncorrelated structural shocks $\{e_t\}_{t=1}^T$ as a so called B-model,

$$\begin{bmatrix} u_t^{inc} \\ u_t^{\pi} \\ u_t^{gdp} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} e_t^{inc} \\ e_t^{\pi} \\ e_t^{gdp} \end{bmatrix}, \tag{1.1}$$

or more compactly as $u_t = \mathsf{B}e_t$. Once we embed the structural model in a VECM with the two suggested cointegration relations the first two structural shocks will have transitory effects only. We interpret these shocks as labor income and profit shocks. The permanent shock, e_t^{gdp}, may be interpreted as a productivity or growth shock, but since that is not at issue, there is no point in exploring the permanent shock further. Admittedly, interpreting residuals in small dimensional systems as structural shocks is always perilous, and our interpretation of the two temporary shocks as labor income and profit shocks is no exception.

The structural model allows to formally define a linear combination of the two transitory shocks such that there is a one-for-one redistribution between labor income and profits.

DEFINITION 1.1: (Redistribution shock) $e_s^{\Delta} = (1, \varepsilon, 0)'$ with $\varepsilon = -(b_{11}+b_{21})/(b_{12}+b_{22})$ such that $u_s^{inc} = -u_s^{\pi}$ at time s when the shock occurs.

The last equation of our structural model contains the effects of a redistribution shock on output, captured by $b_{31}e_t^{inc}$ and $\varepsilon b_{32}e_t^{\pi}$, in which the parameters b_{31} and b_{32} are the ones absorbing the marginal propensities to spend out of labor income and profits. These two parameters principally reflect two different channels through which the shock affects output within the quarter: the direct impact effect after all immediate feedback effects have unfolded, and any discretionary adjustment made to rules and laws that influence wage setting, employment, and profit opportunities. We follow the approach by Blanchard and Perotti (2002) in their study on the effects of fiscal policy and rule out the second channel

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because of decision and implementation lags. It usually takes policymakers more than a quarter to analyze, decide, and implement measures, if any, to respond to unexpected events.

Any effect on output through b_{31} and b_{32} may have an immediate effect back on profits and labor income. For any change in output, profits move under existing markup rates, and firms and workers try to adjust employment and wage rates accordingly. The parameters b_{13} and b_{23} implicitly take up these "automatic" responses though only implicitly as our structural model formulates relations for the shocks rather than the observable variables. The parameters, therefore, do not have an interpretation as automatic responses. This statement will become clear momentarily in Remark 1.1. In the same way, b_{31} and b_{32} are not marginal propensities but are the direct impact effects.

REMARK 1.1: *The structural model in (1.1) nests all models which explicitly formulate relations between the observable variables and the shocks.*[4] *One simple, yet general, way to write such a model is*

$$\begin{aligned} u_t^{inc} &= a_1 u_t^{gdp} + a_2 e_t^{\pi} + e_t^{inc} \\ u_t^{\pi} &= b_1 u_t^{gdp} + b_2 e_t^{inc} + e_t^{\pi} \\ u_t^{gdp} &= c_1 u_t^{inc} + c_2 u_t^{\pi} + e_t^{gdp}, \end{aligned}$$

in which the parameters c_1 and c_2 can be interpreted as marginal propensities to spend, and a_1 and b_1 are the automatic responses. Translated into a B-model we have

$$\begin{bmatrix} u_t^{inc} \\ u_t^{\pi} \\ u_t^{gdp} \end{bmatrix} = \left(\frac{1}{1 - a_1 c_1 - b_1 c_2} \right) \times \begin{bmatrix} 1 - b_1 c_2 + b_2 a_1 c_2 & a_2 - a_2 b_1 c_2 + a_1 c_2 & a_1 \\ b_1 c_1 + b_2 - b_2 a_1 c_1 & 1 + a_2 b_1 c_1 - a_1 c_1 & b_1 \\ c_1 + b_2 c_2 & a_2 c_1 + c_2 & 1 \end{bmatrix} \begin{bmatrix} e_t^{inc} \\ e_t^{\pi} \\ e_t^{gdp} \end{bmatrix}, \tag{1.2}$$

This simple model already shows how complex the underlying structure of the model in (1.1) may be. By estimating directly the B-model we avoid imposing any specific structure on the relations between the observable variables and the shocks. Nevertheless, the model

[4] See Amisano and Giannini (1997) and Lütkepohl (2005) for the different ways to set up a structural vector time series model.

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here is suggestive for one important reason: if we do not allow b_{13} and b_{23} to differ from zero in (1.1), all automatic response effects would disappear from the analysis.

Let us now describe the procedure how to just-identify our structural model. Proposition 6.1 in Lütkepohl (2005) shows that in a VECM y_t can be decomposed in the Beveridge-Nelson fashion into $I(1)$ and $I(0)$ components. Specifically,

$$y_t = \Xi \mathsf{B} \sum_{i=1}^{t} e_i + \sum_{j=0}^{\infty} \Xi_j^* \mathsf{B} e_{t-j} + y_0. \tag{1.3}$$

y_0 are the starting values of the process; $\sum_{j=0}^{\infty} \Xi_j^*$ is an infinite-order polynomial that contains only transitory effects with Ξ_j^* converging to zero as $j \to \infty$; and the common trends term $\Xi \mathsf{B} \sum_{i=1}^{t} e_i$ captures the permanent effects of shocks. Ξ has rank $k - r$ and can be written as

$$\Xi = \beta_\perp \left[\alpha'_\perp \left(I_k - \sum_{i=1}^{p-1} \Gamma_i \right) \beta_\perp \right]^{-1} \alpha'_\perp, \tag{1.4}$$

in which $\alpha_\perp$ and $\beta_\perp$ are orthogonal complements of α and β such that $\alpha' \alpha_\perp = 0$ and $\beta' \beta_\perp = 0$.

We get the restricted maximum likelihood estimator of B by maximizing the concentrated log-likelihood function (omitting the constant),

$$\ln L_c(\mathsf{B}) = -\frac{T}{2} \ln |\mathsf{B}|^2 - \frac{T}{2} \operatorname{tr}\left(\mathsf{B}'^{-1} \mathsf{B}^{-1} \Sigma_u \right), \tag{1.5}$$

subject to the structural short- and long-run constraints,

$$C_{sr} \operatorname{vec}(\mathsf{B}) = c_{sr} \quad \text{and} \quad C_{lr} \operatorname{vec}(\Xi \mathsf{B}) = c_{lr}, \tag{1.6}$$

with the usual definitions for $\operatorname{tr}(\cdot)$ and $\operatorname{vec}(\cdot)$: $\operatorname{tr}(\cdot)$ denotes the trace of a matrix and the vec-operator transforms a matrix into a vector by stacking the columns. Using the rules of the vec-operator and a proper selection matrix $C_{\Xi \mathsf{B}}$ we can reformulate the long-run constraint, C_{lr}, as $C_{\Xi \mathsf{B}}(I_k \otimes \Xi)$, in which the operator $\otimes$ denotes the Kronecker product. The reformulation of the long-run constraint reveals its stochastic nature: C_{lr} includes the estimator for Ξ from (1.4). Finally, C_{sr} specifies short-run constraints by restricting elements of B directly, and Σ_u is the estimated covariance matrix from a reduced-form VECM specified later. We deliberately express the constraints in (1.6) in linear form in order to make the scoring algorithm of Amisano and Giannini (1997) applicable. The Amisano-Giannini scoring algorithm is numerically simpler and faster than maximizing (1.5) subject to nonlinear constraints. The scoring algorithm yields an asymptotically efficient and normally distributed maximum likelihood estimator of B (see, e.g., Lütkepohl 2005, Chap. 9.3.2).

The permanent effects of the structural shocks are given by the matrix $\Xi\mathsf{B}$. As already noted, in a VECM some of the structural shocks have transitory effects only, depending on the cointegrating rank r. We can then restrict r columns in $\Xi\mathsf{B}$ to zero. To be more specific, because the matrix $\Xi\mathsf{B}$ has reduced rank $k-r$, each column of zeros stands for $k-r$ independent restrictions. As such, the r transitory shocks represent $r(k-r)$ independent restrictions only. In total we then have $k(k-1)/2-r(k-r)$ missing restrictions which can be placed on B and $\Xi\mathsf{B}$ based on other statistical or theoretical considerations. From the statistical side, we get some guidance on how many restrictions we need to place on the contemporaneous impact matrix B. Because each of the r transitory shocks corresponds to a zero column in $\Xi\mathsf{B}$, there is no way to disentangle the transitory shocks with further long-run restrictions. The guideline is then to impose $r(r-1)/2$ restrictions on B directly (see, e.g., Lütkepohl 2005, Chap. 9.2).

Applied to our 3-dimensional model these considerations imply the following strategy to get the three required restrictions. With the emphasized two cointegration relations we have two transitory shocks and one permanent shock. From that structure of the model we get two independent restrictions from the long-run properties. So there is one more restriction left which has to be imposed on the contemporaneous impact matrix B in order to disentangle the two transitory shocks. Our set of feasible options contains $b_{12} = 0$ or $b_{21} = 0$. The restriction $b_{12} = 0$ is theoretically more appealing: higher profits do not translate into additional labor income contemporaneously, while profits may react swiftly to labor income shocks. Implicitly we assume some rigidities on the labor market here.

1.3 Estimation Procedures

1.3.1 Data Description

Our data sources are the NIPA and CANSIM tables from the Bureau of Economic Analysis and Statistics Canada. The set of data includes the logarithm of real labor income, corporate profits and output.[5] Specifically, we are using quarterly data from 1947:1 to 2008:4 for the United States and 1961:1 to 2008:4 for Canada. These are the longest possible time spans available for these two countries.

Labor income is the total compensation accruing to employees as remuneration for their work; it is the sum of wage and salary accruals and of supplements to wages and salaries before taxes. There are no transfer payments included. Corporate profits, or profits for short, are the current production incomes before taxes of organizations required to file corporate tax returns. With several differences profits simply consist of receipts less expenses as defined in the tax law. In particular, one such difference in both countries is the exclusion of capital gains and dividends received. Consequently, our two measures of labor income and profits do not add up to output. Multicollinearity is therefore not an issue.

Figure 1.1 plots the trend and cyclical characteristics of the data. All six series display a strong upward trend with profits being quite volatile, while the labor income and profit shares seem to be—with a few qualifications—relatively stable over the time.

In the United States labor income rose faster than productivity in the years after World War II and the labor income share increased steadily from 52 to 56 percent by the early 1960s. Later on in the 1960s President Johnson's Great Society social reforms mark the sharp increase in the labor income share to about 59 per cent. From then on the labor income share stays at this high level through the stagflation years of the 1970s. Strong output growth after the twin recession of the early 1980s led the labor income share to adjust downwards to a new level of 57 percent. Only at the end of the 1990s the labor income share surges again, mainly influenced by the general economic success of that decade. This development was, however, only short lived and came to a halt with the economic turbulence of the 2000s. Although naturally linked, the steady fall in the profit share in the United States by the mid-1980s had mostly other causes: American geopolitical power and thus the ability of the government to manipulate terms of trade in the interests of its large firms eroded over time; the rise in labor militancy brought on

[5] United States (http://www.bea.gov/National/ retrieved on May 16, 2009): labor income (1.12, line 2), corporate profits (1.12, line 13), output (1.1.5, line 1), and the deflator (1.1.4, line 1). Canada (http://cansim2.statcan.gc.ca/ retrieved on July 22, 2009): labor income (380-0001, item 2), corporate profits (380-0001, item 3), output (380-0001, item 1), and the deflator (380-0003, item 1).

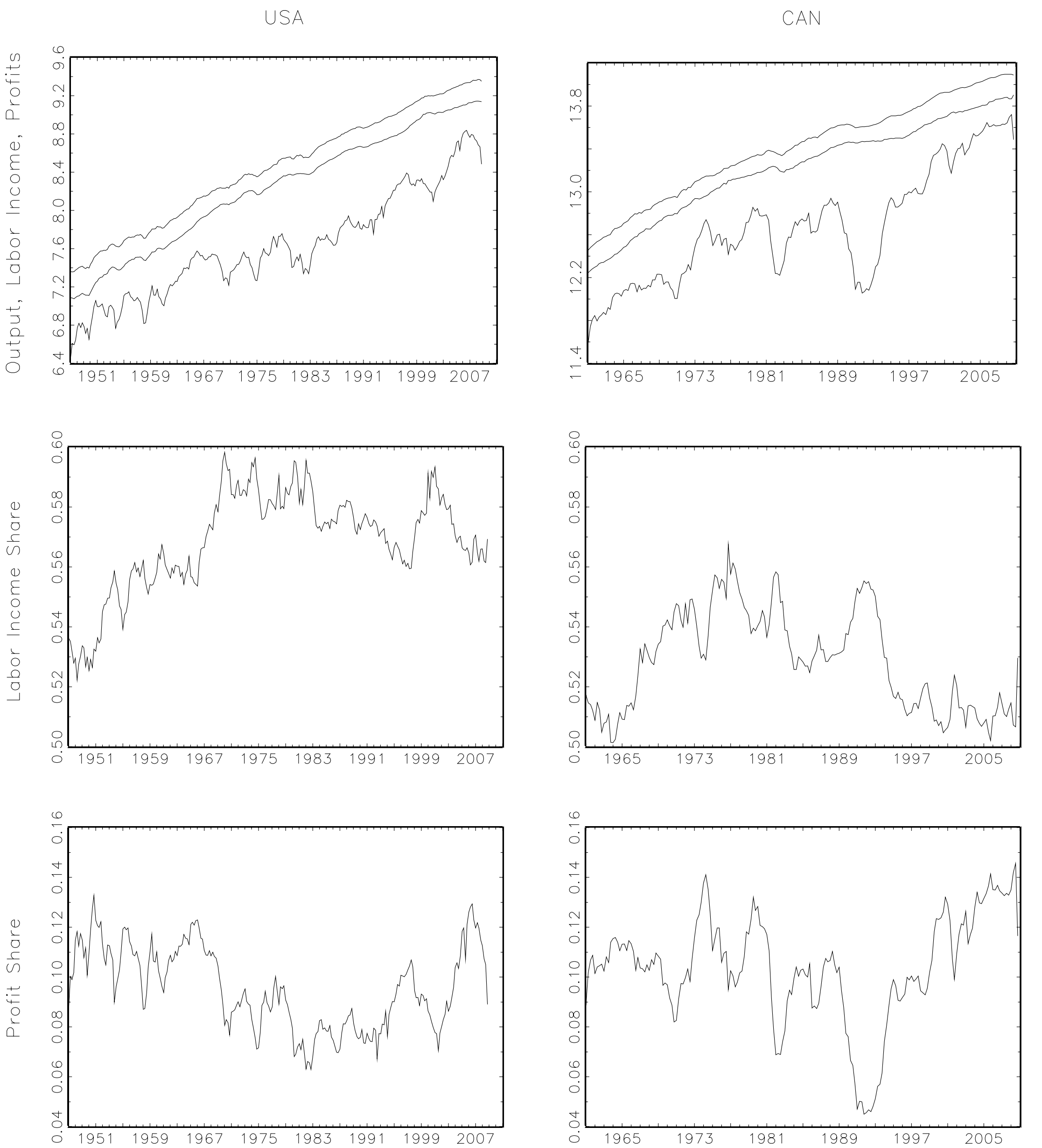

Figure 1.1: The Time Series with Labor Income-Output and Profit-Output Shares

Notes: Top panels: the order of the time series is output, labor income and profits; all variables are in logarithms and in real terms; to facilitate better graphing we add constants to these variables.

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by low unemployment after 1964; and the intensification of competition in the 1960s—reflected both in the erosion of oligopoly pricing power within domestic industries and in increased trade competition from rivals such as Japan and Germany. Then, from the late 1980s onwards labor productivity rose faster than real wages, explaining the bouncing back of the profit share.

On the other side of the border a period known as the Great Canadian Slump dominates the picture. High interest rates, set to bring down inflation to a new target below two percent, played a key role in this deep economic and fiscal crisis of 1990-96 (Fortin 1996, 1999). Moreover, the real wage and employment adjusted such that the labor income share fell persistently back from about 54 percent to its pre-1967 level of 51 percent while the profit share recovered quickly and kept increasing thereafter. Since those turbulent years in the first half of the 1990s the Canadian economy has improved noticeably, in step with the neighbor's boom years. Moreover, Canada has become a role model of fiscal stability as the government has posted surpluses every fiscal year since 1996. Besides the Great Slump the Canadian time series experienced relatively large swings in the shares in the 1970s and early 1980s. During the 1973 oil crisis profits were soaring in oil rich Alberta, before the sharp negative effect of the global oil embargo on the industrial east, which suffered many of the same problems of the United States, swept away the effect of the boom in the west on nationwide profits. Then, from October 1975 to October 1978, the Canadian government installed wage and price controls in order to reduce the rate of inflation while, at the same time, suppressing the Phillips curve effect on unemployment that typically accompanies an anti-inflation policy. The program generally targeted wages by specific numerical guidelines and prices were controlled indirectly through control of profit margins. With these wage and price controls the Canadians followed the United States, which had a similar program in place already a few years early, but building on the experience of its neighbor the Canadians were able to establish a more successful program (see Barber and McCallum 1982, Chap. 2). On top of that, Canada was hard hit by the recession of the early 1980s, with interest rates, unemployment, and inflation all being higher than in the United States.

Taken together, the visual inspection of the data verifies our hunch that output forms a stationary linear combination with both labor income and profits, at least when properly

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accounting for possible breaks in the comovement of the data. Our informal discussion of some historical facts in the United States and Canada will be a useful guide in the next section where the aim is to formally estimate and justify the timing of the breaks. The discussion of the historical events based on the shares is appealing, and without loss of generality in terms of the exact cointegration properties, since what matters are the breaks that show up in the comovements and may therefore disguise the "true" cointegrating rank.

1.3.2 Assumptions and Framework of the Reduced-Form Analysis

Following our empirical strategy we have to estimate the cointegration rank and the break dates. With respect to the latter we extend the setup of Lütkepohl, Saikkonen and Trenkler (2004) to allow for two level breaks of unknown timing. A structural break, or break for short, in our context is a rare event that disguises the otherwise stable stochastic comovements in the data, such as cointegrating relations. Ignoring a break may result in a misleading estimate of the cointegrating rank and the equilibrium relations through distorted size and power properties of conventional cointegration tests. Conversely, overestimating the number of structural breaks has the same negative side effects on rank and equilibrium relations.

We incorporate breaks into our analysis under the assumption that the k-dimensional vector of observable variables, $\{y_t\}_{t=1}^T$, is at most integrated of order one and has cointegrating rank r with a maximum of two structural breaks. Specifically, the vector process evolves according to

$$y_t = \mu_0 + \mu_1 t + \delta_1 d_{1t} + \delta_2 d_{2t} + x_t, \tag{1.7}$$

in which μ_0, μ_1, δ_1, and δ_2 are unknown $k \times 1$ parameter vectors; $d_{it} = 1$ for $t \geq T_i$, $i = 1, 2$, and zero otherwise with T_i denoting the time period when a structural break occurs; and x_t is an unobservable stochastic process which we assume to have a VAR(p) representation,

$$x_t = A_1 x_{t-1} + \cdots + A_p x_{t-p} + u_t. \tag{1.8}$$

The A_j's are the usual $k \times k$ parameter matrices and $u_t = (u_1, \ldots, u_k)'$ are the reduced-form residuals which are i.i.d. vectors with zero mean. This setup of the model can capture the dynamic interactions between the variables and their other properties discussed in

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Figure 1.1, such as the trending behavior and possible breaks. We therefore consider our model as a proper representation of the underlying data generating process.

The VECM$(p-1)$ form of x_t is

$$\Delta x_t = \Pi x_{t-1} + \Gamma_1 \Delta x_{t-1} + \cdots + \Gamma_{p-1} \Delta x_{t-p+1} + u_t, \tag{1.9}$$

in which Δ is the difference operator such that $\Delta x_t = x_t - x_{t-1}$, and with the obvious mapping $\Pi = -(I_k - A_1 - \cdots - A_p)$ and $\Gamma_j = -(A_{j+1} + \cdots + A_p)$ for $j = 1, \ldots, p-1$. The $k \times k$ matrix Π is of reduced rank, that is $\Pi = \alpha\beta'$ in which both α and β are $k \times r$ matrices of full column rank. We further define $\Psi = I_k - \Gamma_1 - \ldots - \Gamma_{p-1} = I_k + \sum_{j=1}^{p-1} jA_{j+1}$.

We can then write the data generating process (1.7) in VECM form, and in terms of observable variables only, as

$$\Delta y_t = \nu + \alpha \left(\beta' y_{t-1} - \theta_1 d_{1t-1} - \theta_2 d_{2t-1}\right) + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \sum_{j=0}^{p-1} (\gamma_{1j} \Delta d_{1t-j} + \gamma_{2j} \Delta d_{2t-j}) + u_t, \tag{1.10}$$

in which Δd_{it-j} are impulse dummies with value one in period $t = T_i + j$ and zero elsewhere. The mapping with the parameters in (1.7) and (1.9) is now a bit cumbersome: for $i = 1, 2$ and $j = 1, \ldots, p-1$ we have $\nu = -\Pi\mu_0 + \Psi\mu_1$, $\beta'\mu_1 = 0$, $\mu_1 \neq 0$, $\theta_i = \beta'\delta_i$, $\gamma_{i0} = \delta_i$, and $\gamma_{ij} = -\Gamma_j \delta_i$. Appendix Appendix 1.1 contains the level VAR version of the VECM without the rank restrictions on Π.

Apparently, we have sneaked in a few non-trivial assumptions along the way which we now state and discuss more explicitly.

ASSUMPTION 1.1: *At most two structural breaks have occurred in the vector of observable variables,* $\{y_t\}_{t=1}^T$.

Admittedly the limit of two structural breaks is arbitrary and mostly determined by computational tractability. We believe, however, that our choice is appropriate and a good compromise to accommodate a sufficiently large number of breaks helping us to uncover the "true" cointegrating rank of Π. If someone wants to estimate a higher number of structural breaks, the paper of Qu and Perron (2007) is a good point of departure. Based on the Bellman principle it offers a quite fast search algorithm over a prespecified maximum

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number of breaks. Although the Bellman principle provides a beautiful way to reduce the computational burden, it comes at a cost. In some preliminary research, we find that the Qu-Perron search algorithm is extremely sensitive to the choice of the minimum regime length and the allowed maximum number of breaks.

ASSUMPTION 1.2: *A structural break is a shift in the level of* $\{y_t\}_{t=1}^T$. *Furthermore,* $\beta'\mu_1 = 0$ *and* $\mu_1 \neq 0$.

In other words, we purge all linear trends from the analysis. In line with the theoretical considerations about the tendency of the economy to return to a steady-state growth path, the equilibrium relations between labor income, profits and output cannot linearly drift apart. Our setup of the data generating process (1.7) with two breaks is, however, flexible enough to allow the equilibrium relations to drift apart over some extended period. In the United States, for instance, the 1950s and 1960s may represent such a period (see Figure 1.1). While we could capture this period with a broken linear trend in the equilibrium relations we choose to model it as an adjustment in the levels. A broken linear trend would "throw away" at least some information in the data (see, e.g., Enders 2009). We will back up our argument here in the next sections.

We pay little attention to the linear trend in the data generating process (1.7) because it is the stochastic part which we are ultimately interested in. Generally, a unit root with drift approximates a trending variable well enough in a vector time series model (see again Enders 2009). The linear trend in (1.7) is then implicitly generated by the intercept in (1.10) and the non-stationary behavior of the individual variables (see the unit root tests in Table 1.2). As such, the matrix Π in (1.9) must be of reduced rank, $r < k$. With full rank, $r = k$, the whole system would be stable and, in such a system, an intercept cannot generate the upward trend apparent in the series.

To bring our framework to life we need to develop procedures to estimate the cointegrating rank, r, and the timing of the two structural breaks, T_1 and T_2. Furthermore, we somehow have to accommodate the "at most two structural breaks" statement of Assumption 1.1, in order to asses the statistical significance of the breaks. These issues will be our main tasks in the remainder of this section.

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1.3.3 Joint Estimation of Cointegrating Rank and Break Dates

Our joint estimation procedure combines the way how Gregory and Hansen (1996) determine the timing of a break with the procedure of Saikkonen and Lütkepohl (2000*a*, 2000*b*) for testing the cointegrating rank of a vector process. The first ingredient, the Gregory-Hansen test, can be thought as the multivariate extension of unit root tests in the tradition of Zivot and Andrews (1992). These tests pick a break date such that the most weight is on the (trend) stationary alternative. The idea behind the second ingredient, the Saikkonen-Lütkepohl test, is to estimate the deterministic terms in (1.7) first and, in a second step, to apply a likelihood ratio (LR) type test, as in Johansen (1995), to the adjusted series. The prior adjustment for deterministic terms offers one crucial advantage: multiple breaks in the level leave the limiting distribution of the LR-statistic unaffected. Theorem 4.1 in Lütkepohl, Saikkonen and Trenkler (2004) and the remarks thereafter provide a formal discussion of this argument.[6] The Saikkonen-Lütkepohl test is therefore appealing for a grid search over all possible combinations of break dates. A Monte Carlo study, summarized in Table 1.5, shows evidence for the practical relevance of our joint estimation procedure.

The joint estimation procedure starts by assigning the optimal lag length, p, to each possible combination of break dates, $\tau = (T_1, T_2)'$. Since, at this point, we do not have any information about the "exact" timing of the breaks and the proper rank specification the level VAR version of (1.10)—which is unrestricted with respect to the cointegrating rank—proves to be useful (see Appendix Appendix 1.1). We estimate this version of (1.10) allowing for a maximum of four lags, $p_{max} = 4$, and under the following definition for T_1 and T_2. Let the breaks be at a fixed fraction, κ_1 and κ_2, of the sample size. Then,

$$T_1 = [\kappa_1 T] \quad \text{and} \quad T_2 = [\kappa_2 T] \quad \text{with} \quad 0.1 \leq \kappa_1 < \kappa_2 \leq 0.9, \tag{1.11}$$

in which we impose a 10 percent trimming to eliminate endpoints and $[\cdot]$ denotes the integer

[6] There is, however, a consistency problem inherent in the Saikkonen-Lütkepohl procedure. The parameter μ_0 in (1.7) is not fully identified. It cannot be estimated consistently in the direction of $\beta_\perp$ and depends partly on the initial values in the procedure. This may be viewed as a drawback of our model setup. Still, we obtain cointegrating rank tests with desirable properties as there is a probability bound on the estimators Saikkonen and Lütkepohl, (see, e.g., Saikkonen and Lütkepohl 2000*b*, Trenkler, Saikkonen and Lütkepohl 2008)

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part of the argument. Moreover, we set $\kappa_1 < \kappa_2$ such that $[\kappa_1 T]+p_{max}+k \leq [\kappa_2 T]$ in order to avoid singularity in the estimation and to sufficiently identify the break parameters in the cointegration space. For each of these possible pairs $\tau = (T_1, T_2)'$ we choose the optimal lag length according to the corrected Akaike information criterion of Hurvich and Tsai (1993) and denote it by τ_p.[7]

The maximum of the LR-statistics determines then the cointegrating rank, r, and the break dates, τ_p, endogenously through a grid search over all possible values for r and τ_p as follows:

$$LR(\tau_p, r_0) = \sup_{\tau_p} -T \sum_{j=r_0+1}^{k} \ln\left(1-\lambda_j(\tau_p)\right) \qquad r_0 = 0, 1, \ldots, k-1, \tag{1.12}$$

subject to

$$-T \sum_{j=\tilde{r}_0}^{k} \ln\left(1-\lambda_j(\tau_p)\right) > LR^c(\tilde{r}_0, k) \qquad \tilde{r}_0 = 0, 1, \ldots, r_0 - 1, \tag{1.13}$$

in which the $\lambda_j(\tau_p)$'s are the ordered eigenvalues obtained by applying reduced rank regression techniques to the adjusted series, again, as in Johansen (1995). $LR^c(\cdot)$ denotes the critical values (see, e.g., Trenkler 2003, Table 2), for which we obtain p-values by approximating the whole asymptotic distribution of the LR-statistic with a Gamma distribution using the response surface procedure of Trenkler (2008). For $r_0 > 0$ the constraint ensures a supremum such that all LR-statistics for ranks lower than r_0 are significant at, say, the 10 percent level.

Finally, from the series of LR-statistics we pick the maximum as

$$LR^* = \max_{r_0=0\ldots,k-2} LR(\tau_p, r_0) \quad \text{such that} \quad LR^* > LR^c(r_0, k), \tag{1.14}$$

and select the corresponding break dates, $\hat{\tau}_p$, and cointegrating rank, $\hat{r} = r_0 + 1$. If the inequality never holds there is no evidence for cointegration. According to Assumption 1.2 we exclude the alternative $\hat{r} = k$ (stationarity) and therefore the rank of Π in (1.9) can be at most $k - 1$.

[7] The Hurvich-Tsai criterion is a correction to Akaike's (1974) criterion and is especially designed for VARs: it makes use of a second order expansion of the Kulback-Leibler divergence and has better small sample properties in VARs than the Akaike criterion.

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Table 1.1 confirms our hunch that a cointegrating rank of two is a proper choice in both countries. We can reject both hypotheses ($\mathrm{H}_0 : r_0 = 0$ and $\mathrm{H}_0 : r_0 = 1$) at least at the 8 percent level of significance. By and large, the estimated break dates fit well into the discussion of historical events in Section 1.3.1. We defer a more in depth discussion of the break dates to the point where we have all statistical facts at hand.

Table 1.1: Joint Estimation of Cointegrating Rank and Break Dates

Country	H_0	Lags, p	Break dates, $\hat{\tau}$		Rank, $\hat{r}$	LR^*-stat.	p-value
USA	$r_0 = 0$	2	1958:1	1988:3		19.442	0.08
	$r_0 = 1$				2	15.370	0.00
CAN	$r_0 = 0$	4	1971:2	1976:2		20.363	0.06
	$r_0 = 1$				2	17.614	0.00

Notes: "Lags" is the order of the VECM in (1.10) which we assign to each possible pair of break dates prior to our joint estimation procedure. We select p based on the unrestricted model (A1.1) and the corrected Akaike criterion of Hurvich and Tsai (1993). The corresponding p-values of the LR^*-statistics follow from the response surface procedure of Trenkler (2008).

Now with $r = 2$ and an optimal lag order $p = 2$ in the United States and $p = 4$ in Canada we find our VECMs to be adequate representations of the data generating process. Although a multivariate Breusch-Godfrey test indicates some leftover autocorrelation we continue our analysis with this lag specification: autocorrelation does not invalidate the cointegration tests (Lütkepohl and Saikkonen 1999). Moreover, increasing the lag order does not fix the problem.

Introducing breaks could potentially render the series trend stationary and Assumption 1.2 obsolete. We use the minimum Lagrange multiplier unit root test of Lee and Strazicich (2003) to bring clarity into this matter. The Lee-Strazicich test has several desirable properties. Most importantly for our purpose is the inclusion of the breaks under both the null and alternative hypotheses. A rejection of the unit root null hypothesis therefore implies unambiguously trend stationarity. Table 1.2 shows the test results. Based on the model A version of the Lee-Strazicich test, the equivalent to our model setup in (1.7), we cannot reject the null for none of the six series at levels lower than the 10 percent level of significance. A result which supports the appropriateness of our Assumption 1.2.

The property of an unaffected limiting distribution is in stark contrast to a Saikkonen-Lütkepohl test with broken linear trends (see, e.g., Trenkler, Saikkonen and Lütkepohl

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Table 1.2: Lee-Strazicich LM Unit Root Test with Two Level Breaks

Country	Variable	Lags, p	Break dates, $\hat{\tau}$		LM-statistic	CV (90%)
USA	Labor income	8	1958:1	1988:3	−2.188	−2.763
	Profits	8			−2.531	
	Output	7			−2.122	
CAN	Labor income	8	1971:2	1976:2	−1.066	−2.763
	Profits	8			−2.380	
	Output	8			−0.664	

Notes: Lee and Strazicich (2003) LM unit root test with two exogenous level breaks (their model A). We determine the optimal number of augmented lags by the general-to-specific procedure, starting with a maximum number of $p_{max} = 8$ and using a 10 percent level of significance as the cut off for the last augmented lag. The 90 percent critical value is from Lee and Strazicich (2003), Table 1.

2008) and to the other branch of cointegration tests with breaks, such as Johansen, Mosconi and Nielsen (2000). These tests require a new set of critical values whenever the timing of a break changes. These critical values are larger the more balanced the various regimes are. Naturally, this property is unpractical for a grid search as it introduces a bias toward picking one relatively long regime: a reason why we refrain from using broken linear trends in our analysis.

To sum up, our joint estimation procedure provides a novel way to estimate cointegrating rank and break dates. It extends the two-step procedure of Lütkepohl, Saikkonen and Trenkler (2004) and Saikkonen, Lütkepohl and Trenkler (2006) in which the break dates follow from minimizing the determinant of the residual covariance matrix of the level VAR version of (1.10) in a first step. Then, in a second step, the cointegrating rank is determined given the breaks. The use of different models at each step introduces a pre-test bias into their procedure. We instead use the level VAR version only to assign the optimal lag order to each possible pair of break dates. Therefore, our joint estimation procedure removes one layer of uncertainty.

1.3.4 The Reduced-Form VECM Estimator with Parameter Restrictions

There is by now one dominant method for estimating a reduced-form VECM: the reduced-rank maximum likelihood (ML) method of Johansen (1995). Although the ML estimation of VECMs is quite common under practitioners it may produce occasional outlying estimates of the cointegration parameters (see, e.g., Brüggemann and Lütkepohl

2005, Johansen 1995, p. 184). A feature arising through the lack of finite-sample moments of the estimator (Phillips 1994).

Instead we use a two-stage feasible generalized least squares (GLS) estimator which does not share the unpleasant feature of the ML estimator. This alternative estimator for VECMs was first proposed by Ahn and Reinsel (1990). In addition, it offers a computationally simple and unproblematic way to place restrictions on the cointegrating matrix. Since the two-stage feasible GLS method has not attracted much attention under practitioners we briefly introduce the estimator here (see, e.g., Lütkepohl 2005, Chap. 7.2.2 for a textbook treatment).

Consider a general k-dimensional sample $\{y_t\}_{t=1}^{T}$ with pre-sample values $\{y_t\}_{t=1-p}^{0}$. To estimate the VECM specification in (1.10), let us define the variable matrices $\Delta Y = (\Delta y_1, \ldots, \Delta y_T)$, $Y_{-1} = (X_0^{lr}, \ldots, X_{T-1}^{lr})$, and $\Delta X = (\Delta X_0^{sr}, \ldots,\ \Delta X_{T-1}^{sr})$ in which the long-run ("lr") and short-run ("sr") matrices are $X_{t-1}^{lr} = (y_{t-1}, d_{1t-1}, d_{2t-1})'$ and $\Delta X_{t-1}^{sr} = (\Delta y_{t-1}, \ldots, \Delta y_{t-p+1}, 1_T, \Delta d_{1t}, \ldots, \Delta d_{1t-p+1}, \Delta d_{2t}, \ldots, \Delta d_{2t-p+1})'$. As in Section 1.3.2, we define the $n_d = 2$ break dummies $\{d_{it}\}_{t=1-p}^{T}$, $i = 1, 2$ such that the sequence is one for $t \geq T_i$ and zero otherwise. The corresponding parameter matrices are $\Pi = \alpha\beta^{*\prime}$ with $\beta^* = (\beta : \theta_1 : \theta_2)$, and $\Gamma = (\nu : \Gamma_1 : \cdots : \Gamma_{p-1} : \gamma_{10} : \cdots : \gamma_{1p-1} : \gamma_{20} : \cdots : \gamma_{2p-1})$.

Then, the VECM (1.10) rewritten in matrix notation is

$$\Delta Y = \Pi Y_{-1} + \Gamma \Delta X + U, \tag{1.15}$$

for which we can write the OLS estimator as

$$\left[\widehat{\Pi} : \widehat{\Gamma}\right] = \left[\Delta Y Y_{-1}' : \Delta Y \Delta X'\right] \begin{bmatrix} Y_{-1}Y_{-1}' : Y_{-1}\Delta X' \\ \Delta X Y_{-1}' : \Delta X \Delta X' \end{bmatrix}^{-1}. \tag{1.16}$$

Our focus is now to disentangle the cointegration matrix β from Π. For this purpose we work with the concentrated version of the VECM and replace the short-run parameters with their OLS estimators given Π, i.e.

$$R_0 = \Pi R_1 + U = \alpha\beta^{*\prime} R_1 + U, \tag{1.17}$$

in which R_0 and R_1 are the residual matrices from regressing ΔY and Y_{-1} on ΔX. We

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further split R_1 into its first r and last $k-r$ rows and denote the two sub-matrices by $R_1^{(1)}$ and $R_1^{(2)}$. Together with the common identifying restriction $\beta^* = (I_r : \beta_{k-r} : \theta_1 : \theta_2)$ we can then rewrite the concentrated model as

$$R_0 - \alpha R_1^{(1)} = \alpha \beta_{k-r}^{*\prime} R_1^{(2)} + U. \tag{1.18}$$

Further, we introduce possible over-identifying restrictions, of the form

$$\text{vec}\left(\beta_{k-r}^{*\prime}\right) = \mathbf{R}\varphi + \mathbf{r}, \tag{1.19}$$

on the cointegration matrix $\beta_{k-r}^* = (\beta_{k-r} : \theta_1 : \theta_2)$. φ is an unrestricted $m \times 1$ vector of unknown parameters, while $\mathbf{r}$ is the $r(k-r+n_d)$-dimensional vector of imposed constants; and $\mathbf{R}$ is an appropriately defined zero-one matrix of dimension $r(k-r+n_d) \times m$ such that (1.19) holds. A simple Wald test can be used to check the restrictions. Under the null hypothesis of statistical valid restrictions the Wald statistic has an asymptotic χ^2-distribution with the number of restrictions as degrees of freedom (see, e.g., Lütkepohl 2004).

We confine ourselves to allowing restrictions on the cointegration matrix only. Our sole aim is to have a statistical tool for analyzing the structural breaks we have estimated with our joint estimation procedure. Essentially, we are testing the significance of the individual break parameters in the θ_1 and θ_2 vectors. Since in (1.10) the θ's are linear combinations of the δ's from our data generating process, a zero restriction here does not automatically imply a zero restriction there. As such, we estimate the parameter vectors of the impulse dummies—the γ's in (1.10)—unrestrictedly. According to Saikkonen and Lütkepohl (2000a), ignoring any form of restrictions on the impulse dummies will not do great damage to the other estimators.

We plug the restrictions (1.19) into the concentrated model (1.18) and solve for the GLS estimator of φ:

$$\breve{\varphi} = \left[\mathbf{R}'\left(R_1^{(2)} R_1^{(2)\prime}\right)\alpha'\Sigma_u^{-1}\alpha\right]^{-1} \times \mathbf{R}'\left(R_1^{(2)} \otimes \alpha'\Sigma_u^{-1}\right)\left[\text{vec}\left(R_0 - \alpha R_1^{(1)}\right) - \left(R_1^{(2)\prime} \otimes \alpha\right)\mathbf{r}\right]. \tag{1.20}$$

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To make GLS operational (i.e. feasible) we need to replace the loading matrix, α, and the residual covariance matrix, Σ_u, with consistent estimators. For Σ_u such an estimator follows from (1.16) and (1.15) in the usual way and for α from the first r columns of $\widehat{\Pi}$. The estimator for α is a direct implication from the common identifying restriction we have imposed on β^*. We denote the resulting feasible GLS estimator by $\breve{\varphi}$. The unrestricted version of $\breve{\varphi}$ is available by defining $\mathbf{R}$ as an identity matrix of dimension $r(k-r+n_d)$ and $\mathbf{r}$ as a vector of zeros.

Proposition 7.6 in Lütkepohl (2005) shows the asymptotic properties of the estimator. $\breve{\varphi}$ goes in distribution to a Normal. Formally,

$$\left[\mathbf{R}\left(R_1^{(2)}R_1^{(2)\prime}\right)\otimes\left(\alpha'\Sigma_u^{-1}\alpha\right)\mathbf{R}\right]^{1/2}\left(\breve{\varphi}-\varphi\right)\rightsquigarrow N\left(0,I_k\right), \tag{1.21}$$

in which $\breve{\varphi}$ converges to its true value at the rate T, faster than the usual rate $\sqrt{T}$. It is therefore what we call a super-consistent estimator. Whether we impose a known cointegration matrix β^* or estimate it will not affect the asymptotic distribution of the OLS estimators of Π and Γ in (1.16).

Then, given the super-consistent estimator $\breve{\varphi}$, we can construct $\breve{\beta}^* = (I_r : \breve{\beta}^*_{k-r})'$ from (1.19) and consistently estimate all the other parameters in the VECM in a second stage. With $\breve{\beta}^*$ and possible zero restrictions of the form

$$\text{vec}\left(\alpha:\Gamma\right)=\mathbf{S}\vartheta, \tag{1.22}$$

we can write (1.15) in vectorized form as

$$\text{vec}(\Delta Y)=\left(\left[Y_{-1}'\breve{\beta}^*:\Delta X'\right]\otimes I_k\right)\mathbf{S}\vartheta+\text{vec}(U), \tag{1.23}$$

in which $\mathbf{S}$ is a fixed zero-one matrix of dimension $k(r*k(p-1))\times n$ and ϑ is a n-dimensional

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vector of free parameters. The GLS estimator of ϑ is now

$$\breve{\vartheta} = \left[\mathsf{S}' \left(\begin{bmatrix} \breve{\beta}^{*\prime} Y_{-1} Y_{-1}' \breve{\beta}^{*} : \breve{\beta}^{*\prime} Y_{-1} \Delta X' \\ \Delta X Y_{-1}' \breve{\beta}^{*} : \Delta X \Delta X' \end{bmatrix} \otimes \Sigma_u^{-1} \right) \mathsf{S} \right]^{-1} \times \mathsf{S}' \left(\begin{bmatrix} \breve{\beta}^{*\prime} Y_{-1} \\ \Delta X \end{bmatrix} \otimes \Sigma_u^{-1} \right) \operatorname{vec}(\Delta Y). \quad (1.24)$$

A consistent estimator for the residual covariance matrix, Σ_u, is readily available from the first stage and, as before, the feasible GLS estimator of ϑ goes in distribution to a Normal (see Lütkepohl 2005, Proposition 7.7):

$$\sqrt{T}(\breve{\vartheta} - \vartheta) \rightsquigarrow N \left(0, \operatorname{plim} T \left[\mathsf{S}' \left(\begin{bmatrix} \breve{\beta}^{*\prime} Y_{-1} Y_{-1}' \breve{\beta}^{*} : \breve{\beta}^{*\prime} Y_{-1} \Delta X' \\ \Delta X Y_{-1}' \breve{\beta}^{*} : \Delta X \Delta X' \end{bmatrix} \otimes \Sigma_u^{-1} \right) \mathsf{S} \right]^{-1} \right), \quad (1.25)$$

in which $\breve{\vartheta}$ converges to its true values at the rate $\sqrt{T}$. A Wald test is again available to check the statistical validity of the restrictions.

1.3.5 Taking Stock

We now put the bits and pieces of the preceding sections together and present the results of the long-run parameters and the breaks. In addition, we provide evidence for the practical relevance of the two-stage feasible GLS estimator and a Monte Carlo study to assess the performance of our joint estimation procedure of cointegrating rank and break dates.

Two results stand out from Tables 1.3 and 1.4. First, there is no evidence for structural breaks in Canada. A joint test for the exclusion of the breaks cannot be rejected by a Wald test ($\chi^2(4) = 2.128$ [0.71]). For this result we get further support from a standard Saikkonen-Lütkepohl cointegration test without breaks: we still find two cointegration relations. Unlike Canada, the 1958:1 and 1988:2 breaks in the United States are partly necessary to reveal a cointegrating rank of two. These dates fit well into our discussion of the historical developments in Section 1.3.1. Specifically, the first break is only significant in the labor income-output equation and adjusts for the long and steady increase of the labor income share after World War II while the 1988:3 break captures the U-shaped

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Table 1.3: United States: Estimated Long-Run Parameters

Model		Labor income	Profits	Output	Break, T_1	Break, T_2
					1958:1	1988:3
M_0:	$\breve{\beta}^{*\prime}$	1.000	0.000	−1.024	−0.037	0.038
				(0.015)	(0.014)	(0.014)
		0.000	1.000	−0.801	0.035	−0.267
				(0.129)	(0.127)	(0.123)
	$\breve{\alpha}'$	−0.135	−0.848	−0.121		
		(0.032)	(0.252)	(0.041)		
		−0.003	−0.131	−0.009		
		(0.004)	(0.030)	(0.005)		
M_1:	$\breve{\beta}^{*\prime}$	1.000	0.000	−1.000	−0.045	0.000
					(0.008)	
		0.000	1.000	−0.865	0.000	−0.116
				(0.078)		(0.091)
					Wald statistic: $\chi^2(3) = 4.020$ [0.26]	
	$\breve{\alpha}'$	−0.092	−0.724	−0.090		
		(0.024)	(0.213)	(0.033)		
		0.000	−0.122	−0.008		
			(0.027)	(0.003)		
					Wald statistic: $\chi^2(1) = 0.173$ [0.68]	

Notes: Estimation by two-stage feasible GLS with $p = 2$ lags. The corresponding standard errors of the parameters are in parentheses; the p-values of the Wald statistics are in brackets. In the second stage (equation (1.22)), we estimate the loading matrix, $\breve{\alpha}$, either under M_0 or M_1 by taking the cointegration matrix, $\breve{\beta}^{*\prime}$, from the first stage (equation (1.19)) as given. The imposed restrictions represent the maximal possible number that cannot be rejected by a Wald test.

profile of the profit share. As we see from the empirical evidence here, our notion of a structural break as rare events that disguise the "true" cointegrating rank seems to be appropriate.

The second result is that a permanent increase in output sets in motion a redistribution from labor income toward profits in Canada, whereas in the United States we observe a redistribution away from profits in favor of other non-labor incomes, such as capital gains and dividends. A Wald test cannot reject a one-by-one long-run movement of labor income and output (see the joint test with the breaks: $\chi^2(3) = 4.020$ [0.26]), while the long-run output elasticity of profits is significantly below one (0.87 percent). Since our measures of labor income and profits do not (and must not) add up to output, a permanent increase in output sets in motion a redistribution toward the "missing" part of

Table 1.4: Canada: Estimated Long-Run Parameters

Model		Labor income	Profits	Output	Break, T_1	Break, T_2
					1972:2	1976:2
M_0:	$\breve{\beta}^{*\prime}$	1.000	0.000	−0.911	0.012	0.009
				(0.038)	(0.039)	(0.041)
		0.000	1.000	−1.420	−0.030	0.260
				(0.297)	(0.306)	(0.321)
	$\breve{\alpha}'$	−0.056	−0.221	−0.051		
		(0.014)	(0.115)	(0.013)		
		0.004	−0.057	−0.000		
		(0.003)	(0.023)	(0.003)		
M_1:	$\breve{\beta}^{*\prime}$	1.000	0.000	−0.896	0.000	0.000
				(0.021)		
		0.000	1.000	−1.231	0.000	0.000
				(0.169)		
					Wald statistic: $\chi^2(4) = 2.128$ [0.71]	
	$\breve{\alpha}'$	−0.053	−0.232	−0.055		
		(0.015)	(0.119)	(0.013)		
		0.006	−0.048	0.000		
		(0.002)	(0.018)			
					Wald statistic: $\chi^2(1) = 0.601$ [0.44]	

Notes: Estimation by two-stage feasible GLS with $p = 4$ lags. The corresponding standard errors of the parameters are in parentheses; the p-values of the Wald statistics are in brackets. In the second stage (equation (1.22)), we estimate the loading matrix, $\breve{\alpha}$, either under M_0 or M_1 by taking the cointegration matrix, $\breve{\beta}^{*\prime}$, from the first stage (equation (1.19)) as given. The imposed restrictions represent the maximal possible number that cannot be rejected by a Wald test.

overall profits, most importantly capital gains and dividends. This trend may reflect the relative dominant role of the stock market in the United States. Across the border in Canada we estimate long-run output elasticities of labor income (0.90 percent) and profits (1.23 percent) significantly below and above unity. These long-run elasticities imply a redistribution from labor income to profits in response to a permanent increase in output: economic growth does not fully show up on Canadians' paychecks. This is a well-known fact in Canada and part of the, sometimes tempered, political discussion.

The interpretation of cointegrating parameters as long-run elasticities can be problematic but works well in our case. The reason is the orthogonality property of the permanent change: it is orthogonal to both cointegrating vectors. To see why this property holds, let us consider a permanent one-percent output change that entails—everything

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else equal—a permanent change of labor income by $-\beta_{13}$ percent.[8] Having in mind the parallel (unknown) effect on profits, say ω, we model the permanent change c as $c(\omega) = (-\beta_{13}, \omega, 1, 0, 0)$. Then,

$$c'(\omega)\beta_1^* = (-\beta_{13}, \omega, 1, 0, 0)(1, 0, \beta_{13}, \theta_{11}, \theta_{12})' = 0$$
$$c'(\omega)\beta_2^* = (-\beta_{13}, \omega, 1, 0, 0)(0, 1, \beta_{23}, \theta_{21}, \theta_{22})' = \omega + \beta_{23},$$

in which we can set $\omega = -\beta_{23}$ to make $c(\omega)$ orthogonal to both cointegrating vectors. It is exactly this change in profits, the variable absent from the labor income-output relation, that keeps the system on the attractor set. Only in cases where this condition is met, the initial permanent change c produces the required effect and we can interpret $-\beta_{13}$ as the long-run output elasticity of labor income. Likewise, $-\beta_{23}$ is the long-run output elasticity of profits. This result is the essence of Propositions 1 and 2 in Johansen (2005).

As a cross-check for the robustness and practical relevance of the two-stage feasible GLS estimator we compare our results with the ones from the reduced-rank ML method of Johansen (1995). While for the United States the long-run parameters are practically identical, the results for Canada are unreasonable and are quite likely outliers. For instance, the output elasticity of profits is -19.03 in the unrestricted model (M_0). We rule it out as a valid result, both sign and size are economically implausible. In the same way, including a linear trend in the cointegrating space causes troubles. In the United States, it suggests an output elasticity of profits of -3.03. The results for Canada are similar. Again, sign and size are hard to reconcile with common theoretical considerations on the long-run relation between profits and output.

Table 1.5 presents the results from our Monte Carlo study on the performance of the joint estimation procedure. We use the parameter estimates of the VECM in unrestricted form (model M_0) and simulate 1,000 series of the the original sample length using multivariate normal residuals. We impose structure on the residuals by pre-multiplying them with the contemporaneous impact matrix B, where B is from the estimation stage. We use the first p observations ($p = 2$ in the United States and $p = 4$ in Canada) to initialize

[8] β_{13} is the output parameter in the labor income-output relation. Formally, in (1.10) we have $\beta^* = \begin{bmatrix} 1 & 0 & \beta_{13} & \theta_{11} & \theta_{12} \\ 0 & 1 & \beta_{23} & \theta_{21} & \theta_{22} \end{bmatrix}$, and we denote the first and second rows of β^* by β_1^* and β_2^*.

Table 1.5: Joint Estimation Procedure: Monte Carlo Analysis

A. United States

	47:1–87:3	87:4–88:2	1988:3	88:4–89:2	89:3–08:4	Sum
47:1–57:1	0.211	0.007	0.001	0.010	0.030	0.259
	(0.41)	(1.00)	(1.00)	(1.00)	(1.00)	
57:2–57:4	0.044	0.001	0.002	0.005	0.019	0.071
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
1958:1	0.072	0.007	0.002	0.022	0.066	0.169
	(1.00)	(1.00)	(1.00)	(1.00)	(0.99)	
58:2–58:4	0.059	0.005	0.006	0.007	0.050	0.127
	(1.00)	(1.00)	(1.00)	(1.00)	(1.00)	
59:1–08:4	0.110	0.021	0.008	0.031	0.209	0.379
	(0.99)	(0.95)	(1.00)	(0.97)	(0.99)	
Sum	0.495	0.040	0.018	0.074	0.372	

B. Canada

	61:1–75:2	75:3–76:1	1976:2	76:3–77:1	77:2–08:4	Sum
61:1–71:2	0.095	0.009	0.004	0.043	0.343	0.494
	(0.88)	(1.00)	(1.00)	(1.00)	(0.99)	
71:3–72:1	0.020	0.002	0.000	0.013	0.067	0.102
	(1.00)	(1.00)		(1.00)	(0.99)	
1972:2	0.002	0.000	0.000	0.002	0.012	0.016
	(0.50)			(1.00)	(0.92)	
72:3–73:1	0.002	0.000	0.000	0.002	0.024	0.028
	(1.00)			(1.00)	(1.00)	
73:2–08:4	0.000	0.001	0.000	0.004	0.355	0.360
		(1.00)		(1.00)	(0.99)	
Sum	0.119	0.012	0.004	0.064	0.801	

Notes: Data generating process based on the unrestricted parameter estimates (model M_0, equation (1.10)) for the two countries. We present the relative frequencies (out of $1,000$ replications) of finding the break dates, $\hat{\tau}$, in a specific time interval and report in parentheses the ratio of how often the estimated cointegrating rank, $\hat{r}$, is $r = 2$ (at the 10 percent level of significance).

all 1,000 runs. We then go through all the steps of Section 1.3.3, while keeping the lag order p fixed, and store the estimated break dates, $\hat{\tau}$, and cointegrating rank, $\hat{r}$, in each run. Table 1.5 shows the frequencies of $\hat{\tau}$ to lie in certain time intervals. Since the shift magnitudes of the breaks are relatively small (see Tables 1.3 and 1.4), our test performs modestly in finding the correct break dates. In an interval of plus-minus three quarters around the two break dates the hit rate is 5.7 percent in the United States and 1.9 percent in Canada. The somewhat larger shift magnitudes in the United States increase the frequency of finding the break dates closer to the true ones. While, at first glance, this

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performance seems to be rather disappointing, what matters most is the success of our test to identify the correct cointegrating rank. In most instances the hit rate is a full 100 percent. Even when the estimated break dates are outside the plus-minus three quarters intervals the cointegration test within our joint estimation procedure performs reasonably well. As a benchmark, using the standard Saikkonen-Lütkepohl cointegration test without breaks, the frequency of finding the correct cointegrating rank is 17.4 percent in the United States and 73.9 percent in Canada. With one exception in Canada, these hit rates are significantly lower than the ones from our joint estimation procedure. Especially so in the United States where the shift magnitudes play a more important role than in Canada.

1.4 Empirical Results on Redistribution

After all these technicalities let us summarize the results of our estimations regarding the effects of a redistribution from profits to labor income. In Figures 1.2 and 1.3 we present the effects of the two components of a redistribution shock—labor income and profits—individually. This intermediate step helps for a better intuition for the driving forces behind the changes set in motion by a combination of these two shocks in the redistribution experiment shown in Figure 1.4. Deriving an interpretation directly from Figure 1.4 is in fact a bit tricky since both effects overlap and the behavior of workers and firms and the respective aggregates becomes less clear.

Although the original estimates have the dimension of elasticities, it is more intuitive to discuss the results on a dollar for dollar basis. As such, we work with derivatives evaluated at the point of means. Moreover, when we talk about "dollars" we do not distinguish between United States an Canadian dollars for ease of reading. This would anyway be only a matter of labeling a unit.

Throughout the discussion of the results we mostly focus on the model with parameter restrictions (M_1) which is our preferred model based on the discussion above. However, to check the robustness and sensitivity we report the results from the unrestricted model M_0 as well.

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1.4.1 Contemporaneous Effects

Table 1.6 reports the estimation results for the B matrix of the structural model (1.1). The estimation procedure follows Section 1.2 which we extend to allow for over-identifying restrictions on the B matrix in the restricted model. Four results stand out. First, the contemporaneous effect from a labor income shock on output dominates the one from a profit shock, i.e. $b_{32} < b_{31}$. Specifically, a one-dollar shock to labor income increases output within the quarter by about 1.15 dollars in both countries. Thus, there is a modest impact multiplier effect at work creating these 15 cents in excess of the initial one-dollar input through the swift effect of the induced extra spending on aggregate demand. In the case of a one-dollar profit shock the retarded capacity effect implies a less than unity increase in output: 0.68 dollars in the United States and 0.82 dollars in Canada.

The second result is that the correlation between the reduced-form labor income and profit residuals is relatively high in the United States (about 0.43 in our sample) yielding a positive effect from a labor income shock on profits ($b_{21} = 0.47$). From a methodological point of view this effect implies that to achieve a one-dollar redistribution from profits to labor income we have to take away more than one dollar from firms, 1.47 dollars to be exact. In Canada the effect from a labor income shock on profits is, if at all, slightly negative which is a direct consequence of the low correlation between the reduced-form residuals (-0.05). In model M_0 this effect is a mere -0.03 and rather imprecisely estimated. Moreover, a Wald test cannot reject the over-identifying restriction $b_{21} = 0$. The parameter is therefore absent from M_1^*.

Third, the parameters b_{13} and b_{23} indicate the qualitative effect of the automatic responses. Indicative only because b_{13} and b_{23} subsume various other effects, for instance the marginal propensities to spend, as in (1.2). The sign of the parameters, however, may ultimately be driven by the sign of the respective automatic response (see Remark 1.1). Both automatic response channels seem to be positive in the United States, whereas in Canada the effect, if any, might be negative.

Fourth, the bootstrapped standard errors under M_0 are quite large which points toward a problematic identification and estimation of at least some of the parameters. These problems disappear in the model with parameter restrictions (M_1^*), where we observe a considerably reduced estimation uncertainty. Still, we might underestimate the "true"

Table 1.6: Contemporaneous Effects

Country	Model		b_{31}	b_{21}	b_{32}	b_{13}	b_{23}
USA	M_0	coeff.	1.199	0.473	0.663	0.190	0.194
		std.err.	(0.732)	(0.473)	(0.660)	(0.225)	(0.358)
	M_1^*	coeff.	1.156	0.471	0.682	0.205	0.186
		std.err.	(0.466)	(0.178)	(0.225)	(0.119)	(0.144)
CAN	M_0	coeff.	1.283	−0.026	0.592	−0.336	0.263
		std.err.	(0.360)	(0.074)	(0.354)	(0.332)	(0.744)
	M_1^*	coeff.	1.295	0.000	0.822	−0.360	0.000
		std.err.	(0.242)		(0.355)	(0.224)	
					Wald statistic: $\chi^2(2) = 5.388$ [0.068]		

Notes: The parameter estimates refer to the B matrix in equation (1.1) under the short-run identifying restriction $b_{12} = 0$. Model M_0 is the same as in Tables 1.3 and 1.4. Model M_1^* extends M_1, the one with parameter restrictions in the long-run relations, and provides a test for the over-identifying restrictions on the B matrix. We present the parameters as derivatives evaluated at the point of means and express them as dollar for dollar. b_{31} and b_{32} are the effects of labor income and profit shocks on output; b_{12} and b_{21} are the effects of a profit shock on labor income and vice versa ; and b_{13} and b_{23} indicate the direction (not the size) of the automatic responses. The imposed restrictions represent the maximal possible that cannot be rejected by a Wald test. Bootstrapped standard errors in parentheses (2,500 replications, see Appendix Appendix 1.2).

estimation uncertainty as we take the restrictions as given in the bootstrap procedure.

What could be the economic explanations behind these results and the differences between the two countries? In the following we shortly discuss two arguments which might comprise important and reasonable explanations.

A first argument could be that the stronger exposure of Canada to international trade brings some unwelcome side effects of a positive labor income shock: an increase in unit labor costs and a loss in competitiveness. These effects will reduce exports and may undo any additional profit opportunities arising through the boost in domestic demand. The automatic response channel from output on profit is, therefore, absent in Canada ($b_{23} = 0$).

A second potential explanation could lie in different expectations of Americans and Canadians. The prospects about the beneficial effects of a labor income shock may heavily influence the decisions of American firms and workers. These positive expectations, then, reinforce the spending effects already within the quarter. Labor income reacts by more than the initial one-dollar shock ($b_{31} = 1.16$) and profits increase by 0.47 dollars. In Canada the picture is less clear. Labor income still reacts by more than the initial input

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($b_{31} = 1.30$), but it does not create the additional boost as in the United States. Firms just manage to maintain their profit levels ($b_{21} = 0$). Canadian firms might interpret a labor income shock in terms of a cost shock and hence do not increase capacities. An explanation for the different interpretations may be the fact that over the last 40 years the quantitative significance of unions and collective bargaining drifted apart in the two countries, with Canada experiencing an increasing unionization and higher bargaining power of workers (Riddell 1993). On the other hand, the effect on Canadian output of a profit shock is with 0.82 dollars relatively high. Taken together, these results give the hunch that spending drives the formation of expectations in the United States, whereas capacity considerations may be the driving factor in Canada.

1.4.2 Dynamic Effects of a Labor Income Shock

Figure 1.2 depicts the effects of a one-dollar labor income shock. One would expect a positive effect on the level of output mainly driven by additional spending. This effect can clearly be seen in the response of output. It is about one-for-one on impact with a multiplier effect at work thereafter, reaching a peak three quarters out at 1.92 dollars in the United States and 1.45 dollars in Canada after one quarter. Output starts then to decline in both countries but rather abrupt in Canada with the effect becoming statistically insignificant already after four to five quarters. The impulse responses from the unrestricted and restricted models lie practically on top of each other. Apparently, the exact specification of the restrictions on the breaks and the contemporaneous effects does not really matter here.

The formation of expectations after a labor income shock drives the dynamic pattern in the Unites States. Workers increase their spending and firms will produce more by using idle capacities or by investing in new capacities. This positive short-run effect is then phasing out over the medium-run as workers ask for higher wages in return for higher productivity and additional labor demand. As a consequence, profits eventually go below trend after six quarters. Together with the general upward adjustment of prices this "classic" channel explains the pronounced hump-shaped response of labor income and output.

In Canada only higher labor income drives the multiplier process. The missing positive

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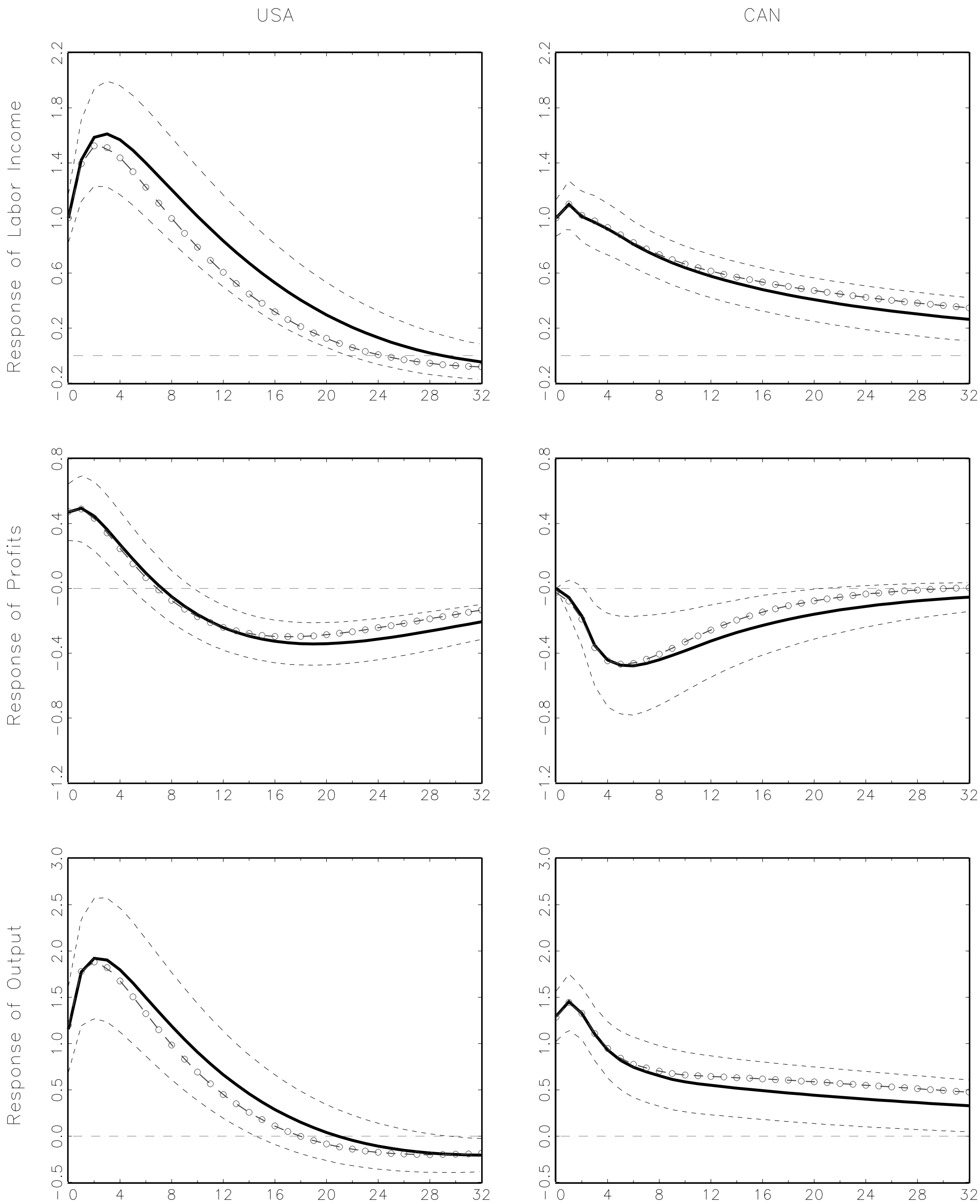

Figure 1.2: Response to a One-Dollar Labor Income Shock

Notes: The thick solid line depicts the impulse response from the model with parameter restrictions on the cointegration and contemporaneous impact matrices (model M_1^*), surrounded by bootstrapped one-standard error bands (2,500 replications, see Appendix Appendix 1.2). The dashed line with circles depicts the response based on the VECM with no parameter restrictions (model M_0).

impact on firms arises, perhaps, through a different formation of expectations or a loss of competitiveness as discussed above. When hit by a labor income shock the spending stimulus does not lead Canadians to revise their expectations as much as their colleagues across the border. This difference induces a much faster decline of output in Canada and a relatively strong negative profit effect that reaches its trough seven quarters out at -0.48 dollars.

1.4.3 Dynamic Effects of a Profit Shock

Let us now turn to the effects of a one-dollar profit shock. We model a negative shock because of its later relevance to resemble a redistribution shock toward labor income according to Definition 1.1. Theoretically, the lower profits will have a negative effect on capacity decisions and will, perhaps, lead to a revision of expectations. In a standard AS-AD model (see, e.g., Blanchard 2009) prices will then adjust downward over the medium-run and output reverts to its initial trend.

Figure 1.3 shows the empirical pattern. In the United States profits start recovering more or less right away, whereas in Canada profits respond in a hump-shaped manner, reaching a trough four quarters out at -1.51 dollars. By our short-run identifying assumption ($b_{12} = 0$), labor income does not change on impact, decreases then relatively smoothly before it reverts to trend. The trend reversion is particularly pronounced and slow in Canada. Output initially decreases by 0.68 dollars and reaches a trough at -0.99 dollars after four quarters in the United States; -0.82 dollars on impact and a trough at -1.91 dollars eight quarters out in Canada. Besides the much larger (negative) multiplier effect the output response in Canada shows more persistence.

Again, the formation of expectations may play a crucial role. After a profit shock, firms will reduce capacities or postpone investment projects and workers will cut down spending eventually. Especially in Canada, the decrease of output by 0.82 dollars on impact, and profits much below par, puts pressure on the labor market. A situation in which firms may become tougher on wage negotiations or adjust employment, thereby reinforcing the negative effect on labor income and output, making the recovery a long one.

The specification of the restrictions, on the breaks in particular, matter more than in

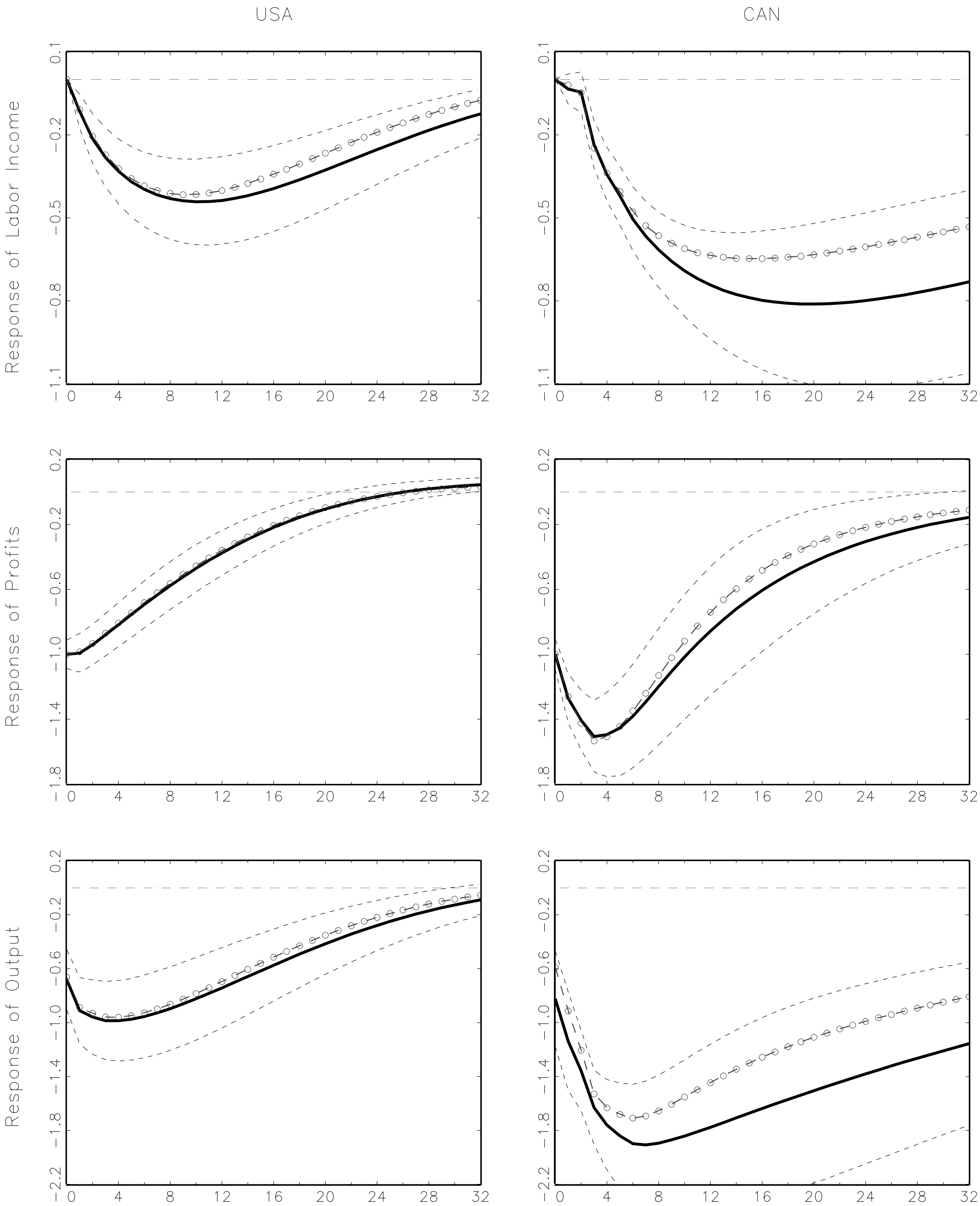

Figure 1.3: Response to a (Negative) One-Dollar Profit Shock

Notes: The thick solid line depicts the impulse response from the model with parameter restrictions on the cointegration and contemporaneous impact matrices (model M_1^*), surrounded by bootstrapped one-standard error bands (2,500 replications, see Appendix Appendix 1.2). The dashed line with circles depicts the response based on the VECM with no parameter restrictions (model M_0).

the labor income shock scenario. While in the United States the impulse responses from the restricted and unrestricted model are virtually the same, the unrestricted model (M_0) would underestimate the effects on labor income and output in Canada.

1.4.4 Dynamic Effects of a Redistribution Shock

Definition 1.1 shows how to linearly combine the labor income and profit shocks to get an exact one-dollar redistribution on impact. Figure 1.4 shows the dynamic effects of a redistribution toward labor income.[9]

What may take one by surprise at first, turns out to be the central difference in the adjustment to a redistribution shock in the two countries. The profit response in Figure 1.3 is pretty much the mirror image of the labor income response in Figure 1.2 and vice versa. Following our discussions of the single shock scenarios, this cross-pattern verifies our hunch of a different formation of expectations in the two countries. Depending on whether expectations manifest through a stimulation of spending, as in the United States, or the adjustment of capacities, as in Canada, the transmission of a redistribution shock differs. Specifically, in the United States, output increases on impact by 0.15 dollars, reaches a peak two quarters out at 0.51 dollars and dips below trend after eight quarters before it steadily reverts to trend. Although in Canada output initially increases by 0.47 dollars, it takes a rather persistent nosedive of 1.73 dollars within the first eight quarters. Put another way, Canadians would benefit more form a redistribution toward profits.

When the transmission of a redistribution shock has a strong spending component, as in the United States, the response of output should be similar to the ones from other attempts to stimulate the economy through a spending stimulus. In fact, the estimated output response for the Unites States is akin to the one Corsetti, Meier and Müller (2009) get from a fiscal stimulus in which a debt-stabilizing policy systematically reduces spending below trend over the medium-run.

1.5 Conclusions

Our paper contributes to the debate about the output effects of a redistribution between labor income and profits. Fiscal stimulus packages or monetary policy measures,

[9] The effects of the opposite experiment would be exactly symmetric.

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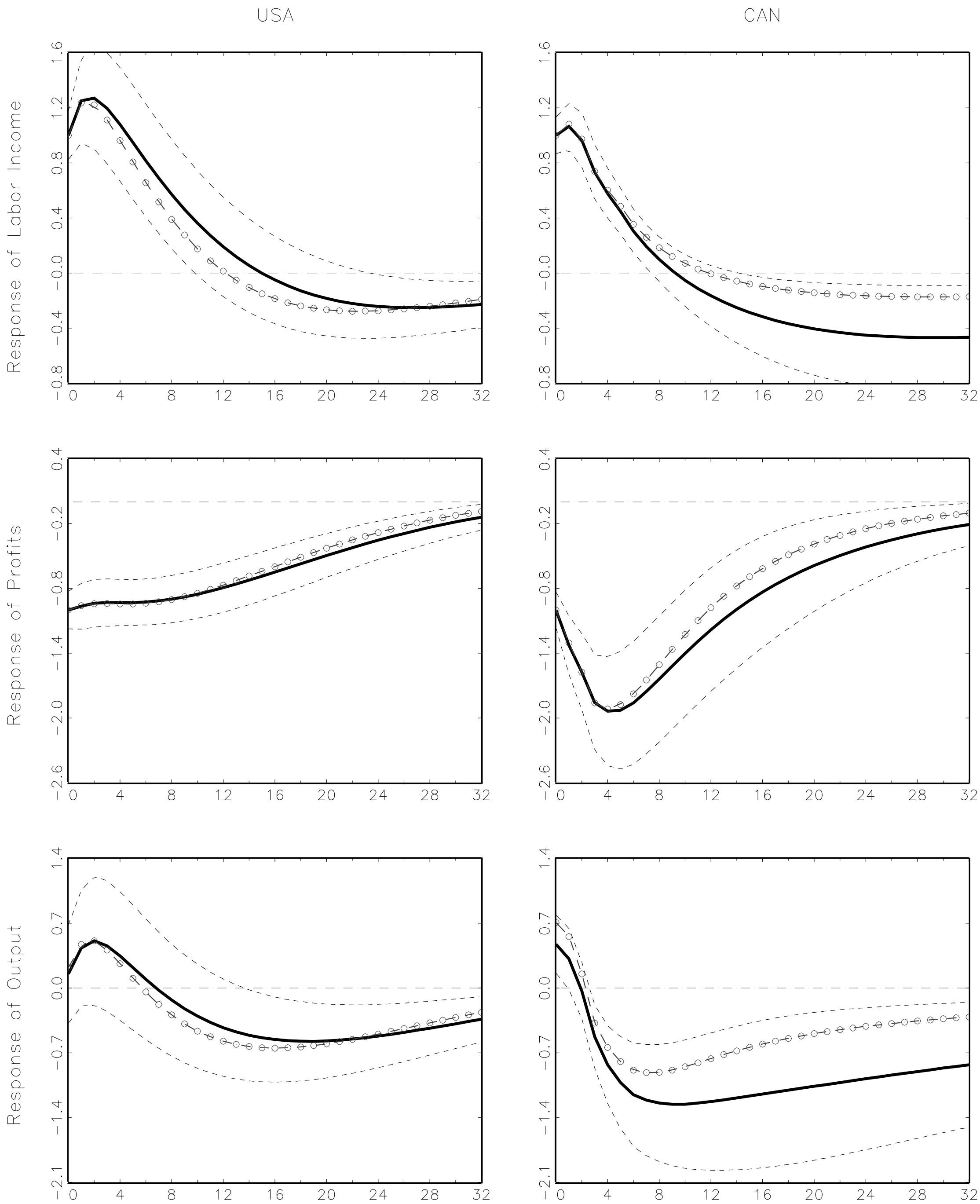

Figure 1.4: Response to a One-Dollar Redistribution from Profits to Labor Income

Notes: The thick solid line depicts the impulse response from the model with parameter restrictions on the cointegration and contemporaneous impact matrices (model M_1^*), surrounded by bootstrapped one-standard error bands (2,500 replications, see Appendix Appendix 1.2). The dashed line with circles depicts the response based on the VECM with no parameter restrictions (model M_0).

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which might have triggered off the recovery after the 2009 crisis, inevitably imply a shift of income between labor and profits. In a more general view the discussion in our paper therefore relates to a long-standing debate on wage-led versus profit-led economic expansion. While most of the recent research focuses directly on the effects of government spending, we elaborate on the possible beneficial output effects of redistributing resources from profits toward labor income. A positive output effect, at least over the short-run, requires two main ingredients: a marginal propensity to spend out of labor income which exceeds the one of firms to spend an additional dollar of profits, and a medium-run capacity effect, brought about by lost profit opportunities, that does not crowd out the first effect too strong and too quickly.

We study how these opposing effects shape the output response in a 3-dimensional structural VECM with up to two breaks at unknown time using quarterly data on labor income, profits and output. Our analyzes focuses on the post-World War II economies of the United States and Canada. While in the United States, a one-dollar redistribution from profits to labor income, in fact, increases output long enough to call the experiment a success, the redistribution fails to produce the welcome output stimulus in Canada. After a short-lived output gain the Canadian economy plunges persistently below trend. As our VECM bestows the symmetry property, this results actually suggests a redistribution toward profits.

We discuss several related economic arguments in turn to provide explanations for our results. One argument concerns the formation of expectations generally. American firms and workers thrive on the spending stimulus triggered off by the labor income shock. This positive impulse on expectations overcompensates the effects from the negative profit shock. The United States economy therefore expands after a one-dollar redistribution toward labor income, at least over the short-run. In Canada the revision of expectation is however not strong enough to absorb the effects from the decline of profits. Stated differently, growth is wage-led in the United States whereas it is profit-led across the border. Finally, because of the stronger exposure of Canada to international trade, a labor income shock brings some unwelcome side effects: an increase in unit labor costs and a loss in competitiveness. These effects will reduce exports and may undo any additional profit opportunities arising through the boost in domestic demand. The automatic response

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channel from output back on profits is, therefore, absent in Canada while it is positive in the United States.

Developing a proper econometric tool that jointly estimates break dates and cointegrating rank was, besides the economic question, the main objective of our paper. We provide Monte Carlo evidence showing the basic consistency of this joint estimation procedure.

The low-dimensionality of the VECM helps to keep econometric issues with break dates, cointegration, and identification at a minimum but, at the same time, limits the accuracy of our economic explanations. In ongoing work we draw on our conclusion from this paper and build a dynamic stochastic general equilibrium (DSGE) model which can explicitly shed more insights on the transmission mechanism of a redistribution shock.

Furthermore, allowing for country interdependencies, for instance, or comparing evidence across a larger set of countries strikes us as promising directions for future research. The global error-correcting framework of Pesaran, Schuermann and Weiner (2004) or the global VAR of Dees et al. (2007) may be good starting points for an extension along this line. An extensive cross-country study was beyond the scope of the paper. Our results for the United States and Canada are, however, suggestive for the possible benefits and pitfalls of redistributing income between labor and profits.

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Appendix 1.1 The Reduced-Form Level VAR

The level VAR version of the VECM in (1.10) proves useful whenever we have to make a statistical judgement, for instance about the lag order, before we have actually determined the cointegrating rank. We leave the cointegrating rank unrestricted in (1.10), that is $\beta = I_k$, and rewrite the model as

$$y_t = \mu_0^* + \mu_1^* t + \delta_1^* d_{1t} + \delta_2^* d_{2t} + \sum_{j=1}^{p} A_j y_{t-j} + \sum_{j=0}^{p-1} \left(\gamma_{1j}^* \Delta d_{1t-j} + \gamma_{2j}^* \Delta d_{2t-j}\right) + u_t. \quad \text{(A1.1)}$$

After some rearranging we get the mapping with the parameters in (1.7), (1.9), and (1.10) as $\mu_0^* = \nu + \Pi\mu_1$, $\mu_1^* = -\Pi\mu_1$, $\delta_i^* = -\Pi\delta_i$, $\gamma_{i0}^* = \delta_i - \delta_i^*$, and $\gamma_{ij}^* = \gamma_{ij}$ for $i = 1, 2$ and $j = 1, \ldots, p-1$. Obviously the linear trend has found its way back into the model. With β being the identity matrix we can no longer maintain Assumption 1.2.

Appendix 1.2 Bootstrapped Standard Errors

All the results in Section 1.4 come with bootstrapped standard errors. While the method is more general and applies to error bands for impulse responses and so on, we show it with the help of the contemporaneous impact matrix B. We derive the covariance matrix of B as

$$\text{vec}(\hat{\Sigma}_{\mathsf{B}}) = N^{-1} \sum_{n=1}^{N} \left(\text{vec}(\hat{\mathsf{B}}_n) - \text{vec}(\hat{\mathsf{B}})\right)^2, \quad \text{(A1.2)}$$

in which N is the number of bootstrap replications and $\hat{\mathsf{B}}_n$ is the estimate of the contemporaneous impact effect from the n-th replications. Using the estimate $\hat{\mathsf{B}}$ instead of the mean value of all $\hat{\mathsf{B}}_n$ $(n = 1, \ldots, N)$ in the bootstrap, automatically accounts for the stochastic nature of the long-run constraint (see Section 1.2, Brüggemann 2006, Vlaar 2004).

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Chapter 2

Flexible Regime-Switching Projections to Estimate the Dynamic Effects of a Government Spending Stimulus

I use a novel way to assess the impact of a government spending stimulus on U.S. activity in the postwar period. The novelty lies in the combination of Jordà's (2005) flexible projections with regime switches between recessions and expansions. This combined approach has numerous advantages: it captures asymmetries over the business cycle; it can approximate other important smooth nonlinearities in the DGP; it is more robust to misspecification; and estimation can be simply done by least squares. I find a stimulus to be considerably more effective in recessions with a prolonged period of high spending, steadily increasing output, surging federal debts, and well working multiplier effect which, over time, drive debt levels back to trend. During expansions, or in a symmetric model without regime switches, there is only a short lived positive effect on output, too short for the multiplier to kick in. Constraint in its capacity to increase taxes the government systematically cuts spending below trend to control the level of federal debts. (JEL: E62, H30, H50, C32, C53)

Keywords: asymmetric effects of fiscal policy, spending reversals, local projections, regime-switching with smooth transition

2.1 Introduction

The biblical story of Joseph and the Pharaoh was, perhaps, the first documented example of a successful economic stabilization plan. When Joseph tells the Pharaoh to expect seven years of plenty followed by seven lean years, it was the Pharaoh's proper grain management that helped to alleviate the woes of the famine. As the world economy tiptoes back from the 2009 global recession, issues about the usefulness of such stabilization or stimulation measures are again at the fore. But how effective should a government spending stimulus be expected to be over the course of the business cycle and how will it affect government spending in the future?

Most of the empirical research on postwar-U.S. data, however, focuses on issues related to whether consumption will increase or decrease after a stimulus. The two extremes of a continuum of approaches to address this question theoretically, the entirely Walrasian real-business-cycle models and the traditional Keynesian models, while consistent about the qualitative response of output, differ exactly with respect to the behavior of consumption. And as always, the ingenuity of econometricians has generated results on both sides of the question. The ongoing debate culminates in the recent empirical studies of **?** and Perotti (2007). While Ramey finds evidence in favor of real-business-cycle models, that is consumption decreases in response to a stimulus, Perotti's evidence suggests that the transmission is in the Keynesian tradition with positive effects on consumption.[1]

Although different in their conclusions and identification methods, these papers have in common the use of inherently linear and iterative vector autoregressive (VAR) techniques to derive impulse response functions. The linear and iterative nature has numerous drawbacks: one cannot assess the effectiveness of a stimulus at various stages of the business cycle, most importantly the size of the spending multiplier in recessions; other nonlinearities in the underlying data generating process (DGP) can possibly bias the estimator; and misspecification of the DGP will be multiplied over the response horizon. There are papers dealing with either of these issues in different contexts but there is no empirical research trying to tackle them in a unified framework. Filling that gap is what

[1] Other empirical studies, addressing more or less the same question, are Ramey and Shapiro (1998), Burnside, Eichenbaum and Fisher (2004) and Cavallo (2005)—supporting Ramey's results; and Blanchard and Perotti (2002), Mountford and Uhlig (2009), Caldara and Kamps (2008), and Galí, López-Salido and Vallés (2007)—supporting Perotti's results.

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I do in this paper.

To this end, I modify and combine two strands of research. The first ingredient is the *local projection* method of Jordà (2005). The method exploits the efficiency of VARs for one-step ahead forecasts (even if the model may be misspecified, see Stock and Watson 1999) and instead of iterating these forecasts forward we simply estimate a separate VAR for each impulse response horizon. As such, impulse responses by local projections are relatively robust to misspecifications. Moreover, the whole method is quite *flexible* as one can easily increase the fit of each projection by using a smooth nonlinear approximation—a Taylor series expansion—to the unknown DGP. The second ingredient, as in Auerbach and Gorodnichenko (2010), constitutes a *regime-switching* VAR model where a business cycle indicator assigns weights to each observation or, say, probabilities of being in either a recession or expansion through a logistic transition function. I call the combined method flexible regime-switching projections.

To identify a government spending stimulus I take the method of Blanchard and Perotti (2002), and Perotti (2007) as the point of departure. Decision and implementation lags in the political process, which take presumably longer than a quarter, imply little or no discretionary response of government spending to unexpected events. Therefore, a stimulus can be disentangled from the residuals of the first flexible projection (essentially the usual VAR) by means of a Choleski decomposition with government spending ordered first. Implementation lags, however, may obscure the identification and the disentangled stimuli might in fact be a mix of anticipated and unanticipated changes: the critique of Ramey (2011). One way to handle this problem and to get "truly" unanticipated stimuli is to use a proxy for future government spending. One such proxy is the expected discounted value of military expenditures, a series developed by Ramey (2009).[2]

Two empirical results stand out: (1) during expansions, or in a symmetric model without regime switches, the government typically reduces spending below trend after a stimulus, and (2) the stimulus is considerably more effective in recessions. While both findings square well with political economy arguments, the first result was mostly overlooked in the empirical and theoretical literature. In a recent paper, Corsetti, Meier and Müller

[2] This way to solve, or at least mitigate, the anticipation problem was pointed out by Jordi Galí in his NBER discussion of an earlier version of Ramey (2011); see also Zubairy (2009).

(2009) highlight these medium-term spending dynamics—dubbed as *spending reversal*—in a standard new-Keynesian model with a debt-sensitive fiscal policy rule. The problem lies more in the empirical justification of this quite intuitive theoretical result. Using quarterly postwar-U.S. data, the results of linear and iterative VAR techniques show little, if any, tendency toward a spending reversal,[3] nor is the reversal a spurious result of the flexible projections. The projections nest linearity and, as shown in the Monte Carlo experiment of Jordà (2005), they in fact detect linearity if present. The reason for not finding a spending reversal with linear and iterative VAR techniques can be found elsewhere. Except until recently the use of fiscal policy in the U.S. as a stabilization device has gradually vanished (see, e.g., Solow 2005). This gradual change (i.e. smooth nonlinearity), together with the Great Moderation, may lead to biased estimators in linear models.

The spending reversal is not characteristic for recessions, however, at least over a horizon of three years. The stimulus, then, sets in motion a steady increase in output and consumption with a cumulative multiplier effect on output of approximately two dollars. This multiplier effect is considerably higher than the modest effect—around one in value—I estimate in expansions or which we typically find in papers in the traditional linear and iterative fashion. With spending persistently above trend, federal debt levels initially surge and reach a peak that is about three times as high as the initial one-dollar spending stimulus. Then, after a year, the multiplier effect kicks in and federal debt levels revert to trend. These debt dynamics, in a way, support the view of the current U.S. administration that without spending driven growth now, future debt levels might be even higher. Finally, the Fed stands ready and fosters the stimulus by lowering the federal funds rate.

2.2 The Modeling Cycle

To lay out the econometric methodology as plain as possible, I explain the estimation and inference of impulse responses by flexible projections first in its symmetric version before I elaborate on the regime-switching mechanism. This modeling cycle has emerged naturally as I got more and more involved into the whole matter of characterizing the effects of a government spending stimulus. An earlier version of the paper ignored asym-

[3] A good reference is the large-scale comparative study of Caldara and Kamps (2008) on VAR-based approaches to estimate the effects of fiscal stimuli.

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metries altogether; an ignorance which was especially unsatisfactory in light of the massive stimulus programs that were launched during the 2009 global recession. The impulse response functions capture history, the average values of output and so forth following a stimulus. So, naturally, if one looks just on these average values in a symmetric framework, it is hard to assert the much advocated spending multiplier. Nothing can be said about the effectiveness of stimulus programs. In order to overcome this shortcoming, Section 2.2.5 introduces a special regime-switching mechanism between recessionary and expansionary periods.

2.2.1 Impulse Responses by Flexible Projections

The prevalent way to compute structural impulse response functions is to take the difference between two different realizations of the best (linear) mean-squared estimator $E_t(y_{t+s}|\cdot)$. The $\{y_t\}_{t=1}^{T}$ sequence is identical up to y_{t-1}, but one realization assumes that there is an innovation at time t, while the other realization evolves along its regular innovation-free path. Following Koop, Pesaran and Potter (1996) we can write

$$
\begin{aligned}
IR(t,s,w_i) = {} & E_t(y_{t+s}|u_t = w_i, u_{t+1} = 0, \ldots, u_{t+s} = 0; y_{t-1}, \ldots, y_{t-p}) \\
& - E_t(y_{t+s}|u_t = 0, u_{t+1} = 0, \ldots, u_{t+s} = 0; y_{t-1}, \ldots, y_{t-p}) \quad (2.1)
\end{aligned}
$$

for $s = 0, 1, 2, \ldots, h$. y_t and u_t are the k-dimensional vectors of observations and reduced-form residuals and w_i is the $k \times 1$ vector containing the experimental innovations.

Jordà (2005) provides a way to apply (2.1) which is different from just iterating a VAR model forward. Consider projecting y_{t+s} onto the nonlinear space generated by $f_s(y_{t-1}, \ldots, y_{t-p})$. Using a Taylor series expansion we can write $f_s(\cdot)$ as

$$
f_s(y_{t-1}, \ldots, y_{t-p}) = \sum_{j=0}^{\infty} \left\{ \frac{1}{j!} \left[\sum_{i=1}^{p} (y_{t-i} - a_i) \frac{\partial}{\partial y'_{t-i}} \right]^j f_s(y'_{t-1}, \ldots, y'_{t-p}) \right\}_{y'_{t-1}=a_1, \ldots, y'_{t-p}=a_p} . \quad (2.2)
$$

This expression looks slightly intimidating but if we impose a few restrictions it boils down to a tractable, yet flexible, approximation which we can easily estimate by least squares.

As in Jordà (2005) I restrict nonlinearities to y_{t-1}, the terms involved in the impulse response functions (this convention will become clear momentarily). I also do not allow for cross-product terms and restrict y_{t-1} to be cubed at most.[4] With these restrictions (2.2) simplifies to

$$y_{t+s} = \nu_s + B_{s+1} y_{t-1} + Q_{s+1} y_{t-1}^2 + C_{s+1} y_{t-1}^3 + \sum_{i=2}^{p} B_{i,s+1} y_{t-i} + u_{s,t+s} \tag{2.3}$$

for $s = 0, 1, 2, \ldots, h-1$. The collection of the h regressions are the flexible local projections. Without the squared and cubed terms the projections are local linear.

Given definition (2.1) we can now derive the impulse responses from the difference of the two realizations of the s-step ahead forecasts as

$$\begin{aligned} \widehat{IR}(t, s, w_i) &= \left\{ \hat{B}_s (y_{t-1} + w_i) + \hat{Q}_s (y_{t-1} + w_i)^2 + \hat{C}_s (y_{t-1} + w_i)^3 \right\} \\ &- \left\{ \hat{B}_s y_{t-1} + \hat{Q}_s y_{t-1}^2 + \hat{C}_s y_{t-1}^3 \right\} \\ &= \hat{B}_s w_i + \hat{Q}_s (2 y_{t-1} w_i + w_i^2) + \hat{C}_s (3 y_{t-1}^2 w_i + 3 y_{t-1} w_i^2 + w_i^3) \end{aligned} \tag{2.4}$$

for $s = 0,\ 1,\ 2,\ \ldots,\ h$ and with $B_0 = I_k$, $Q_0 = 0_k$, and $C_0 = 0_k$. Obviously, the responses will differ over the possible range of experimental values for y_{t-1}. In order to have impulse responses comparable to the ones we get by standard linear and iterated methods or by projections without the squared and cubed terms we need to evaluate (2.4) at the sample mean of y_{t-1}.

The impulse responses are collections of local approximations which are optimally designed for one-period ahead forecasts. Flexible projections are therefore robust to misspecification of the dynamic structure up to a certain extent. A benefit which, however, does not come without a cost: if we can actually identify the "true" data generating process, estimating impulse responses by iterating this process forward in time will be more efficient. First, with the flexible projections we lose the entire impulse response horizon on observations and, second, we impose less structure on the estimation problem. As Jordà (2005) shows in a Monte Carlo experiment the loss of efficiency is practically negligible.

[4] Allowing for a more flexible specification will consume a considerable amount of degree of freedoms and, as Jordà (2005) points out, the gain of doing so is therefore small.

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The same Monte Carlo experiment confirms the consistency and underlines the benefits of the flexible projection estimator. As a results, if the VAR is misspecified, flexible projections are more accurate at capturing the specific patterns of the "true" dynamic structure. Moreover, if the data generating process is linear the flexible projections will virtually lie on top of the true impulse responses.

Projections, in general, can also help on another front. Lin and Tsay (1996) demonstrate that the projections, or direct forecasts in their terminus, perform better in the presence of unknown unit roots and cointegration than iterating on a vector error correction model (VECM) even though we ignore unit roots and cointegration in the projections altogether. In a VECM the uncertainty about the order of integration and cointegration rank introduces another potential source of misspecification. In addition, Marcellino, Stock and Watson (2006) describe situations, like low-order autoregressive processes or when a series has a large moving-average root, where projecting locally has some advantages.

Flexible projections are, however, not a universal cure. Besides the efficiency issue, Kilian and Kim (2009) point out the lack of knowledge about the extent of small-sample biases. We know little about these unwelcome effects for the properties of the flexible projection estimator, at least compared with the well-known small-sample biases in VARs (see Pope 1990). So all in all, there is no definite answer to the question whether one should back all his or her horses on flexible projections or if one is well advised to stick to standard VAR methods. As usual the question is ultimately an empirical one. The important issue for this paper is to look at the traditional way to estimate the effects of changes in government spending another way.

The next three subsections focus on the ingredients to compute and evaluate the impulse response functions in (2.4): the estimation of the reduced-form parameters; the identification of the innovation vector w_i; and statistical inference.

2.2.2 The Reduced-Form Estimator with Parameter Restrictions

Besides the advantages (and disadvantages) just discussed, flexible projections can be easily implemented and estimated by least squares. As the squared and cubed terms may play an important role in shaping the impulse responses and a large number of parameters will imply imprecise estimates, I allow for zero restrictions that lead to a minimum value

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of a prespecified criterion at each impulse response horizon. The setup of the estimator is as follows.

DEFINITION 2.1: *Let us consider a k-dimensional sample* $\{y_t = y_{1t}, \ldots, y_{kt}\}_{t=1}^{T}$ *of endogenous variables augmented by* k^* *exogenous variables,* $\{y_t^*\}_{t=1}^{T}$*. Taking into account the order (p) of the autoregressive process and an impulse response horizon (h) the adjusted length of the sample for the flexible projections is* $\tilde{T} = T - h - p + 1$*. Then,*

$$Y_j^m = \left\{ \left(y_t - \frac{1}{\tilde{T}} \sum_{i=p+j}^{T-h+j} y_i \right)^m \right\}_{t=p+j}^{T-h+j} \qquad : j = -p+1, \ldots, -1, 0, 1, \ldots, h \quad m = 1, 2, 3$$

$$Y_j^* = \{y_t^*\}_{t=p+j}^{T-h+j} \qquad : j = -p+1, \ldots, -1, 0, 1$$

$$Y = (Y_0 : Y_1 : \cdots : Y_h) \qquad : \tilde{T} \times k(h+1)$$

$$X = (Y_0^1 : Y_0^2 : Y_0^3) \qquad : \tilde{T} \times 3k$$

$$Z = (1_{\tilde{T}} : Y_{-1}^1 : \cdots : Y_{-p+1}^1 : Y_1^* : Y_0^* : \cdots : Y_{-p+1}^*) \qquad : \tilde{T} \times ((p-1)k + 1 + (p+1)k^*)$$

$$M = I_{\tilde{T}} - Z(Z'Z)^{-1}Z' \qquad : \tilde{T} \times \tilde{T}$$

$$\hat{U} = (0 : \hat{U}_0 : \cdots : \hat{U}_{h-1}) \qquad : \tilde{T} \times k(h+1)$$

$$\hat{\Theta}_{0:h} = \begin{bmatrix} I_k & 0_k & 0_k \\ B_1 & Q_1 & C_1 \\ \vdots & \vdots & \vdots \\ B_h & Q_h & C_h \end{bmatrix} \qquad : k(h+1) \times 3k$$

in which Y *contains all the regressands;* X *includes the linear, squared and cubed first lag regressors;* Z *captures all the other regressors with* $1_{\tilde{T}}$ *denoting a column vector of ones with length* $\tilde{T}$ *meant for the constant term;* M *is the associated projection matrix of* Z*; and* $\hat{U}$ *subsumes the residuals from the h projections.* $\hat{\Theta}_{0:h}$ *collects the linear, squared and cubed reduced-form impulse response parameters corresponding to the k variables; and let the matrix* $\hat{\Xi}_{0:h}$ *collect all the other parameters. I express each series in its demeaned version which leads automatically to impulse responses evaluated at the sample mean, specifically*

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$y_{t-1} = 0$ *in (2.4).*

Now the reduced-form estimator of the local projections with parameter restrictions can be obtained by generalized least squares as

$$\hat{\Gamma}_s = \left\{ R_s' \left[\Sigma_s^{-1} \otimes \begin{pmatrix} X'X : X'Z \\ Z'X : Z'Z \end{pmatrix} \right] R_s \right\}^{-1} R_s' \left[\Sigma_s^{-1} \otimes (X:Z)' \right] \text{vec}(Y_s) \tag{2.5}$$

and

$$\text{vec}\left(\hat{\Theta}_s : \hat{\Xi}_s\right) = R_s \hat{\Gamma}_s \tag{2.6}$$

for $s = 1, 2, \ldots, h$. As usual the operator $\text{vec}(\cdot)$ transforms a matrix into a vector by stacking the columns and $\otimes$ denotes the Kronecker product. $\hat{\Theta}_s$ refers to the corresponding row in $\hat{\Theta}_{0:h}$, $\hat{\Gamma}_s$ is the $m \times 1$ vector of non-zero parameters we want to estimate, and R_s is the $n \times m$ selector matrix. So m is the number of non-zero parameters that ultimately remain in the model for a specific horizon, s, and $n = k(1+(p+2)k+(p+1)k^*)$ is the total number of parameters. To pin down R_s, I use a top-down strategy (see Lütkepohl 2005, Chap. 5.2) and start from an unrestricted model with $p = 4$ lags. The choice of four lags seems to be common practice in the empirical fiscal policy literature and that is why I adopt it here.[5] I then estimate each of the equations in the model separately and search over the set of possible zero restrictions for individual coefficients—excluding the constants—until I reach the minimum of Akaike's (1974) criterion. The corresponding residuals of the restricted model and the covariance matrix from the one-step ahead projections which I will use for identification are

$$\hat{U}_s = Y_s - (X:Z)(\hat{\Theta}_s : \hat{\Xi}_s)' \quad \text{and} \quad \hat{\Sigma} = \hat{U}_0' \hat{U}_0 \tilde{T}^{-1}. \tag{2.7}$$

To make generalized least squared operational (i.e. feasible) we need a consistent estimator for Σ_s in (2.5). Lütkepohl (2005) shows that we can use the covariance matrix

[5] The reason for overruling information criteria in the empirical literature and mechanically opting for four lags goes back to Blanchard and Perotti (2002). In their paper the goal was to capture seasonal patterns in the collection of taxes by allowing for quarter dependence, hence, the four lags. Although this seasonality is now typically ignored, Blanchard and Perotti's (2002) way to pick the number of lags has remained.

of the unrestricted model,

$$\hat{\Sigma}_s = \left[Y_s' M \left(I_{\tilde{T}} - MX(X'MX)^{-1}X'M\right) MY_s\right] \tilde{T}^{-1}. \tag{2.8}$$

Propositions 2 and 4 in Jordà (2009) provide the asymptotic distribution of the impulse responses $\hat{\Theta}_{0:h}$. In both stationary and non-stationary systems the deviations of the estimated impulse responses from their "true" values go in distribution to a Normal with a mean of zero and a covariance of Ω. A consistent estimator for this impulse response covariance matrix, Ω, can be found in Proposition 2 of Jordà and Kozicki (2009). Specifically,

$$\hat{\Omega} = (X'MX)^{-1} \otimes \left[Y'M \left(I_{\tilde{T}} - MX(X'MX)^{-1}X'M\right) MY\right] \tilde{T}^{-1}. \tag{2.9}$$

Throughout the paper, the $3k^2(h+1)$ square matrix $\hat{\Omega}$ will be the basis to compute standard error bands and to formally draw inference on the impulse responses. I deliberately ignore here the previously imposed restrictions. Taking them into account would imply to compute the numerous $(h+1) \times (h+1)$ blocks in $\hat{\Omega}$ one at the time. In every case, by ignoring the restrictions I inflate the whole covariance matrix and, therefore, $\hat{\Omega}$ presents an upper bound asymptotically for the restricted estimator (see Lütkepohl 2005, Chap. 5.2). Test statistics will be more conservative (i.e. less likely to reject a null hypothesis); not an entirely unwanted side effect since it controls, although only rudimentary, for the uncertainty with respect to the validity of the restrictions.

2.2.3 Short-Run Identification

At the heart of the VAR approach lies the timing assumption on decision and implementation lags: there is no automatic or discretionary response of government spending to output and other shocks within the quarter. Hence, a stimulus can be identified by means of a Choleski decomposition in which government spending comes first in the list of variables. If one, like me, is interested only in the response to a stimulus and if there is no immediate feedback from other variables on government spending (see, e.g., Blanchard and Perotti 2002), solving a recursive system is all that is needed. The ordering of the

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variables other than government spending is immaterial.[6]

DEFINITION 2.2: *Let W be the lower triangular matrix obtained by a Choleski decomposition of the covariance matrix of the one-step ahead projections in (2.7), i.e. $\hat{\Sigma} = \hat{W}\hat{W}'$, and let w_{ij} be the elements of W. Now define the squared and cubed versions of W,*

$$W^m = \{w_{ij}^m\}_{i,j=1,2,\ldots,k} \qquad : \; k \times k, \; m = 2, 3,$$

as an element-wise matrix operation.

The structural innovations are then given by $\{\hat{\varepsilon}_t\}_{p+1}^{T-h+1} = \hat{U}_0 \hat{W}'^{-1}$ and the impulse responses follow from (2.4) and the definition of $\hat{\Theta}_{0:h}$. Specifically, $\hat{\Phi}_{0:h} = \hat{\Theta}_{0:h}(\hat{W}' : \hat{W}^{2\prime} : \hat{W}^{3\prime})'$. The first column of the $\hat{W}$ matrix, say $\hat{w}_1$, contains the relevant impact effects of a stimulus. Because a structural innovation has unit variance, $\hat{W}^{-1}\hat{\Sigma}\hat{W}'^{-1} = I_k$, a one-unit innovation has the size of one-standard deviation.

Because $\hat{\Phi}_{0:h}$ contains the impulse responses to all k possible shocks in the system, we need a procedure to read out the responses to the first shock (i.e. the stimulus). More generally, let us define the impulse response of variable i to a shock in variable j by the vector $\hat{\phi}_{ij} \in \hat{\Phi}_{0:h}$ and a selector matrix $S_{ij} = e_j' \otimes (I_{h+1} \otimes e_i)'$ in which e_q is the q-th column of I_k for $m = i, j$ (see Jordà 2009). Then,

$$\hat{\phi}_{ij} = S_{ij}\text{vec}(\hat{\Phi}_{0:h}) \tag{2.10}$$

for $i, j = 1, \ldots, k$ in general and for the impulse responses to a stimulus $j = 1$, $i = 1, \ldots, k$ in particular.

2.2.4 Standard Error Bands and Wald Statistics

When using short-run identification assumption through a Choleski decomposition we can obtain the corresponding covariance matrix, Ω^*, of the structural impulse responses $\hat{\Phi}_{0:h}$ as

$$\hat{\Omega}^* = \frac{\partial \text{vec}(\hat{\Phi}_{0:h})}{\partial \text{vec}(\hat{\Theta}_{0:h})} \hat{\Omega} \frac{\partial \text{vec}(\hat{\Phi}_{0:h})}{\partial \text{vec}(\hat{\Theta}_{0:h})'} + \frac{\partial \text{vec}(\hat{\Phi}_{0:h})}{\partial \text{vec}(\hat{W})} \frac{\partial \text{vec}(\hat{W})}{\partial \text{vech}(\hat{\Sigma})} \hat{\Omega}_{\Sigma} \frac{\partial \text{vec}(\hat{W})}{\partial \text{vech}(\hat{\Sigma})'} \frac{\partial \text{vec}(\hat{\Phi}(0,h))}{\partial \text{vec}(\hat{W})'}, \tag{2.11}$$

[6] See, for instance, Perotti (2007) for the same argument. Playing around with different orderings did not produce any obvious differences in the contemporaneous effects.

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in which the first additive component reflects the uncertainty associated with the reduced-form impulse response parameters, $\hat{\Theta}_{0:h}$, and the second component incorporates the estimation uncertainty involved in the identification of $\hat{W}$.

The above expression looks a bit intimidating but computing the various subcomponents turns out to be rather straightforward. Jordà (2009) summarizes the results for the linear projections, the projections without squared and cubed terms. I provide the extension to accommodate those extra terms. Specifically, from the link between the structural and reduced-form impulse response parameters, $\hat{\Phi}_{0:h} = \hat{\Theta}_{0:h}(\hat{W}' : \hat{W}'^2 : \hat{W}'^3)'$, it follows

$$\frac{\partial \text{vec}(\hat{\Phi}_{0:h})}{\partial \text{vec}(\hat{\Theta}_{0:h})} = (\hat{W}' : \hat{W}^{2\prime} : \hat{W}^{3\prime}) \otimes I_{k(h+1)},$$

$$\frac{\partial \text{vec}(\hat{\Phi}_{0:h})}{\partial \text{vec}(\hat{W})} = I_k \otimes \left(\hat{\Theta}_{0:h}(I_k : 2\hat{W}' : 3\hat{W}^{2\prime})'\right).$$

The other results derive from Proposition 3.6 and Remark 4 in Lütkepohl (2005),

$$\frac{\partial \text{vec}(\hat{W})}{\partial \text{vech}(\hat{\Sigma}_u)} = L_k' \left(L_k(I_{k^2} + K_{kk})(\hat{W} \otimes I_k)L_k'\right)^{-1},$$

$$\hat{\Omega}_\Sigma = 2D_k^+(\hat{\Sigma} \otimes \hat{\Sigma})D_k^{+\prime}.$$

in which the vec(·) is defined as before, i.e. a column-stacking operator, and vech(·) is for symmetric matrices and stacks the elements on and below the main diagonal only. The elimination matrix, L_k, and the duplication matrix, D_k, link these two operators. For any $k \times k$ matrix A we have $\text{vech}(A) = L_k\text{vec}(A)$ and $\text{vec}(A) = D_k\text{vech}(A)$. Further, $D_k^+ = (D_k'D_k)^{-1}D_k'$ and thus $D_k^+\text{vec}(A) = \text{vech}(A)$. The commutation matrix, K_{kk}, links the vec(·) operator itself in the form $\text{vec}(A') = K_{kk}\text{vec}(A)$.

As in the reduced-form case the structural impulse responses have, at least asymptotically, the property

$$\sqrt{\tilde{T}}\left(\text{vec}(\hat{\Phi}_{0:h}) - \text{vec}(\Phi_{0:h})\right) \rightsquigarrow N(0, \hat{\Omega}^*), \tag{2.12}$$

which will be particularly useful to construct standard error bands and Wald statistics. From the huge $k^2(h+1)$ square matrix $\hat{\Omega}^*$, which gathers all covariance structures across the structural impulse responses, we can read out the actual covariance of the response of variable i to a shock j with the help of the selector matrix S_{ij} defined in (2.10). Then,

$$\hat{\Omega}^*_{ij} = S_{ij}\hat{\Omega}^* S'_{ij} \tag{2.13}$$

for $i, j = 1, \ldots, k$ in general and for the responses to a stimulus $i = 1$, $j = 1, \ldots, k$ in particular.

We can now construct the error bands in the usual way as

$$\hat{\phi}_{ij} \pm z_{\alpha/2}\sqrt{\text{diag}(\hat{\Omega}^*_{ij})} \tag{2.14}$$

in which the diag($\cdot$) operator transforms a square matrix into a column vector containing the entries on the main diagonal, and $z_{\alpha/2}$ denotes the appropriate critical value of a standard normal random variable at the $100(1-\alpha)$ confidence level.

These error bands are, however, quite conservative as the presence of autocorrelation between the impulse response parameters at horizon s with $s-1$ and so forth, carries forward the variability of the estimates from one horizon to the next. Jordà (2009) provides an in depth discussion of this autocorrelation issue. What is important here from his work is the equivalence of standard Wald statistics, λ^W_{ij}, of autocorrelated impulse response parameters with the sum of individual t-statistics of which each of them is conditional on the past response path:

$$\lambda^W_{ij} = \sum_{s=1}^{h+1} t^2_{ij}(s|s-1, \ldots, 1), \qquad i, j = 1, \ldots, k. \tag{2.15}$$

Wald statistics implicitly control for the autocorrelation across the parameters and, therefore, give a better sense about the statistical significance of impulse responses. The exact expressions for the statistic of, say, the null of *cumulative* significance up to a specific horizon, s, is given by

$$(R^W_s\hat{\phi}_{ij})'(R^W_s\hat{\Omega}^*_{ij}R^{W\prime}_s)^{-1}(R^W_s\hat{\phi}_{ij}) \rightsquigarrow \chi^2_{(1)}, \tag{2.16}$$

with $R^W_s = (1_s : 0_{h-s+1})$ being a zero-one row vector of length $h+1$. I emphasize the cumulative version of the test, as opposed to the more common test of joint significance, because in the light of a government spending stimulus and its consequences the cumulative effects will be the economically relevant ones. A test for the cumulative equality of two impulse responses i and j to a shock i follows readily as

$$\begin{pmatrix} \hat{\phi}_{ii} \\ \hat{\phi}_{ij} \end{pmatrix}' R_s^{W\prime} \left[R_s^W \begin{pmatrix} \Omega^*_{ii} & \Omega^*_{ij} \\ \Omega^*_{ji} & \Omega^*_{jj} \end{pmatrix} R_s^{W\prime} \right] R_s^W \begin{pmatrix} \hat{\phi}_{ii} \\ \hat{\phi}_{ij} \end{pmatrix} \rightsquigarrow \chi^2_{(1)}, \tag{2.17}$$

in which $R_s^W = (-1_s : 0_{h-s+1} : \psi 1_s : 0_{h-s+1})$ is a zero-one row vector of length $2(h+1)$ and ψ is a proper scale factor.

2.2.5 Adding Asymmetries: Impulse Responses and Regime-Switching

The idea of impulse response analysis is old, as old as Quesnay writing on interdependent systems (François Quesnay, *Tableau Économique*, 1759). Despite that long history, and even more so to the extent governments use fiscal policy in recessions to stimulate demand, both the theoretical and empirical literature remained remarkably silent on how the effectiveness of such a stimulation might vary over the business cycle. One notable exception is Auerbach and Gorodnichenko (2010). They embed the structural VAR method of Blanchard and Perotti (2002) to characterize the effects of a stimulus into a regime-switching VAR where the transition across recessions and expansions is smooth. Implementing the switching mechanism into the flexible projections we then have

$$\begin{aligned} y_{t+s} = {} & (B^E_{s+1} y_{t-1} + Q^E_{s+1} y^2_{t-1} + C^E_{s+1} y^3_{t-1} + \cdots + u_{s,t+s})(1 - F(z_{t-1})) \\ & + (B^R_{s+1} y_{t-1} + Q^R_{s+1} y^2_{t-1} + C^R_{s+1} y^3_{t-1} + \cdots + u_{s,t+s}) F(z_{t-1}), \end{aligned} \tag{2.18}$$

$$F(z_t) = \frac{\exp(-\gamma z_t)}{1 + \exp(-\gamma z_t)}, \quad \gamma > 0,\ E(z_t) = 0,\ \mathrm{Var}(z_t) = 1, \tag{2.19}$$

for $s = 0, 1, \ldots, h-1$. $\{z_t\}_{t=1}^T$ is a standardized business cycle index, γ controls the smoothness of the transition across regimes, $u_{s,t+s}$ are the reduced-form residuals from the estimation stage, and $u^r_{0,t}$ with $r = \{R, E\}$ denote the individual residuals in recessions and expansions. The logistic transition function (2.19) assigns weights (i.e. probabilities) to each observation conditional on the state of the business cycle. Because of the weighing we always exploit the variation in the entire sample, independent of which regime we are going to estimate. A key advantage which is in stark contrast to methods where one splits the sample in two parts. Especially in recessions, with only a handful observations, sample splitting is problematic: estimates will lack stability and precision. But, then, using observations of one regime to estimate in part the dynamics of the other regime introduces a bias toward not finding any differences across regimes. Any identified differences between regimes will, therefore, be on the conservative side.

Besides the estimation of the regime-switching model (2.18), choosing a proper business cycle index, z_t, and calibrating the smoothness parameter, γ, are the main issues one has to deal with in one way or the other.

Economic theory lacks a precise guideline for econometricians on how to choose a business cycle index. At any rate, what one requires is a good match with the National Bureau of Economic Research (NBER) reference dates for U.S. recessions and expansions. The NBER researchers Burns and Mitchell, in their 1946 seminal work, found that U.S. business cycles typically last between six and 32 quarters. I adopt these limits in the approximate band-pass filter of Baxter and King (1999) and applied to the growth rate of output it yields a series where the troughs match the NBER recession dates well; as can be seen in Figure 2.1. Because the band-pass filter explicitly allows to specify the periodicity of the business cycle, I prefer it over Auerbach and Gorodnichenko's (2010) less flexible seven quarter centered moving-average filter.

One can estimate all the parameters in (2.18) jointly by conditional maximum likelihood (see, e.g., Teräsvirta 2004, Arits, Galvão and Marcellino 2007). As in Auerbach and Gorodnichenko (2010), I follow a different approach and calibrate the smoothing parameter γ in the transition function (2.19) to match the 20 percent of time the U.S. economy experienced a recession since 1955.[7] Specifically, $\Pr(z_t \leq z^*) = 0.2$ and at the "imaginary" threshold z^* the logistic transition function (2.19) must assign a recession weight, i.e. probability, of $F(z^*) = 0.8$. Under the assumption of a standard normal distributed business cycle index, z_t, we then get $z^* = -0.84$ and $\gamma = 1.65$. Calibrating the smoothing parameter, γ, in advance has one major advantage: given γ, and consequently $F(z_t)$, the regime-switching model (2.18) turns out be linear in parameters and can be estimated by least squares with the following setup.

DEFINITION 2.3: *Let us append to the variables* y_t *and* y_t^* *in Definition 2.1 the stan-*

[7] See the U.S. business cycle reference dates on http://www.nber.org/cycles/cyclesmain.html.

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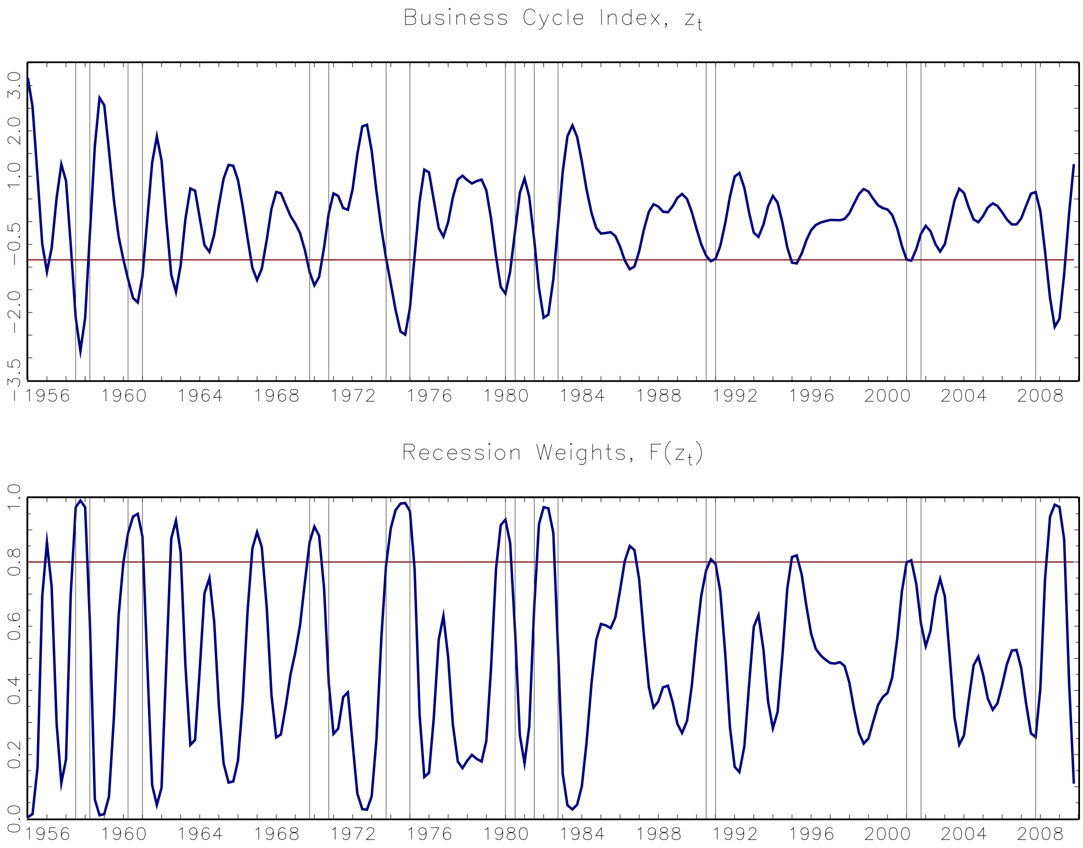

Figure 2.1: Business Cycle Index and Recession Weights

Notes: The business cycle index ,z_t, reflects the periodic fluctuations of the output growth rate between six and 32 quarters; filtered using the band-pass filter of Baxter and King (1999) and standardized. Appendix Appendix 2.1 has the details. Recession weights, $F(z_t)$, computed using the logistic transition function (2.19) with a smoothing parameter of $\gamma = 1.65$. Superimposed are the peaks and troughs of the NBER business cycle dates, and the "imaginary" thresholds.

dardized business cycle index, $\{z_t\}_{t=1}^{T}$, and the binary index, $\{z_t^I\}_{t=1}^{T}$, which takes on the value one if t falls into a NBER recession period and zero otherwise. Further, transform the logistic transition function (2.19) into a $\tilde{T} \times \tilde{T}$ diagonal matrix $F = I_{\tilde{T}} \cdot \{F(z_t)\}_{t=p}^{T-h}$. I keep the focus on defining the variables which characterize recessions; variables for expansions derive straightforwardly, using $1 - F$ instead of F in the following expressions. Then,

$$Y_j = \{y_t\}_{t=p+j}^{T-h+j} \qquad : j = -p+1, \ldots, -1, 0, 1, \ldots, h$$

$$\left(Y_0^R\right)^m = \left\{ \left(y_t - \frac{1}{T^R} \sum_{i=p}^{T-h} z_i^I y_i \right)^m \right\}_{t=p}^{T-h} \qquad : \tilde{T} \times k,\ m = 1, 2, 3$$

$$X^R = F\left(\left(Y_0^R\right)^1 : \left(Y_0^R\right)^2 : \left(Y_0^R\right)^3 \right) \qquad : \tilde{T} \times 3k$$

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$$
\begin{aligned}
Z^R &= F\big(1_{\tilde{T}} : Y_{-1} : \cdots : Y_{-p+1} : \\
&\qquad Y_1^* : Y_0^* : \cdots : Y_{-p+1}^*\big) && : \tilde{T} \times ((p-1)k + 1 + (p+1)k^*) \\
\hat{U}^R &= F\big(0 : \hat{U}_0 : \cdots : \hat{U}_{h-1}\big) && : \tilde{T} \times k(h+1) \\
\hat{\Sigma}^R &= \hat{U}_0' F' F \hat{U}_0 \tilde{T}^{-1} && : k \times k \\
\hat{\Theta}_{0:h}^R &= \begin{bmatrix} I_k & 0_k & 0_k \\ B_1^R & Q_1^R & C_1^R \\ \vdots & \vdots & \vdots \\ B_h^R & Q_h^R & C_h^R \end{bmatrix} && : k(h+1) \times 3k
\end{aligned}
$$

and $X = X^R : X^E$, $Z = Z^R : Z^E$, *and* $\hat{\Theta}_{0:h} = \hat{\Theta}_{0:h}^R : \hat{\Theta}_{0:h}^E$, *in which* $I_{\tilde{T}}$ *is a* $\tilde{T}$*-dimensional identity matrix;* T^R *denotes the number of observations that fall in recessions;* $\bar{Y}^R$ *is the respective mean; and everything else as in Definition 2.1.*

With one exception the estimator of Section 2.2.2 goes through with the same notation (equations (2.5) to (2.8)); identification and inference can be done as in Sections 2.2.3 and 2.2.4 by replacing all the variables with their regime-dependent counterparts. Only the covariance matrix (2.9) of the reduced-form impulse responses has to be modified:

$$
\hat{\Omega}^r = (X^{r\prime} M^r X^r)^{-1} \otimes \left[Y' M \left(I_{\tilde{T}} - MX(X'MX)^{-1}X'M\right) MY\right] \tilde{T}^{-1}, \quad r = \{R, E\}. \tag{2.20}
$$

The feature of the flexible regime-switching projections to estimate each impulse response horizon separately is in contrast to previous applications of non-linear time series models for analyzing changes in the dynamic relationship between macro variables (see, e.g. AGalvão 2006). These applications typically specify only a one-period model and derive forecasts or impulse responses for longer horizons by means of Monte Carlo methods to take into account the nonlinearity of the conditional expectation. In the context of the paper here, "endogenous" regime switches would then bring the responses in recessions and expansions closer together, but Auerbach and Gorodnichenko (2010) find only little tendency toward such a narrowing in their one-period model.

The modeling cycle is now complete. The cycle is simple, yet rigorous, and keeps the analysis strictly in the least squares fashion. The simplicity makes it appealing for

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applied researchers and as a fast-to-get benchmark for other more computational intensive estimation methods.

2.3 Results of the Modeling Cycle

After all this rigor and technicalities one wants finally numbers; estimates not equations and definitions. Figure 2.2 plots the responses to a government spending stimulus under symmetry, Figure 2.3 collects the different responses in recessions and expansions, and Table 2.2 presents the size of the government spending multipliers. Appendix Appendix 2.1 describes the data in detail.

All models cover the time between the first quarter of 1955 and the last quarter of 2009, and consist of six endogenous variables and one exogenous: the logarithms of real per capita government spending, output, nondurable and services consumption, and federal debt held by the public; the average personal income tax rate, the federal funds rate, and as exogenous variable the defense news measure of Ramey (2011). The original estimates of the responses will have the dimension of elasticities for the four logarithmic variables and semi-elasticities for the two rates. To discuss and interpret the responses it is more intuitive to translate the elasticities into derivatives. The response for the logarithmic variables will therefore be on a dollar for dollar basis evaluated at the point of means.

While the responses of spending, output, and consumption are at the center stage, the selection of the other variables follows two criteria. One is parsimony, to avoid estimating a large number of parameters simultaneously and to keep the huge impulse response covariance matrix (2.9) tractable. The other one is to control for effects that would otherwise bias the results. Specifically, ignoring the debt dynamics after a stimulus and the possible feedback effect from debts to spending can lead to such a bias. Favero and Giavazzi (2007) emphasize the importance of this feedback channel. In the same vein, the effects of spending, taxation, and interest rates on output are presumably not independent. Estimating the output effects of one variable, a model must include the others. Finally, Ramey's defense news measure controls for anticipated government spending effects; the measure is based on foreign political events, hence, exogenous in the model. From the day the government starts discussing a stimulus package until it gets approved and pays out, there may lie several months. If it takes more than a quarter the identified spending stimuli will, in fact, be anticipated. Or better say, anticipated and unanticipated effects get mixed up. As our own behavior in general differs to events we know about to something that takes us by surprise, keeping them separated as good as possible is important.[8]

There is another criterion hidden in my selection of variables: the choice of the average personal income tax rate over total tax revenues. Choosing a rate is important for the identification of Section 2.2.3 to go through. Any change in output has an immediate feedback effect on tax revenues. Such a feedback renders the identification problem to be non-recursive; a Choleski decomposition would no longer be applicable. By using a tax rate I assume that the feedback on revenues and the tax base cancel out. Many other papers like Perotti (2007), Ramey (2011), and Burnside, Eichenbaum and Fisher (2004) implicitly make the same assumption when the focus is on the effects of a government spending stimulus and not on changes in taxes. Corsetti, Meier and Müller (2009), and Fisher and Peters (2009) ignore taxes altogether in their empirical models.

2.3.1 Results under Symmetry

Now, under symmetry a one-dollar stimulus does not bring about the much wanted government spending multiplier effect (see Table 2.2 and the thick solid lines in Figure 2.2). Output increases by roughly the same as spending: the multiplier is close to one over the first year before it gradually declines and eventually goes below zero. I define the multiplier here as the ratio of the accumulated output and spending responses. I prefer the definition of a cumulative multiplier, advocated by Woodford (2010), over the usual peak response measure, as it takes into account the influence of future spending levels on the size of the multiplier.

And it is exactly the response of spending that distinguishes my results from most others in the literature. While the flexible projections uncover a strong reversion of spending below trend three years out, linear projections and standard VAR iterations predict a quite persistent response of spending.[9] The persistency is emblematic for the tradi-

[8] See, for instance, Cochrane (1998) for an empirical paper on the different output effects of anticipated and unanticipated monetary policy. Further, the idea of Fisher and Peters (2009) to constructing news series for government spending on the basis of accumulated excess stock returns of large U.S. military contractors is another promising way to control for anticipation effects.

[9] Like Perotti (2007) and Ramey (2011) I use a VAR model with four lags and a linear trend for the impulse responses by standard VAR iterations.

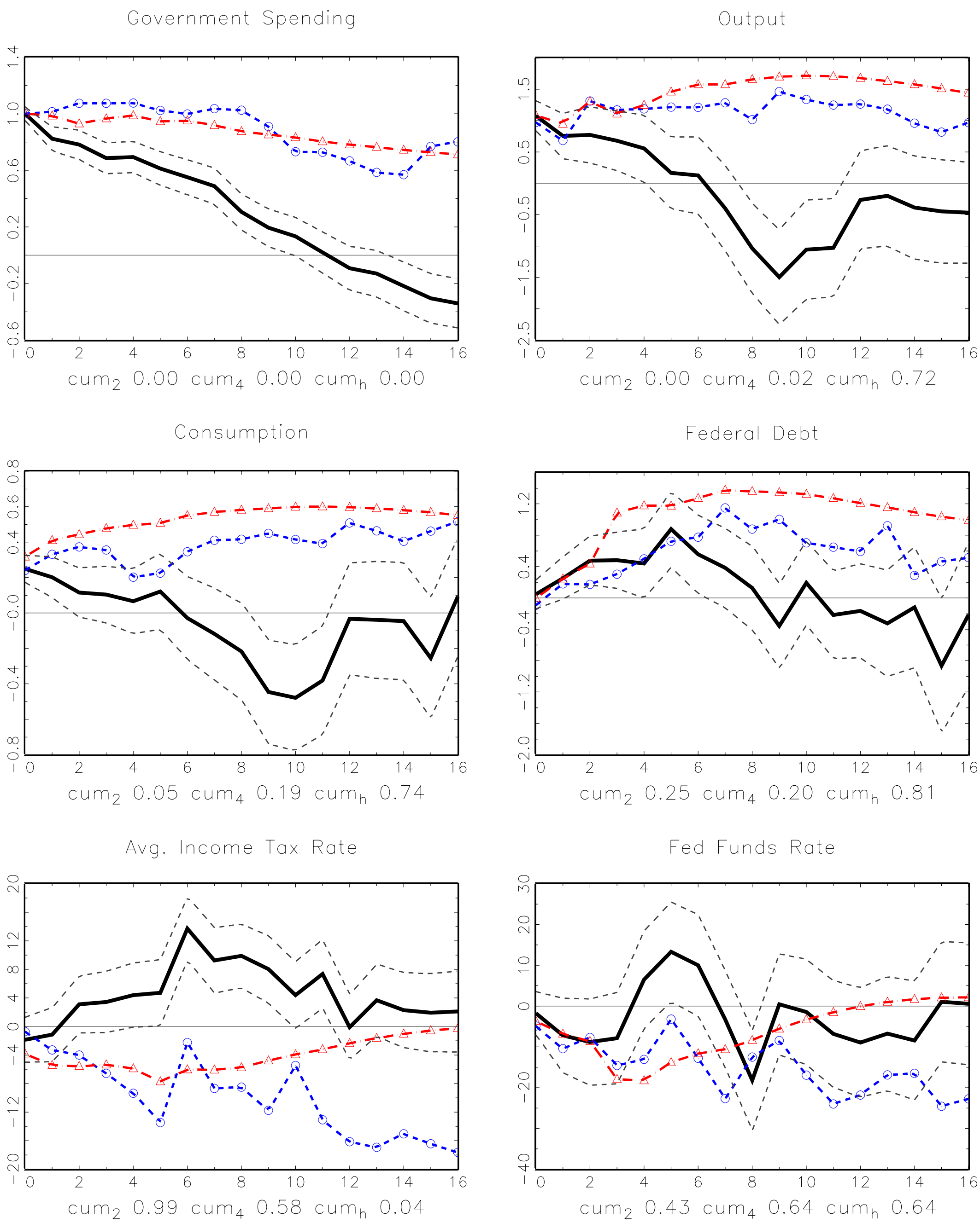

Figure 2.2: Symmetric Impulse Responses to a Government Spending Stimulus

Notes: The thick solid lines are the responses calculated with flexible projections, surrounded by one-standard error bands. The dashed lines with circles depict the linear projections and the dashed-dotted lines with triangles show iterated responses based on a VAR(4). "cum_2", "cum_4", and "cum_h" refer to the p-values of the null for the accumulated responses being equal to zero after two and four quarters, and the entire response horizon. Effects are expressed as dollar for dollar and as change in basis points to a one-percent spending shock (tax and fed funds rate).

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Table 2.1: Model Fit of Flexible and Linear Projections

Horizon s	1	2	3	4	6	8	10	12	16
A. Linear Projections									
AIC	−38.52	−34.95	−32.95	−31.59	−29.41	−28.21	−27.49	−26.97	−25.92
Parameters	81	73	74	71	74	79	73	75	62
B. Flexible Projections									
AIC	−38.61	−35.43	−34.22	−33.37	−32.24	−31.67	−31.30	−30.89	−29.47
Parameters	114	119	121	122	114	127	127	108	107

Notes: Akaike's (1974) information criterion; residuals and number of parameters retrieved from the reduced-form estimator (2.5). I get the zero restrictions—excluding the constants—from the top-down search algorithm, by means of minimizing the Akaike criterion for each horizon $s = 1, 2, \ldots, 16$. For the linear projections, I set all parameters on the squared and cubed terms to zero.

tional VAR-based literature (see, e.g., Caldara and Kamps 2008). A notable exception is Corsetti, Meier and Müller (2009). They find a strong reversion of spending below trend and dub this behavior spending reversal. What makes the difference in their analysis is the use of federal debts as an additional regressor and a relatively short sample size, starting in the first quarter of 1980 only. If I was to trim my sample accordingly, I would arrive at the same conclusion, which then again disappears if I was to omit the debt variable from the model.[10] The feedback from the level of debts to spending, as highlighted by Favero and Giavazzi (2007), has some bite. Reasons for the subsample instability is the Great Moderation on the one hand and, as Solow (2005) remarks, the gradual vanishing of fiscal policy as stabilization device. The smooth nonlinearities the polynomial terms in the flexible projections can capture, seem to be a step in right direction to control for these changes: in terms of model fit the flexible projections, though more variables have to be estimated, outperform the linear ones. See Table 2.1 for the evidence. The lesson is, if we were to take the responses from the linear projections and standard VAR iterations as the true ones, we would get a misleading guide of the effects to a stimulus!

In Figure 2.2 the spending reversal also shows up in the responses of output and consumption. Both increase statistically significant over the first quarters before they dip below trend after about one and a half years. The one-dollar stimulus leads us, as the cogs of the economy, to raise consumption by 0.25 dollars in turn. While consistent with the

[10] Even in the 1955-1980 subsample I find a tendency toward spending reversal. Although the reversal is not complete, the response of spending is much less persistent than in the full sample.

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Table 2.2: Government Spending Multipliers

Horizon	impact	2 qrts	4 qrts	8 qrts	12 qrts	16 qrts	peak
A. Symmetric Case							
Linear projection	0.97	0.96	1.02	1.08	1.24	1.28	1.30 (14)
	(1.00)	(0.69)	(0.83)	(0.73)	(0.40)	(0.20)	(0.27)
Flexible projection	1.07	1.01	0.96	0.45	−0.19	−0.51	1.07 (0)
	(0.74)	(0.93)	(0.92)	(0.20)	(0.01)	(0.00)	(0.74)
B. Flexible Regime-Switching Projections							
Recession	0.34	0.33	1.26	1.65	1.99	—	1.99 (12)
	(0.00)	(0.00)	(0.07)	(0.06)	(0.02)		(0.02)
Expansion	1.27	0.56	−0.44	−2.47	−3.37	—	1.27 (0)
	(0.17)	(0.19)	(0.01)	(0.00)	(0.00)		(0.17)

Notes: I define the government spending multiplier as the ratio of the sum of the output response to the sum of the government spending response up to the respective horizon. The p-values in parentheses underneath indicate whether the multiplier is different from one. Next to the peak response in parentheses is the quarter in which the multiplier reaches its maximum.

traditional Keynesian school of though, the raise does not accord well with the predictions of standard real-business-cycle and new-Keynesian models. We supposedly feel us less wealthy after a stimulus because of the higher tax burden that awaits us. Our rational response, according to these models, would be to cut consumption and to work more. This is the transmission mechanism Ramey (2011) finds with her narrative method based on military events. Her finding crucially depends on the Korean War. Military spending increased by 600 percent during the involvement in Korea and remained at elevated levels thereafter. Using the narrative method and a sample excluding the Korean War, Caldara and Kamps (2008), and Fisher and Peters (2009), among others, cannot find a negative consumption response.

Because of the reversal pattern in output and consumption the p-values, reported below the graphs, lead to the conclusion of statistically non-significant cumulative responses over the entire forecast horizon of four years ($\text{cum}_h = 0.72$ and 0.74). The economically relevant null hypothesis is a range around half a year and one year, not longer. In that range the effectiveness of a stimulus is typically assessed and further policy actions, if any, will follow. At two and four quarters the cumulative output effect is highly significant and at least marginally significant for consumption. A statistically significant output response is not yet what we need to assert if the stimulus was effective and created more money

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than the government pumped into the economy. The relevant null hypothesis for such a question is whether the multiplier exceeds one. Table 2.2 reports, along with the multiplier at various horizons, such test statistics: under symmetry the multiplier at two and four quarters is statistically not different from one.[11]

In Figure 2.2 both federal debts and the average personal income tax rate increase, whereas the federal funds rate meanders around zero and does not show a clear pattern. The level of debts steadily increases, peaks at about one dollar five quarters out, before returning to its old level. Similarly, the personal income tax rate goes up by 14 basis points (i.e. 0.14 percentage points) and reverts to trend thereafter. As we are dealing with a rate here the initial stimulus has now the size of one percent. The cumulative null hypotheses for debts and the income tax rate are statistically insignificant; they do not respond "too" much. Such a response is emblematic for a government that wants to keep debts under control after a stimulus but faces a constraint to raise taxes. What is left to do to control the level of debts is a systematic cutting back of spending below trend: the spending reversal.

In every case, under symmetry the evidence is in line with the view of Solow (2005). According to him fiscal policy in the U.S. was harmless at best over the last 60 years and de facto vanished as stabilization device from the political toolbox.

2.3.2 The Different Effects in Recessionary and Expansionary Periods

At the first glance there is a remarkable difference between the workings of a stimulus in recessions (the solid lines with circles in Figure 2.3) and expansions. Remarkable because the weighing of observations in the flexible regime-switching projections, instead of splitting the sample, introduces a bias toward not finding different responses across the two regimes. The one-standard error bands do not intersect over extended periods and we can safely reject the null hypotheses of cumulative equality for all variables except the tax and fed funds rate. But sill, the rates respond quite differently in the first year and a half.

[11] As the multiplier is the ratio of the accumulated output and spending responses up to a certain horizon s, I can transform the decision problem into a Wald test of the null of cumulative equality, given by (2.17). The scale factor ψ reflects the ratio of means between output and spending; it accounts for the conversion of the response parameters from elasticities into derivatives.

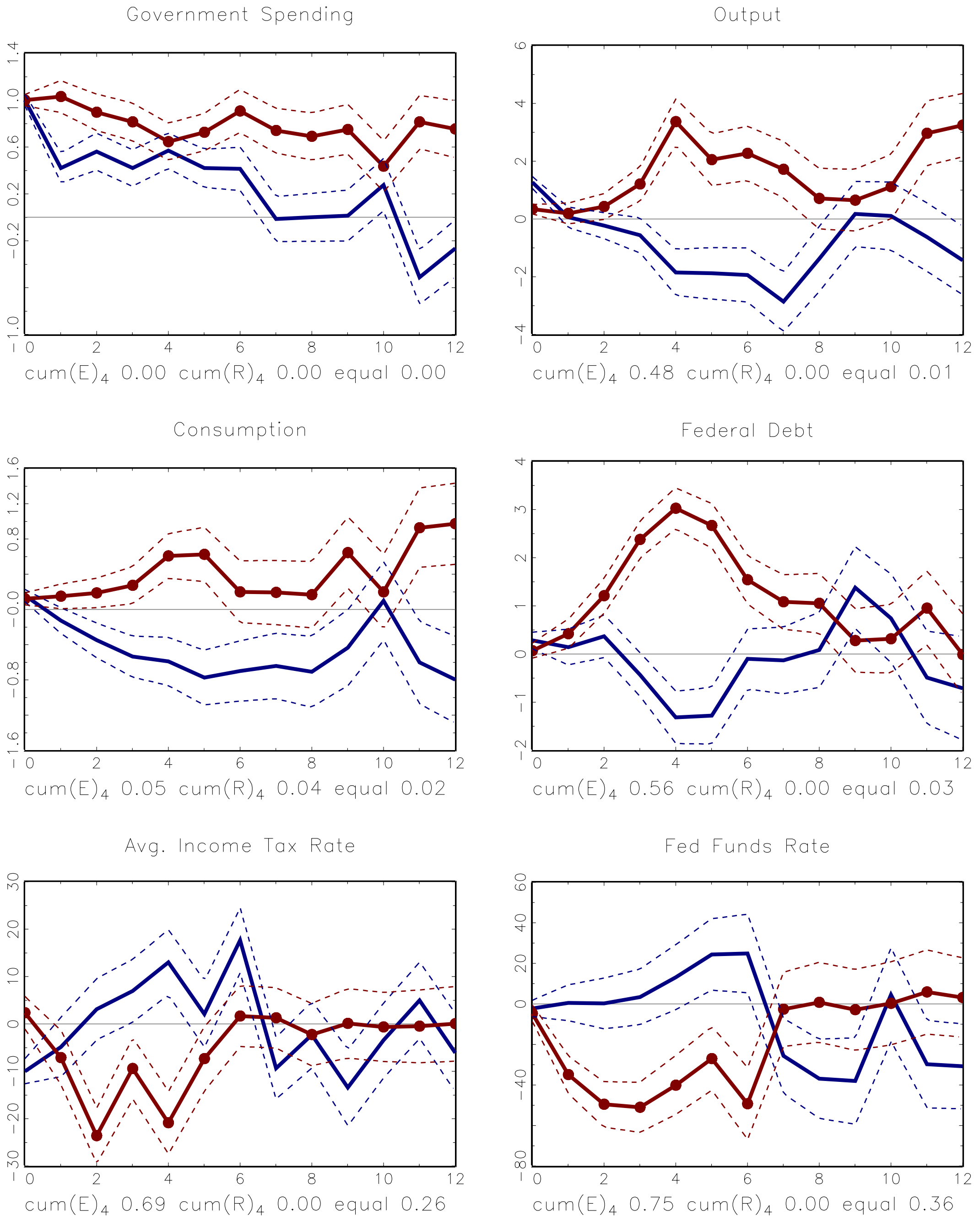

Figure 2.3: Impulse Responses in Recessions and Expansions

Notes: The thick solid lines with circles depict the responses by flexible regime-switching projections in recessions, in expansions otherwise; all responses surrounded by one-standard error bands. "cum(E)$_4$" and "cum(R)$_4$" refer to the *p*-values of the null for the accumulated responses being equal to zero after two and four quarters; and "equal" is the *p*-value of a test for the cumulative equality between the responses in the two regimes. Effects are expressed as dollar for dollar and as change in basis points to a one-percent spending shock (tax and fed funds rate).

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Opposed to the regime-switching model of Auerbach and Gorodnichenko (2010), in expansions, I again observe a trend toward spending reversals which carries over to the responses of output and consumption. Although output increases on impact by 1.27 dollars it then plummets below trend and starts recovering only after two years. Consumption shows a similar behavior with an initial increase of about 0.35 dollars and an extended time below trend afterwards. The response of consumption here looks a bit more like the one from a dynamic stochastic general equilibrium (DSGE) model in the real-business-cycle or new-Keynesian fashion in which the negative wealth effect after a stimulus dominates: expecting a larger tax burden in the future we tend to save more and consume less. Likewise, more of us have access to the asset or credit markets and can smooth consumption over time.

Recessions, then, constrain more and more people to participate in the asset or credit market. They simply spend all their disposal income. Such "hand-to-mouth" consumers naturally spend more in response to a rise in income through the stimulus. Although I cannot draw on my own results, the higher income is likely to result from a shift in labor demand and firms constrained in price-setting.[12] Corsetti, Meier and Müller (2009) and Galí, López-Salido and Vallés (2007) have fiscal DSGE models, though symmetric ones, in which the positive demand effects from the hand-to-mouth consumers, among other model features, outweigh the negative wealth effect.

During recessions the government keeps spending high. While output increases by just 0.34 dollars on impact, the economic recovery picks up pace rather quickly and reaches a peak at about four dollars one year out. With the common definition of the multiplier as the peak response one would call the stimulus a great success. This conclusion can be deluding. With no sign of a spending reversal it is better to bring the quadrupling of output into perspective with the persistently high spending levels (see Woodford 2010). The cumulative multiplier after one year is 1.26 dollars and is significantly different from one at the 7 percent level (see Table 2.2); after three years the effect is 1.99 dollars. Using the same multiplier concept, Auerbach and Gorodnichenko (2010) find a recession effect in a similar range: 2.24 dollars after four years.

[12] See Bilbiie, Meier and Müller (2008) for evidence and a theoretical foundation in this direction.

With spending persistently above trend in recessions and a drop of the average personal income tax rate by about 25 basis points over the first two quarters, federal debt levels surge and reach a peak that is about three times as high as the initial one-dollar stimulus. Then, after a year, the multiplier effect kicks in through the positive output effect, the tax rate goes back to its previous level, and federal debts revert to trend. Spending driven growth now does not have an adverse effect on future debt levels. Finally, the Fed stands ready and helps to reinforcing the effects of a stimulus: the federal funds rate goes down by about 50 basis points and stays at that level for six quarters.

2.4 Sensitivity Analysis

To check the sensitivity of the results under asymmetry, I substitute the proposed method to compute recession weights from a business cycle index, band-pass filtering the growth rate of output and a logistic transition function, with two different concepts.

One concept is to use a simple seven quarter centered moving-average filter as in Auerbach and Gorodnichenko (2010). The other one is a bit more involved and questions the logistic transformation, equation (2.19), and the calibration of the smoothing parameter, γ. Instead of transforming the business cycle index into weights by a deterministic logistic function, I treat the weights, or better say the change in regimes, as a random variable. Specifically, the index follows a mean switching model, $z_t = \mu_{r_t} + \varepsilon_t$, in which the regime indicator, $r_t = \{R, E\}$, follows a two-state Markov chain with a probability of p^*_{RR} to stay in a recession, $1 - p^*_{RR}$ to recover and so forth. $\Pr(r_t = E|y_t, y_{t-1} \ldots)$ and one minus that value denote the probabilities of being in a recession or expansion; these probabilities are then the respective weights in the flexible regime-switching projections. Details of estimating Markov-switching models can be found in Hamilton (1994).

Figure 2.4 plots the "band-pass weights" from Section 2.2.5 along with the two alternative weighting methods. Centered moving-average filtering and its mechanistically imposed seven quarter window has some troubles to mimic times when the economy dips into two recessions within a few years, as happened in the early 1980s. The correlation between the two methods is therefore with 0.60 relatively low. Markov-switching weights, on the other hand, correlated highly with the band-pass weights (0.88) and show a sharp distinction between recessionary and expansionary periods. The somewhat abrupt tran-

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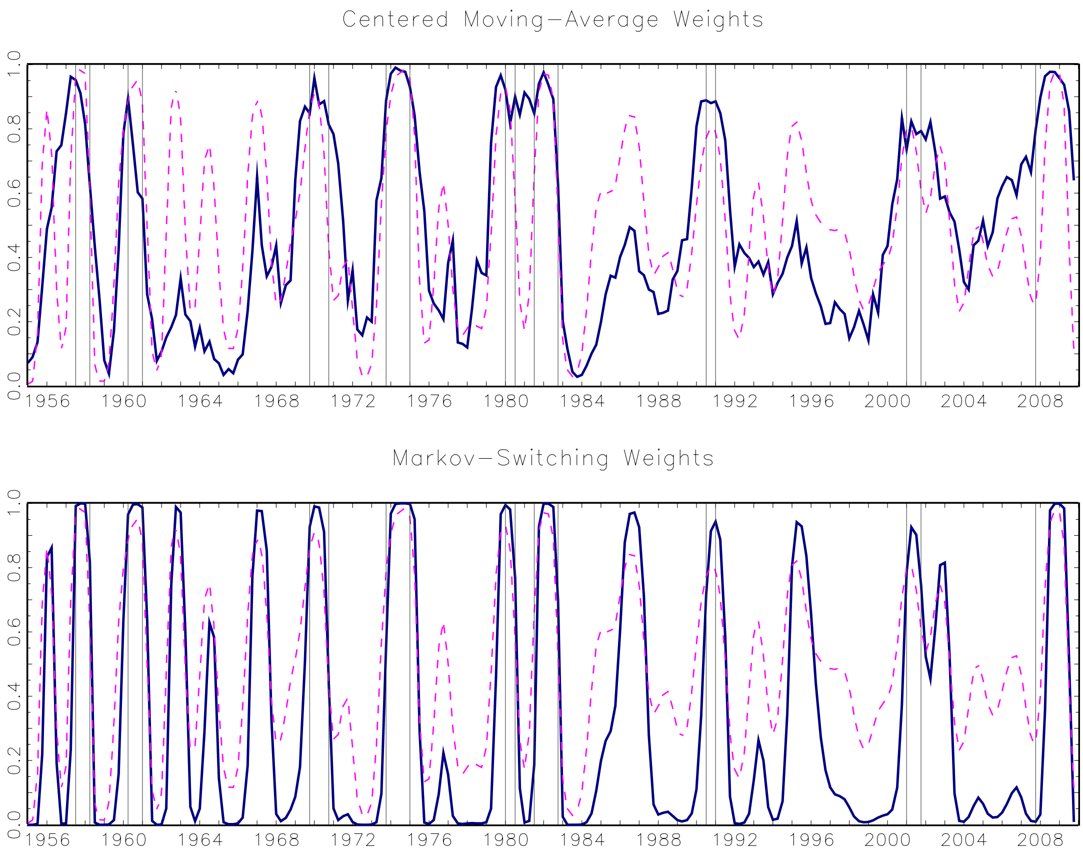

Figure 2.4: Two Alternative Recession Weights

Notes: Two alternative ways to extract recession weights from the growth rate of output. The top panel shows the recession weights coming from a seven quarter centered moving-average filter and the logistic transition function (2.19) with a smoothing parameter $\gamma = 1.65$. The bottom panel presents the weights derived from a Markov-switching model in the mean of the (band-pass filtered) business cycle index. Superimposed are the peaks and troughs of the NBER business cycle dates.

sition across regimes matches the band-pass weights closely up until the mid-1970s but cannot account for the Great Moderation and the subsample instability that goes along with the dampened fluctuations. Moreover, the Markov-switching model implies a probability that the economy was in a recession 35 percent of the time, compared to the 20 percent according to the NBER business cycle dates.

Figures 2.5 and 2.6 show the impact of the different weighting methods on the impulse responses. Compared to the band-pass benchmark, both alternatives to assign recession weights yield qualitative similar responses. Quantitatively, I cannot reject the cumulative equality between the responses of the band-pass/moving-average and the band-pass/Markov-switching methods in 18 out of 21 instances: the moving-average method

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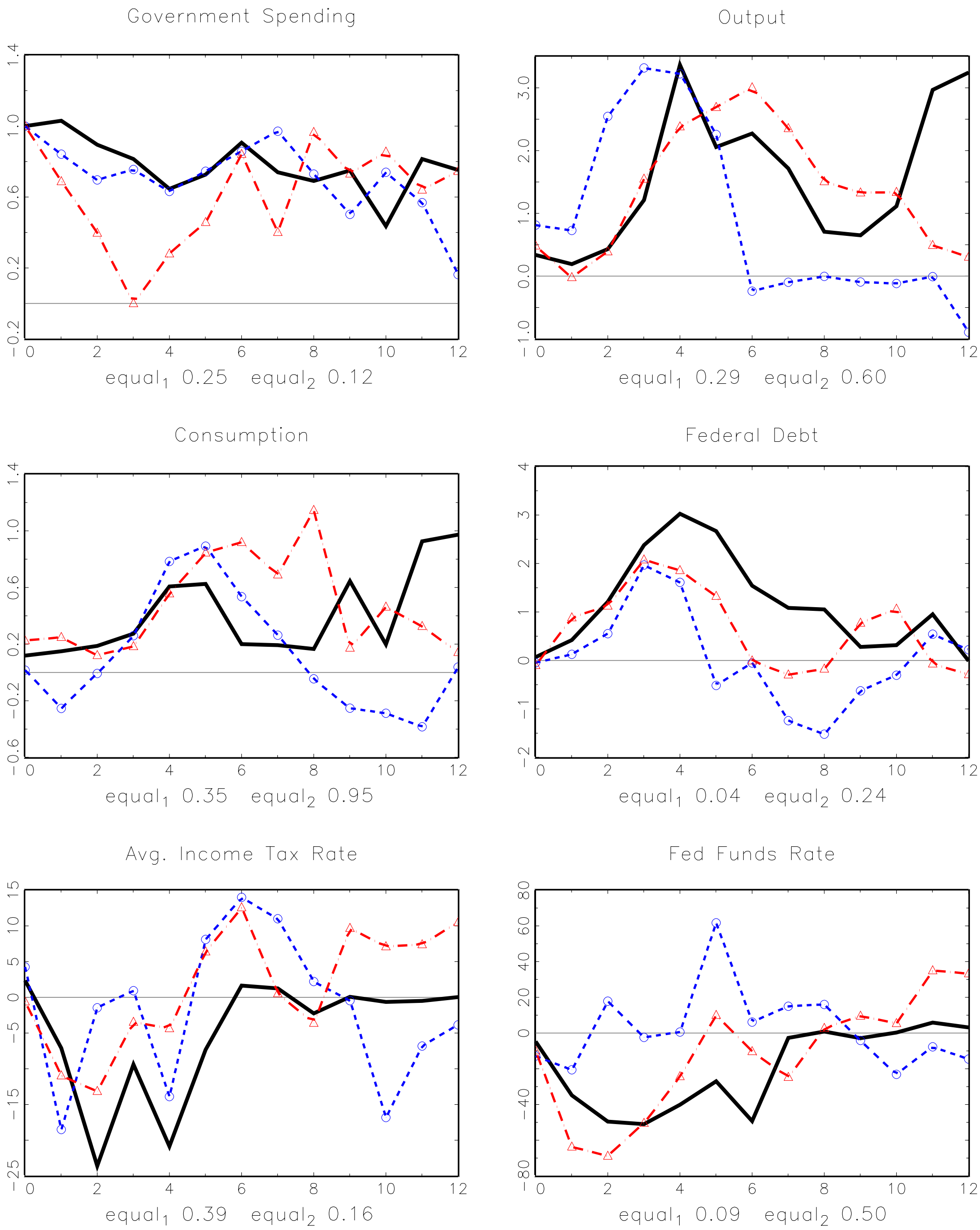

Figure 2.5: Impact of Different Weighting Methods on the Recession Responses

Notes: The thick solid lines show the responses when using the band-pass weights—the band-pass filtered growth rate of output to compute the business cycle index and the logistic transition function (2.19) with a smoothing parameter $\gamma = 1.65$ to transform it into weights (see Figure 2.3). The broken lines with circles depict the responses with a seven quarters centered moving-average instead of the band-pass filter; and in the underlying model of the broken-dotted lines with triangles I replace the logistic transition function by a Markov-switching process in the mean of the (band-pass) business cycle index. "equal$_1$" and "equal$_2$" are the p-values of the test for the cumulative equality between the responses of the band-pass/moving-average and the band-pass/Markov-switching methods. Effects are expressed as dollar for dollar and as change in basis points to a one-percent spending shock (tax and fed funds rate).

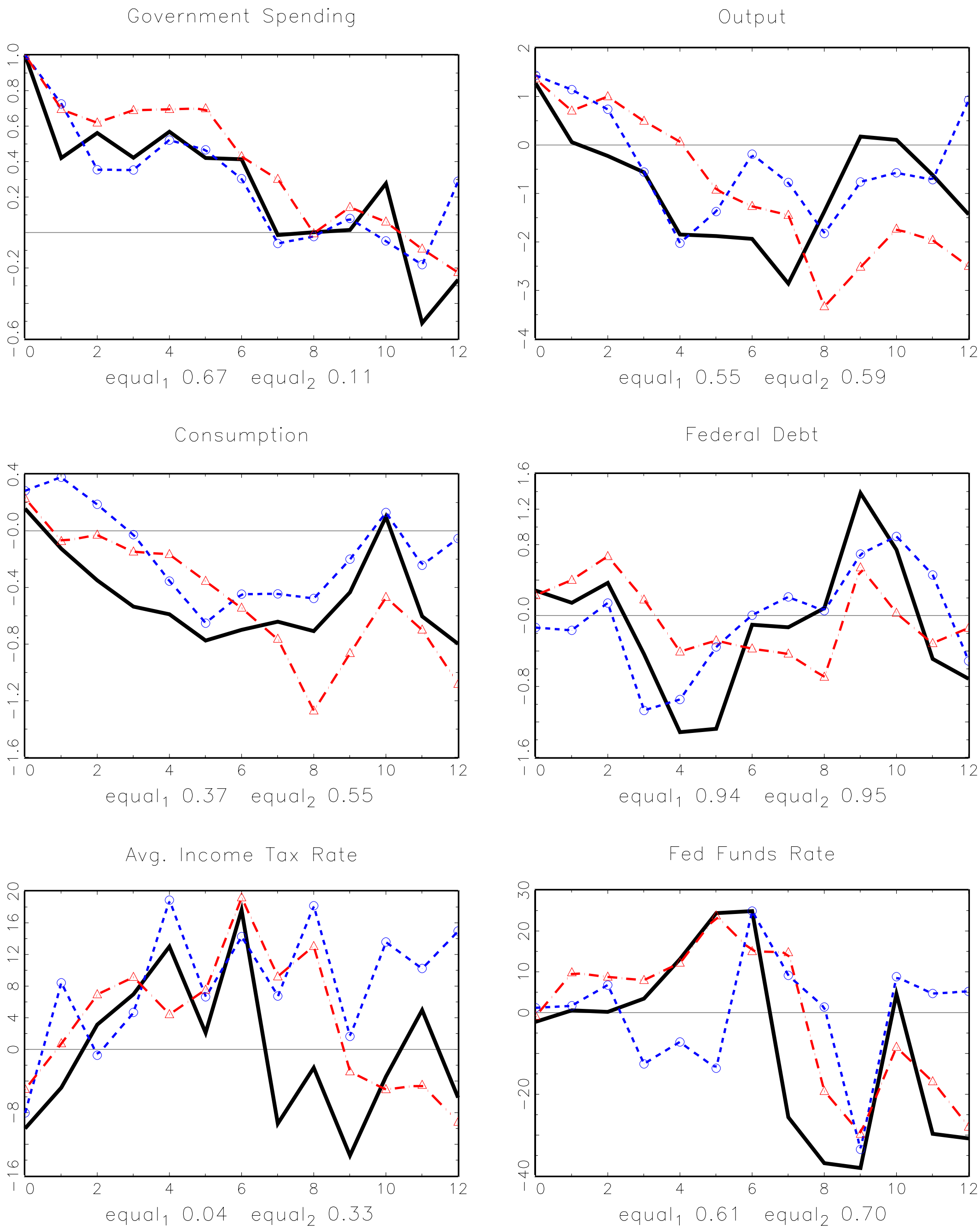

Figure 2.6: Impact of Different Weighting Methods on the Expansion Responses

Notes: The thick solid lines show the responses when using the band-pass weights—the band-pass filtered growth rate of output to compute the business cycle index and the logistic transition function (2.19) with a smoothing parameter $\gamma = 1.65$ to transform it into weights (see Figure 2.3). The broken lines with circles depict the responses with a seven quarters centered moving-average instead of the band-pass filter; and in the underlying model of the broken-dotted lines with triangles I replace the logistic transition function by a Markov-switching process in the mean of the (band-pass) business cycle index. "equal_1" and "equal_2" are the p-values of the test for the cumulative equality between the responses of the band-pass/moving-average and the band-pass/Markov-switching methods. Effects are expressed as dollar for dollar and as change in basis points to a one-percent spending shock (tax and fed funds rate).

predicts a modest debt increase with a fast reversal and no teamwork between fiscal and monetary policy in recessions, and the expansion response of the average personal income tax rate is more persistent. I read these results as evidence for the robustness to the details of constructing the recession weights.

2.5 Conclusions

Geologists and astrophysicists thinking about continental drift and stellar evolution all day long are a rare species among their profession. Economists spending day after day answering questions about the effects or effectiveness of fiscal policy are not much of a different kind. The Great Recession has now brought exactly these questions to the fore and many economists, coming from other fields of specialization, attempt to shed light on the issue with great enthusiasm. As always, then, many different approaches producing different results are on the market and establishing a common denominator, something most economists would agree on, seems to be a difficult and drawn-out process.

The major debate so far has been on the behavior of consumption after a spending stimulus. I think this debate has come close to a resolution. We should by now generally accept the Keynesian view: consumption increases through the effect on aggregate demand. Papers by Perotti (2007), Caldara and Kamps (2008), and Fisher and Peters (2009), among others, make this point clear. I show further evidence in this direction, but I also try to add some other points to the common denominator.

My results show the importance of two methodological innovations: approximating smooth nonlinearities by means of flexible projections and considering asymmetries over the business cycle. The flexible projections of Jordà (2005) are a series of VARs that approximate a Taylor series expansion to the unknown DGP at each impulse response horizon. A traditional VAR linearly approximates the DGP and iterates the coefficients forward in time to trace out the response paths; an inherently misspecification-prone method. Impulse responses by flexible projections are therefore a natural alternative. These advantages become evident in the response of spending itself after a stimulus. Characteristic is a reversal below trend (see Corsetti, Meier and Müller 2009). The government wants to maintain the level of debts with respect to output but faces a political constraint to increase taxes. Such a pattern toward spending reversals is exactly what I find with the

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flexible projections. Because of gradual changes over the post-WWII period, for instance the Great Moderation or the steady vanishing of fiscal policy as a stabilization device, traditional VAR approaches have difficulties to detect this pattern.

The Great Moderation plays also a role in the other methodological innovation, though only a supporting one. Here I am mainly concerned about the different effects of a stimulus in recessionary and expansionary periods. To address the issue one would typically split the sample according to the NBER business cycle dates with only a few observations in recessions. Estimates will, therefore, be unstable and imprecise. To have the full sample at disposal, no matter which regime one wants to estimate, Auerbach and Gorodnichenko (2010) propose to weighting each observation by a recession probability. I cast their approach within the flexible projections along with some refinements for assigning the weights. Besides the advantage of an increased sample size the reduced recession probabilities from the mid-1980s onwards reflect the Great Moderation. The weighting, therefore, implicitly controls also for this nonlinearity in the DGP.

With the flexible regime-switching projections I find remarkable differences between the effects to a one-dollar stimulus in the two regimes. In recessions the government keeps spending high throughout, output and consumption increase steadily. The government spending multiplier is slightly above one dollar after one year and about two dollars after three years. The average personal income tax does not change much and consequently the level of debts surges. After a year the multiplier effect kicks in and the level of debts returns to its pre-stimulus level. The Fed reinforces the effectiveness of the stimulus by letting the federal funds rate decline. Finally, in expansions I still observe a spending reversal pattern together with output and consumption responses which turn negative rather quickly. To the extent the government typically tries to stimulate the economy in recessions, the different sign of the consumption response does not contradict the Keynesian view. These differences pose a challenge on how to encompass the changing behavior of most of us in recessions and expansions into a theoretical model. In the DSGE model of Corsetti, Meier and Müller (2009), making the number of people who are constraint to live from hand to mouth regime dependent, which it presumably is, may be a good starting point.

Besides the effectiveness of a stimulus in recessions and the sign of the consumption response I can draw another conclusion. This last concluding remark sheds some light on the political debate of proper fiscal policy actions *after* the Great Recession. The debt dynamics in recessions, together with a prolonged high level of spending and roughly unchanged tax rates, support the view of the Obama administration, that without spending driven growth now, future debt levels might be even higher. Some European governments, notably Germany, take in principle the opposite view: there will be no growth without budget discipline. The just mentioned nonlinear DSGE model with changing consumption behavior can, perhaps, offer a deeper insight on this chicken-and-egg question. Altogether, developing a nonlinear DSGE for assessing fiscal policy strikes me as a promising direction for future research.

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Appendix 2.1 The Data in Detail

Below I describe and Figure A2.1 plots the U.S. data used in my analysis and the respective sources. All series are on a quarterly basis and run from 1955:1 to 2009:4 (vintage June 8, 2010).

Deflator and population.—I take the output deflator from NIPA table 1.1.4. (line 1) and the civilian population over 16 from FRED (table CNP16OV). I convert the monthly population figures into quarterly ones by taking the means of 3-month intervals. Throughout, these two series will be used to transform current dollars into real per-capita dollars

Output components.—I use data from NIPA table 1.1.5. for output (line 1), and nondurables and services consumption (lines 5 and 6); transformed into the logarithms of real per-capita dollars.

Interest rate.—I use the geometric mean of the monthly federal funds rate (FRED, table FEDFUNDS).

Fiscal variables.—Government spending consists of government consumption expenditures and gross investment taken from NIPA table 1.1.5. (line 21); expressed in logarithms of real per-capita dollars.

I define the tax rate following Jones (2002) as the average personal income tax rate. To construct the series I use NIPA tables 3.1. (line 3) and 1.12. (lines 3, 9, 12, 13, and 18) and compute the ratio of personal current taxes to the sum of wage and salary accruals, proprietors' income, rental income, corporate profits, and net interest. I multiply the resulting series by 100 to express it in percent. Burnside, Eichenbaum and Fisher (2004) apply the same definition. Perotti (2007) and Ramey (2011) use a different concept: the Barro-Sahasakul marginal income tax rate. The marginal rate has not been updated beyond 2006 however (see Barro and Redlick 2009). An average rate is therefore appealing because of its simple way to construct. In every case, the correlation of the two series of tax rates is with about 0.85 relatively high and reassuring.

To construct the public debt series I combine yearly and quarterly observations on gross federal debt held by the public from FRED (tables FYGFDPUB and FYGFDPUB). The quarterly federal debt series is only available from 1970 onwards. I recursively backcast the quarterly series until 1955 by using an autoregressive distributed lag model with one lag of the federal debt variable itself and the current and lagged values of the inflation rate,

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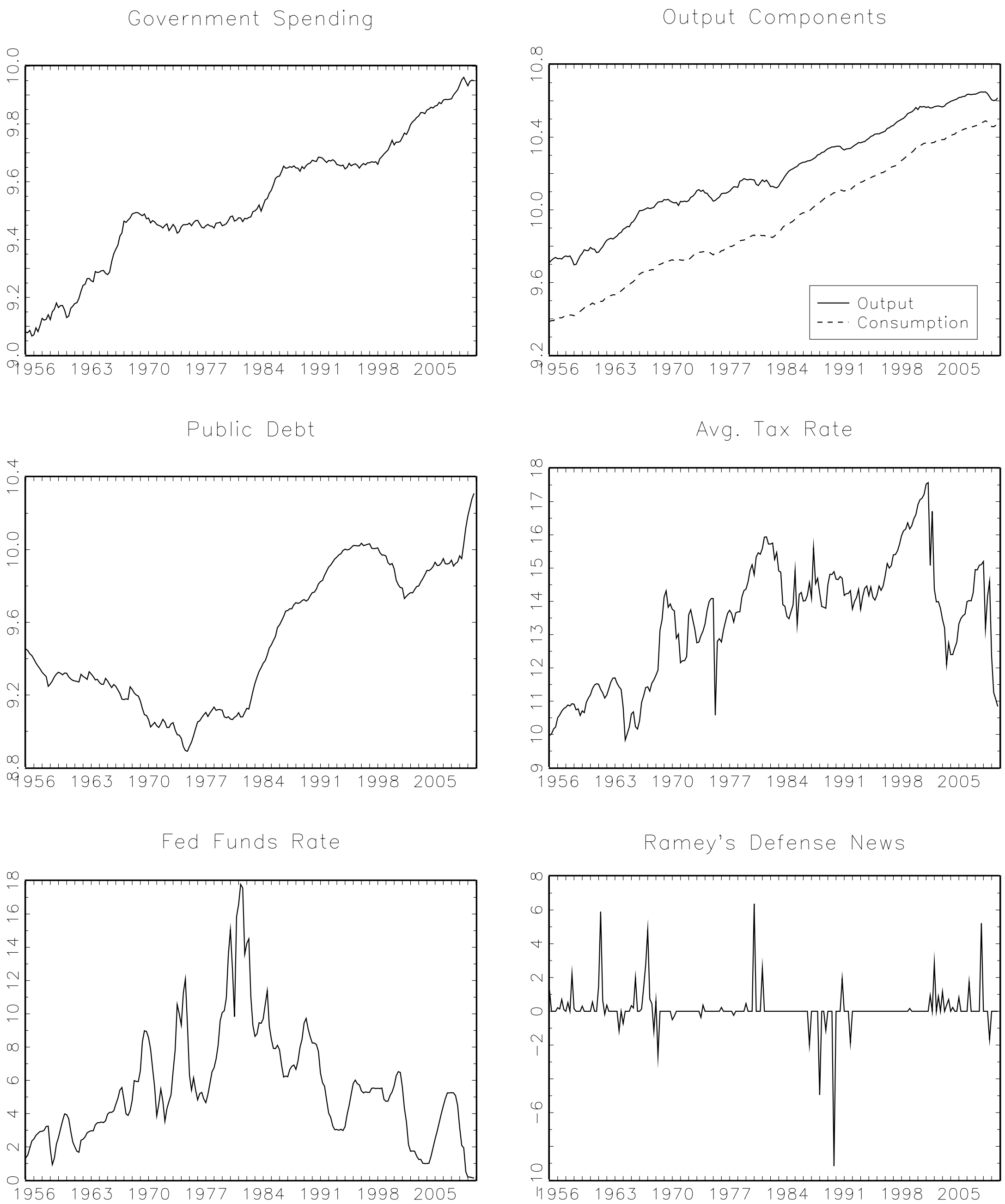

Figure A2.1: Quarterly U.S. Macroeconomic Time Series

Notes: I present the variables here as described above and as used in the econometric analysis: the logarithms of real per-capita government spending, output, consumption, and public debt; the average personal income tax rate; the federal funds rate; and Ramey's defense news variable.

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the federal funds rate, output, federal expenditures and federal receipts (NIPA table 3.2, lines 1 and 20). I use the yearly observations to update the backcasts every four quarters. The inflation rate is the growth rate of the output deflator and federal expenditures and receipts are from NIPA table 3.2. (lines 1 and 20). This set of variables comprises the main driving factors behind the evolution and accumulation of the federal debts (see Favero and Giavazzi 2007). The series enters the analysis as the logarithm of real per-capita dollars.

Ramey's defense news variable.—Ramey (2009, 2011) measures the expected discounted value of foreign political events and the related changes in government spending. In order to construct the series she gathers information from periodicals and official sources with a particular focus on properly gauging the expectations of the public. The series is expressed as the share of previous quarter output and multiplied by 100.

Business Cycle Index.—I extract the business cycle index from the real-per capita output growth rate with a band-pass filter eliminating frequencies below six and above 32 quarters. The band-pass filter is the one of Baxter and King (1999) with a truncation point of 200 quarters. To mitigate the endpoint problem inherent in this two-sided filtering concept, I pad the output series by 200 quarters of back and forecasts using an autoregressive model of order four. I standardize the index to have $E(z_t) = 0$ and $\text{Var}(z_t) = 1$.

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Chapter 3

A Time-Varying Structural VAR Model to Estimate the Effects of Changes in Fiscal Policy

In this paper I study the dynamic macroeconomic effects of changes in government spending or taxes by means of a time-varying parameter structural VAR. My results accord well with the notion of important changes in the transmission of fiscal policy in the United States: the effectiveness of fiscal policy in stabilizing the economy has decreased, more or less so for tax shocks and de facto with respect to spending. I also find evidence, through counterfactual policy simulations, for positive long-run effects on output when the government actively reduces the level of debts by cutting spending. A passive debt reduction in the form of faster tax adjustments in response to past expenditures has adverse effects on output. (JEL E62; H30; H50; C32; C53)

Keywords: fiscal policy; transmission of shocks; policy counterfactuals; time-varying parameter structural VAR; Markov chain Monte Carlo

3.1 Introduction

What are the effects of changes in fiscal policy? The longest and the deepest recession since the Great Depression that started in December 2007 and the various stimulus and reinvestment measures enacted by the U.S. Congress to facilitate the recovery have ended the eclipse of fiscal policy in the economic literature. Since then, many economists from various fields of specialization have returned their interest to this classical question.

During my own research on the empirical effects of fiscal policy shocks over the last years, I have encountered two main road blocks on the way, which make precise and unbiased inference difficult: the identification of shocks, especially the tax shocks,[1] and the regime-dependent or changing transmission mechanism.[2] These issues leave, of course, plenty of room for new econometric approaches or just older ones used elsewhere in the literature. To be clear where this paper is heading, the objective is to provide one possible solution for one of these road blocks: the changing transmission mechanism and the resulting differences in the effectiveness of fiscal policy. The particular application is to the U.S. economy over the 1970:1-2010:3 period.

The proposed solution is the time-varying parameter structural vector autoregressive model (TVP-VAR) of Primiceri (2005) in which all coefficients, covariances and volatilities vary over time. The laws of motion for the parameters allow for smooth and gradual changes. As such, the method differs from the flexible regime-switching model of Chapter 2 where the objective was to study the different effects of fiscal policy in recessions and expansions rather than the evolution of its effectiveness. The estimation of the TVP-VAR is in the Bayesian tradition of Markov chain Monte Carlo algorithms, Gibbs sampling in particular, for the numerical evaluation of the posterior distributions of the parameters.

To identify government spending and tax shocks I follow Blanchard and Perotti (2002). Their method is the most compelling and cited VAR-based approach to identifying fiscal policy shocks and I will take it as given throughout this paper. Simply put, identification

[1] See among others the seminal papers of Romer and Romer (2010) and Perotti (2011) for measures of tax changes based on the narrative record of all major postwar tax policy acts; and Leeper, Walker and Yang (2008) on the problems arising through fiscal foresight.

[2] Papers in this direction are Auerbach and Gorodnichenko (2010), Kirchner, Cimadomo and Hauptmeier (2010) and Pereira and Lopes (2010); Chapter 2 of this thesis deals with regime-dependency and the differences in the transmission mechanism of fiscal policy between recessions and expansions.

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rests on the ability to disentangle, from the residual changes in government spending and revenues, the discretionary part (i.e. the shocks) and the automatic adjustment to output. The difficulty, then, and methodological innovation of this paper is to cast this essentially non-recursive identification strategy into the one of Primiceri (2005), a strategy that relies on a triangular structure of the identifying matrix. The triangularity assumption is convenient because it allows one to translate the TVP-VAR into a linear state space model.

The paper further innovates in a second direction. Besides tracing out the effects of the policy shocks, I estimate impulse response functions of changes in the parameters of the government's decision rules on spending and taxes. Specifically, I simulate a government that tries to reduce the level of debts in two different ways: in an active one by cutting spending and in a passive one by just adjusting taxes to cover past expenditures. I adopt the design for the policy counterfactuals from the monetary policy literature, especially from the work of Canova and Gambetti (2009). Their approach is particularly appealing because it provides a way to take the estimated covariance structure among the coefficients into account, essentially the Lucas critique. Moreover, including the level of debts in the model, controls for the constraints the debt path puts on future spending and tax decisions, a channel typically ignored in the VAR-based fiscal policy analysis (see Favero and Giavazzi 2007).

While there is a huge recent literature using TVP-VARs to evaluate monetary policy (see, e.g., Primiceri 2005, Cogley and Sargent 2001, Canova and Gambetti 2009, Benati and Surico 2008), applications for fiscal policy are scarce. Two notable exceptions are Kirchner, Cimadomo and Hauptmeier (2010) and Pereira and Lopes (2010). The first of these two papers traces out the effects of government spending shocks in the euro area and the second one identifies both spending and tax shocks for the postwar U.S. economy. Both papers confirm the notion of important changes in the transmission mechanism over time: the effectiveness of fiscal policy in stabilizing the economy has decreased on both sides of the Atlantic.

The first set of my results is much in line with this general finding of Kirchner, Cimadomo and Hauptmeier (2010) and Pereira and Lopes (2010). Changes in government spending had a stronger positive effect on output, especially after six or seven quarters, in the 1970s and early 1980s. The picture is a bit different for the impulse responses to tax shocks. Still, one can observe the same pattern between the 1970s and 2000s, but the late 1980s and early 1990s now seem to be the period when tax shocks were most effective. Unlike the other periods, this mid-period was mainly characteristic for a few deficit-driven shocks (see Romer and Romer 2010), with a more persistent response of tax revenues and the then desired effect of a significant reduction of federal debts.

The results from the debt-reducing counterfactual policies suggest that the spending cuts in the active government stance have hardly any adverse effects on the private sector and output increases in the long-run. The anticipation of lower future spending rather than higher taxes drives this result. Not surprisingly then, just levying taxes to achieve budget surpluses without changing the spending behavior has detrimental effects on output.

3.2 Econometric Framework

Time-varying parameter structural VARs put quite a challenge on an econometrician because of the sheer amount of parameters to estimate: 8,732(!) to be exact in the model presented in this section. While it is still possible to write down the likelihood for the estimation problem, it comes close to a mission impossible to maximize it over such a high dimension, let alone the problem of multiple maxima in ranges where the parameter values are anything but plausible. This classical maximum likelihood approach to estimation is basically a special case of a Bayesian one with flat priors. Bayesian estimation with informative or diffuse priors is therefore the natural choice to tackle the problem. Section 3.3 has the details.

Compared to the unproblematic and relative uncontroversial identification of monetary policy, disentangling fiscal policy shocks is far from trivial. Because, strictly speaking, there is no such thing as a "universal" fiscal shock that accounts for the numerous strings policy makers can pull to counteract the business cycle by changing in spending and taxes. A billion dollars spent for public infrastructure, education, or defense will hardly have the same effects both on the individual citizen or the economy as a whole. In this paper I am, however, pragmatic about this problem and keep the focus on the traditional macroeconomic issue of the aggregate economy. Focusing on the aggregate economy and, by implication, on total government spending and tax revenue shocks is in line with seminal

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papers such as Blanchard and Perotti (2002) and Mountford and Uhlig (2009).

Even though the traditional macroeconomic approach simplifies matters considerably, identifying fiscal policy shocks remains difficult because of endogeneities. Fiscal variables and the business cycle are closely linked. For instance, both higher taxes and higher economic growth, at an unchanged tax code, fill the Federal Treasury and, as a consequence, we do not know whether the rise in tax revenues comes from a tax or business cycle shock.

To deal with the problem of endogeneity in identifying spending and tax shocks I follow closely Blanchard and Perotti (2002). At the heart of their structural VAR methodology lies the identification of the just sketched automatic "feedback" of economic activity on tax revenues and government spending. In order to pin down these feedback elasticities, Blanchard and Perotti (2002) use additional information from outside the VAR model about the tax and transfer system. Their method also rests on a timing assumption. The quasi-impossibility of any discretionary within-quarter adjustment of fiscal policy in response to economic shocks attributes any contemporaneous changes to the feedback effects.

3.2.1 Data Description

The sample covers quarterly observations for the U.S. economy from 1970:1 until 2010:3. To keep my results, with respect to the definition of the fiscal data, comparable with the seminal work of Blanchard and Perotti (2002) and other studies in their tradition, I define these variables accordingly: spending includes both government consumption expenditures and gross investment, and net taxes are the current receipts less net transfers and net interest paid. The model further includes data on output and federal debts. As Favero and Giavazzi (2007) forcefully argue and show, it is important to control for the restrictions the debt path puts on future government spending and tax decisions. Ignoring this channel would potentially introduce a bias.

All variables enter the analysis in the logarithmic form of their respective real per capita values. The sources for nominal output, government spending, the necessary items to construct net taxes, the deflator, population and federal debts are the NIPA tables and the FRED data base.[3]

[3] Specifically, NIPA tables 1.1.4 (line 1), 1.1.5 (lines 1 and 21), 3.1 (lines 1, 9, 11, 17 and 22),

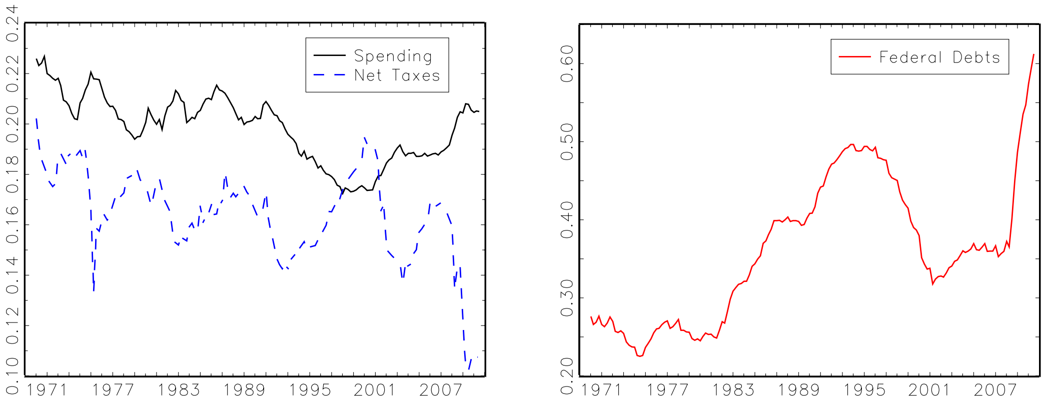

Figure 3.1: Spending, Net Tax and Debt Shares of Output

Figure 3.1 shows some of the high frequency properties of the data. While, in the econometric analysis, I use the variables in the level-form described above, for a quick visual inspection it is more appealing to look at, say, the shares of spending, net taxes and federal debts with respect to output. Most importantly, the shares display patterns that make the time-varying parameter model a natural choice. For instance, the spending share declines steadily until the beginning of the new millennium but increase since then. Likewise, the debt share remains either stable, increases, or decreases over periods of several years. Besides these "long swings", which can be perfectly captured by TVP-VARs, there are a couple of large quarterly changes in taxes and federal debts. The first episode is President Ford's large temporary tax rebate of 1975:2 and the second one are the recent effects of the Great Recession. Depending on how much time variation one allows for, a TVP-VAR could potentially capture such episodes of large and quick changes. This catch-all strategy is, however, not warranted. Intuitively, the more time variation one allows for in the VAR the more will be explained by the shocks as opposed to the dynamics of the model.

3.2.2 Model Specification

The k-dimensional vector of quarterly observable variables, $\{y_t\}_{t=1}^{T}$, includes the four variables—real per capita output, government spending, net taxes and federal debts—

7.1 (line 18); and FRED data base (series FYGFPUN). All variables downloaded on February 21, 2011.

in their logarithmic form. I assume $y_t = (y_{g,t}, y_{t,t}, y_{x,t}, y_{d,t})'$ evolves according to the TVP-VAR(p) process,

$$y_t = C_t + B_{1,t}y_{t-1} + \cdots + B_{p,t}y_{t-p} + u_t, \tag{3.1}$$

in which C_t is a $k \times 1$ vector of time-varying intercepts, $B_{i,t}$ $(i = 1, \ldots, p)$ are $k \times k$ matrices of time-varying coefficients and u_t are possibly heteroscedastic reduced-form residuals with time-varying covariance matrix Ω_t. Iterating on (3.1) yields the infinite moving average representation, i.e.

$$y_t = \mu_t + \sum_{h=1}^{\infty} \Theta_{h,t} u_{t-h}. \tag{3.2}$$

$\mu_t = I_k + \sum_{h=1}^{\infty} \Theta_{h,t} C_t$ and $\Theta_{h,t} = J\tilde{B}_t^h J'$ in which $\tilde{B}_t$ is the corresponding VAR(1) companion form of the VAR(p) in (3.1) and J a selector matrix:

$$\tilde{B}_t = \begin{bmatrix} B_t \\ I_{k(p-1)} : 0_{k(p-1)\times k} \end{bmatrix} \quad \text{and } J = \left(I_k : 0_{k\times k(p-1)}\right). \tag{3.3}$$

The parameters $\Theta_{h,t}$ for $h = 1, \ldots, H$ represent the reduced-form impulse response functions. To transform these responses into ones with a structural interpretation I use the fairly simple model of Blanchard and Perotti (2002) that links the reduced-form residuals u_t with the structural shocks e_t:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -\alpha^*_{23,t} & 0 \\ -\alpha_{31,t} & -\alpha_{32,t} & 1 & 0 \\ -\alpha_{41,t} & -\alpha_{42,t} & -\alpha_{43,t} & 1 \end{bmatrix} \begin{bmatrix} u_{g,t} \\ u_{t,t} \\ u_{x,t} \\ u_{d,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e_{g,t} \\ e_{t,t} \\ e_{x,t} \\ e_{d,t} \end{bmatrix}, \tag{3.4}$$

in which (minus) $\alpha^*_{23,t}$ is the predetermined tax elasticity with respect to output. Following Favero and Giavazzi (2007) and Perotti (2007) I use a value of 1.85 for this elasticity for all $t = 1, \ldots, T$ and, implicitly, a zero spending elasticity.[4] Blanchard and Perotti (2002) have the details on how to construct these elasticities based on institutional information about the tax and transfer system.

[4] The fact that government spending, defined as in Section 3.2.1, does not include transfer payments justifies the assumption of no feedback effect of spending to movements in the business cycle. See also the evidence in Blanchard and Perotti (2002).

The non-recursive structure of the Blanchard-Perotti model, however, imposes a twist on the time-varying parameter framework of Primiceri (2005). In his model, identification relies on a recursive Choleski-like decomposition and consequently on a lower triangular matrix linking the reduced-form residuals with the structural shocks. Now, the specific form of (3.4) allows me to recast the problem into a lower triangular matrix that contains all the parameters we want to estimate and a second matrix that collects the remaining predetermined variables.[5] Specifically,

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & -\alpha^*_{23,t} & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_{g,t} \\ u_{t,t} \\ u_{x,t} \\ u_{d,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ \tilde{\alpha}_{21,t} & 1 & 0 & 0 \\ \tilde{\alpha}_{31,t} & \tilde{\alpha}_{32,t} & 1 & 0 \\ \tilde{\alpha}_{41,t} & \tilde{\alpha}_{42,t} & \tilde{\alpha}_{43,t} & 1 \end{bmatrix} \begin{bmatrix} e_{g,t} \\ e_{t,t} \\ e_{x,t} \\ e_{d,t} \end{bmatrix}, \tag{3.5}$$

in which the mapping between (3.4) and (3.5) is

$$\begin{aligned} \tilde{\alpha}_{21,t} &= \alpha_{21,t}, \\ \tilde{\alpha}_{31,t} &= \alpha_{31,t} + \alpha_{32,t}\alpha_{21,t}, \\ \tilde{\alpha}_{32,t} &= \alpha_{32,t}, \\ \tilde{\alpha}_{41,t} &= \alpha_{41,t} + \alpha_{42,t}\alpha_{21,t} + \alpha_{43,t}\alpha_{31,t} + \alpha_{43,t}\alpha_{32,t}\alpha_{21,t}, \\ \tilde{\alpha}_{42,t} &= \alpha_{42,t} + \alpha_{43,t}\alpha_{32,t}, \quad \text{and} \\ \tilde{\alpha}_{43,t} &= \alpha_{43,t}. \end{aligned} \tag{3.6}$$

We can write the structural model more compactly as

$$A^*_t u_t = \tilde{A}_t \Sigma_t \varepsilon_t. \tag{3.7}$$

with the normalized structural shocks ε_t, i.e. $\mathrm{Var}(\varepsilon_t) = I_k$ and $\mathrm{Var}(e_t) = \Sigma_t$ is the diagonal matrix

$$\Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & 0 & 0 \\ 0 & \sigma_{2,t} & 0 & 0 \\ 0 & 0 & \sigma_{3,t} & 0 \\ 0 & 0 & 0 & \sigma_{4,t} \end{bmatrix}, \tag{3.8}$$

[5] This way to reparameterize (3.4) follows in principle the idea of Pereira and Lopes (2010).

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and a reduced-form covariance matrix Ω_t given by

$$\Omega_t = A_t^{*-1}\tilde{A}_t\Sigma_t\Sigma_t'\tilde{A}_t'A_t^{*-1\prime}. \tag{3.9}$$

The structural impulse responses follow then from

$$\Phi_{h,t} = \Theta_{h,t}A_t^{*-1}\tilde{A}_t\Sigma_t, \qquad h = 1, \ldots, H. \tag{3.10}$$

For the estimation it will be practical to collect the slope coefficients $B_t = (B_{1,t} : \cdots : B_{p,t})$ in a $k \times kp$ matrix and to transform it together with the constants into a $k(kp+1)$ vector by stacking the columns, i.e. $\beta_t = \mathrm{vec}\left((C_t : B_t)'\right)$. The model (3.1) can now be rewritten as

$$\begin{aligned} y_t &= X_t'\beta_t + A_t^{*-1}\tilde{A}_t\Sigma_t\varepsilon_t, \\ X_t' &= I_k \otimes \left(1 : y_{t-1}' : \cdots : y_{t-p}'\right), \end{aligned} \tag{3.11}$$

in which the operator $\otimes$ denotes the Kronecker product. Like the constants and the slope coefficients, I bring the non-zero and non-one elements of the covariances $\tilde{A}_t$ and volatilities Σ_t into vector form. Specifically, $\tilde{\alpha}_t = (\tilde{\alpha}_{21,t}, \tilde{\alpha}_{31,t}, \tilde{\alpha}_{32,t} \cdots, \tilde{\alpha}_{k1,t}, \cdots, \alpha_{kk-1,t})'$ and $\sigma_t = (\sigma_{1,t}, \cdots, \sigma_{k,t})'$ where the corresponding row dimensions are $k(k-1)/2$ and k.

The vectors α_t, β_t, and σ_t summarize all the time-varying parameters of the model. As in Primiceri (2005) I let the coefficients α_t and β_t evolve as random walks and the volatilities σ_t follow a geometric random walk:

$$\tilde{\alpha}_t = \tilde{\alpha}_{t-1} + \zeta_t \tag{3.12}$$

$$\beta_t = \beta_{t-1} + \nu_t, \tag{3.13}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t. \tag{3.14}$$

The specification for σ_t falls into the class of models known as stochastic volatility. While in infinite samples a random walk hits any bound for sure, the use of finite samples makes it possible to maintain the random walk assumption. A great advantage as we do not have to estimate any further parameters, although, in principle, we could extend (3.12), (3.13), and (3.14) to represent more general autoregressive processes (for details see Section 4.4.2

in Primiceri 2005).

The innovations ε_t, ζ_t, ν_t, and η_t are mutually uncorrelated Gaussian white noises with zero mean and covariances I_k, Q, S, and W, known as the hyperparameters in the Bayesian literature. Summarized in the matrix V we have

$$V = \text{Var}\left(\begin{bmatrix} \varepsilon_t \\ \nu_t \\ \zeta_t \\ \eta_t \end{bmatrix}\right) = \begin{bmatrix} I_k & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \quad \text{and } S = \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ 0 & S_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & S_{k-1} \end{bmatrix} \tag{3.15}$$

with all matrices, besides the k-dimensional identity matrix I_k, being positive definite. The covariance of the innovation term in the state equation for the log volatilities is block diagonal, i.e. $S_1 = \text{Var}([\Delta\tilde{\alpha}_{21,t}])$, and $S_{i-1} = \text{Var}([\Delta\tilde{\alpha}_{i1,t}, \cdots, \Delta\tilde{\alpha}_{ii-1,t}]')$ for all $i = 3, \ldots, k$. The rather specific assumptions on the structure of V and S are standard in the literature (see, e.g., Primiceri 2005, Canova and Gambetti 2009, Benati and Surico 2008) and are not essential to keep the estimation feasible. They offer, however, numerous advantages: The first one is the clear structural interpretation of the various sources of uncertainty which would be cumbersome in the case of more non-zero blocks. Second, the block-diagonality of S with blocks corresponding to parameters in separate equations enables us to model the blocks $[\tilde{\alpha}_{21,t}]$, $[\tilde{\alpha}_{31,t}, \tilde{\alpha}_{32,t}], \ldots,$ $[\tilde{\alpha}_{k1,t}, \cdots, \tilde{\alpha}_{kk-1,t}]$ in linear state space form. The advantage of linearity will become clear momentarily in Section 3.3. And, finally, assuming mutually uncorrelated innovations does not exaggerated the curse-of-dimensionality problem inherent in all time-varying parameter models any further.

3.2.3 Counterfactual Fiscal Policy Scenarios

What would have happened to output had the government pursued a more aggressive policy to reduce to the level of debts? Questions like this appear to be simple with time series models: just change the relevant parameters in the decision rules and trace out the effects. But the effect of changing one parameter typically spreads over all the other parameters, the essence of the Lucas critique. Canova and Gambetti (2009), in an experiment that mimics a more aggressive monetary policy, provide a natural solution to the critique by explicitly taking into account the covariance structure, i.e. the matrix Q

in (3.15), of the whole coefficient set.

Let us define $G_t = A_t^{*-1}\tilde{A}_t\Sigma_t$ in (3.11) and rewrite the reduced-form model (3.1) in structural form,

$$G_t^{-1}y_t = G_t^{-1}C_t + G_t^{-1}B_{1,t}y_{t-1} + \cdots + G_t^{-1}B_{p,t}y_{t-p} + \varepsilon_t, \tag{3.16}$$

or equivalently

$$G_t^{-1}y_t = X_t'\left(G_t^{-1} \otimes I_{kp+1}\right)\beta_t + \varepsilon_t = X_t'\gamma_t + \varepsilon_t, \tag{3.17}$$

in which X_t' is defined as in (3.11) and γ_t are the structural coefficients. Using (3.13) and after some rearranging we get

$$\gamma_t = \left(G_t^{-1} \otimes I_{kp+1}\right)\left(G_{t-1}^{-1} \otimes I_{kp+1}\right)^{-1}\gamma_{t-1} + \left(G_t^{-1} \otimes I_{kp+1}\right)\nu_t \tag{3.18}$$

as the law of motion for the structural coefficients on the lagged variables. The last term, $\omega_t = \left(G_t^{-1} \otimes I_{kp+1}\right)\nu_t$, contains all the $k(kp+1)$ shocks. Let $\tilde{\omega}_t \subset \omega_t$ be the subvector containing the n shocks of interest and the submatrix $\tilde{G}_t$ consists of the n corresponding rows of $G_t^{-1} \otimes I_{kp+1}$ such that $\tilde{\omega}_t = \tilde{G}_t\nu_t$. Given the last expression and the covariance matrix Q from (3.13), we can write ν_t conditional on $\tilde{\omega}_t$ in turn as

$$\nu_t = Q\tilde{G}_t'\left(\tilde{G}_tQ\tilde{G}_t'\right)^{-1}\tilde{\omega}_t. \tag{3.19}$$

Now to compute the impulse response function of the policy counterfactual I use the method of Koop, Pesaran and Potter (1996) and take the difference between two distinct realizations of the forecast $E_t(y_{t+i}|\cdot)$. The two realizations are identical up to $t-1$, but one realization assumes that there is a shock at date t of size $\tilde{\omega}_t = \delta$, while the other realization evolves along its regular shock-free path. Specifically,

$$\begin{aligned}\Phi_{h,t}^c = E_t\left(y_{t+h}|\tilde{\omega}_t = \delta, \{\tilde{\omega}_{t+j}\}_{j=1}^h = 0, Q, \tilde{G}_t, \beta_{t-1}, \{y_{t-j}\}_{j=1}^p\right)\\ - E_t\left(y_{t+i}|\{\tilde{\omega}_{t+j}\}_{j=0}^h = 0, Q, \tilde{G}_t, \beta_{t-1}, \{y_{t-j}\}_{j=1}^p\right)\end{aligned} \tag{3.20}$$

for $h = 0, 1, 2, \ldots, H$. Although δ is only a one-time shock its effects are permanent through the random walk nature of the law of motion for the time-varying parameters. To further ensure against the Lucas critique, I calibrate δ to represent, in the sense of Leeper and Zha (2003), only a modest or typical policy intervention relative to the sample. One posterior standard deviation of the corresponding shock ν_t to the reduced-form parameters β_t (i.e. the square root of the associated diagonal element of Q) is consistent with such a typical intervention.

My interest centers around two counterfactual fiscal policies that involve the structural equations for government spending and taxes. Similar to Taylor rules, these structural equations provide simple descriptions of fiscal policy-making, approximating the many complex mechanisms and constraints that influence the government's decisions. Now, in both counterfactual experiments, the objective is to bring the level of federal debts down. The ways to get there differ, however. In the first experiment, I simulate a government that actively pursues its objective by cutting spending more aggressively with respect to past debt levels. The other experiment shows what I call a passive government. It achieves the debt reduction not by actively reacting to debt levels as before. Rather, the government runs surpluses by adjusting taxes faster to cover recent expenditures.

For the technical implementation of the first experiment—the active government stance—I set up the matrix $\tilde{G}_t$ to contain the rows corresponding to the lagged coefficients of spending and debts in the spending equation. The specific shocks in the vector δ hit the debt coefficients by minus one-standard deviation and leave the spending coefficients (i.e. the autoregressive component) unaltered. As the autoregressive component has typically the highest weight in each VAR equation, any "indirect" effect induced by changing other coefficients may therefore dominate the dynamic effects of the counterfactual experiment. Setting this indirect effect to zero ensures a clear interpretation of the results with respect to the objective of the experiment (see Canova and Gambetti 2009). Similarly, the second experiment—the passive stance—involves the lagged coefficients on spending and taxes in the tax equation; the shocks to the spending coefficients are now plus one-standard deviation and the ones affecting the autoregressive component are again zero.

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3.3 Bayesian Estimation

Starting with the papers of Cogley and Sargent (2005) and Primiceri (2005), structural time-varying parameter VARs with a recursive identification scheme have spread into the macroeconometric literature, especially with applications to monetary policy. Their method is appealing because it estimates the joint posterior of all parameters in the model, a distribution from which it is difficult to sample directly, by splitting the problem into smaller blocks. The parameters within each block can then be drawn from the conditional distributions through Gibbs sampling.

The Gibbs sampler is a variant of a Markov chain Monte Carlo (MCMC) algorithm: it exploits the principle that it is typically easier to sample from a lower dimensional distribution, conditional on other parameters (i.e. the blocks). Gelman et al. (1995, chap. 11) show that the stationary distribution of the Markov Chain generated by the Gibbs sampler is the joint distribution we are looking for. Furthermore, MCMC algorithms yield smoothed estimates of the time-varying parameters as they use information based on the entire set of observations. Compared to particle filters, smoothing methods lead to more efficient estimates when, like in this paper, the interest is in the evolution of the observable states (see, e.g., Sims 2001, Primiceri 2005).

As a notational convention, a generic vector or matrix x^τ consists of a sequence of observable variables or estimates up to time τ, i.e. $x^\tau = \{x_t\}_{t=1}^{\tau}$. I further express a realization x_t conditional on an information set, say, x^τ as $x_{t|\tau}$ and, likewise, I abbreviate the conditional mean and variance of an arbitrary parameter θ as $\theta_{t|\tau}$ and $V_{t|\tau}^{\theta}$. The function $p(\cdot)$ denotes a generic density and $\dim(\cdot)$ specifies the dimension of a vector.

3.3.1 Priors

An obvious choice to calibrate the priors are simple estimates from time-invariant ordinary least squares regressions on (3.1) and (3.5). Such a strategy has already been used by Cogley and Sargent (2005) and Primiceri (2005), among others. In its original form this strategy requires to run these "auxiliary" regressions on a training sample that covers data which are then discarded for the main analysis. As quarterly observations for federal debts are only recorded after 1970 sacrificing, say, ten years of data for a training sample throws away a lot of information and might leave us with a too short sample. If a training

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sample is not available, Canova and Ciccarelli (2009) suggest to estimate the features of the priors on the entire sample (see also Kirchner, Cimadomo and Hauptmeier 2010). As a side effect, using a "full sample" prior, minimizes the uncertainty involved in choosing proper priors. To denote the time-invariant estimator I will use "hats".

The details for the specification of the prior densities follow Canova and Gambetti (2009) and are quite similar to the ones in Primiceri (2005) and other papers. For the initial states of all time-varying parameters the priors $p(\beta_0)$, $p(\tilde{\alpha}_0)$ and $p(\log \sigma_0)$ are normally distributed, while the hyperparameters $p(Q)$, $p(S_i)$ and $p(W)$ have an inverse Wishart distribution. Given the laws of motion (3.12), (3.13) and (3.14), this choice of prior distributions for the initial states and the hyperparameters leads to normal priors for the entire sequences β^T, $\tilde{\alpha}^T$ and $\log \sigma^T$. Like the normal distribution the Wishart distribution requires two input arguments, the scale factor and the degrees of freedom. For the prior to be proper the degrees of freedom must exceed the dimension of the respective hyperparameter at least by one; a choice of "just one" puts as little weight as possible on the prior. As the inverse Wishart distribution is a conjugate prior for the covariance matrix of the corresponding time-varying parameters β_t, $\tilde{\alpha}_t$ and $\log \sigma_t$, the scale factor has to be a multiple of the time-invariant covariance used to calibrate the prior for the initial states and the degrees of freedom. Bringing everything together we have the following set of prior densities for the parameters,

$$
\begin{aligned}
p(\beta_0) &= N\big(\hat{\beta},\, \mathrm{Var}(\hat{\beta})\big),\\
p(\tilde{\alpha}_0) &= N\big(\hat{\tilde{\alpha}},\, \mathrm{Var}(\hat{\tilde{\alpha}})\big),\\
p(\log \sigma_0) &= N\big(\log \hat{\sigma},\, I_k)\big)
\end{aligned}
\tag{3.21}
$$

and hyperparameters,

$$
\begin{aligned}
p(Q) &= IW\Big(\big(0.0003 \times (\dim(\hat{\beta}) + 1) \times \mathrm{Var}(\hat{\beta})\big)^{-1},\, \dim(\hat{\beta}) + 1\Big),\\
p(S_i) &= IW\Big(\big(0.001 \times (i + 1) \times \hat{S}_i\big)^{-1},\, i + 1\Big), \quad i = 1, \ldots, k-1,\\
p(W) &= IW\Big(\big(0.001 \times (\dim(\hat{\sigma}) + 1) \times I_k\big)^{-1},\, \dim(\hat{\sigma}) + 1\Big),
\end{aligned}
\tag{3.22}
$$

in which the variance $\hat{S}_i$ refers to the i-th block of S in (3.15) and the variance for $\log \sigma_0$ and W is arbitrarily chosen to be the identity matrix. The factors 0.0003 and 0.001 and

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the degrees of freedom in the prior specification correspond to the values in Canova and Gambetti (2009). This choice transforms the initial informative priors $\text{Var}(\hat{\beta})$ and $\hat{S}_i$ into diffuse and uninformative ones where more weight is on the sample information. This practice is more or less standard in the TVP-VAR literature, although slight differences can be found for $p(Q)$. Primiceri (2005), for instance, uses a factor of 0.0001 and $2 \times \dim(\beta)$ for the degrees of freedom. The results for the two prior specifications are, however, very similar; see Cogley and Sargent (2005) for another paper that specifies the prior for $p(Q)$ as in (3.22).

3.3.2 Sampling Algorithm

The Gibbs sampling algorithm set forth here specifies three blocks of conditional distributions for all parameters in the model: the coefficient states β_t; the covariance states $\tilde{\alpha}_t$; the volatility states σ_t; and the hyperparameters Q, S and W. The first two blocks can easily be cast into a linear and Gaussian state space form and therefore the standard algorithm for Gibbs sampling of Carter and RKohn (1994) can be used. Drawing volatility states is a bit more tricky as they have a nonlinear and nonnormal state space form. Kim, Shephard and Chib (1998) provide a linear and approximately Gaussian reformulation of the problem with the advantage of restoring the assumptions needed for the standard sampling algorithm to work. The approximation is necessary because the linear transformation leads to innovations in the observation equation that are distributed as $\log \chi^2(1)$. Following Kim, Shephard and Chib (1998), I approximate this $\log \chi^2$ distribution with a mixture of seven normals. The indicator matrix s^T defines, out of the seven components, the selection of normal approximations for these innovations over $t = 1, \ldots, T$.

Step 1: Coefficient states $p\left(\beta^T | y^T, \tilde{\alpha}^T, \sigma^T, s^T, V\right)$ and algorithm in detail. — Equations (3.11) and (3.13), rewritten here for convenience,

$$y_t = X_t' \beta_t + u_t \quad \text{and} \quad \beta_t = \beta_{t-1} + \nu_t, \tag{3.23}$$

constitute a state space model in which both u_t and ν_t are normally distributed with a zero mean and variances Ω_t and Q. Further, the block diagonal structure of (3.15) assumes that u_t and ν_t are mutually uncorrelated. Now, conditional on the data, $\tilde{\alpha}^T$, σ^T and V

the covariance Ω_t in the observation equation is known from (3.9) and we can therefore generate the whole sequence β^T as in Lemma 2.1 of Carter and Kohn (1994):

$$p\left(\beta^T|y^T,\tilde{\alpha}^T,\sigma^T,s^T,V\right)=p\left(\beta_T|y^T,\tilde{\alpha}^T,\sigma^T,s^T,V\right)\prod_{t=1}^{T-1}p\left(\beta_t|\beta_{t+1},y^t,\tilde{\alpha}^t,\sigma^T,s^T,V\right). \tag{3.24}$$

Then, to get β^T from $p(\beta^T|y^T,\cdots)$ we, first, generate β_T from $p(\beta_T|y^T,\cdots)=N(\beta_{T|T},V^{\beta}_{T|T})$ and, second, for $t=T-1,\ldots,1$ we draw β_t from $p(\beta_t|\beta_{t+1},y^t,\cdots)=N(\beta_{t|t+1},V^{\beta}_{t|t+1})$. Starting from $\beta_{0|0}=\hat{\beta}$ and $V^{\beta}_{0|0}=\mathrm{Var}(\hat{\beta})$ the Kalman filter recursion over $t=1,\ldots,T$, i.e.

$$\begin{aligned}
\beta_{t|t-1}&=\beta_{t-1|t-1},\\
V^{\beta}_{t|t-1}&=V^{\beta}_{t-1|t-1}+Q, \qquad\qquad (3.25)\\
\beta_{t|t}&=\beta_{t|t-1}+V^{\beta}_{t|t-1}X_t\left(X_t'V^{\beta}_{t|t-1}X_t+\Omega_t\right)^{-1}\left(y_t-X_t'\beta_{t|t-1}\right)\quad\text{and}\\
V^{\beta}_{t|t}&=V^{\beta}_{t|t-1}-V^{\beta}_{t|t-1}X_t\left(X_t'V^{\beta}_{t|t-1}X_t+\Omega_t\right)^{-1}X_t'\beta_{t|t-1},
\end{aligned}$$

leads to a draw of β_T form the normal distribution using the elements $\beta_{T|T}$ and $V^{\beta}_{T|T}$ from the last recursion. We now plug the results of the filter and the draw of β_T into a reversed version of the Kalman filter to derive $\beta_{T-1|T}$ and $V^{\beta}_{T-1|T}$. This backward updating delivers a draw for β_{T-1} and so forth until we arrive at β_1. Specially, the backward updating steps for $t=T-1,\ldots,1$ are

$$\begin{aligned}
\beta_{t|t+1}&=\beta_{t|t}+V^{\beta}_{t|t}\left(V^{\beta}_{t|t}+Q\right)^{-1}\left(\beta_{t+1}-\beta_{t|t}\right)\quad\text{and} \qquad (3.26)\\
V^{\beta}_{t|t+1}&=V^{\beta}_{t|t}-V^{\beta}_{t|t}\left(V^{\beta}_{t|t}+Q\right)^{-1}V^{\beta}_{t|t}.
\end{aligned}$$

For more details on Gibbs sampling for state space models and the Kalman filter see Carter and Kohn (1994) and Anderson and Moore (1979).

So far nothing ensures that draws of β^T result in stable VAR processes. In fact, the use of data in level form with a more or less clear upward drift and possible nonstationarity leads hardly to any stable draw because a stable VAR process is by definition stationary (see Proposition 2.1 in Lütkepohl 2005) As such, a strict "rule" as in Cogley and Sargent (2001) that discards every sequence of draws β^T where at least one draw β_t has an unstable

VAR representation is simply infeasible. For the analysis of monetary policy, stability is a sensitive matter since the central bank's main objective is to maintain price stability. The advantage in a monetary policy VAR, however, is that the variables typically enter in first differences and the rule has therefore less bite and will not slow down the sampling algorithm significantly. In a fiscal policy VAR, on the other hand, the whole stability issue may be less of a concern. As Kirchner, Cimadomo and Hauptmeier (2010) argue, certain episodes may be well described by fiscal instabilities. In every case, I take a compromise here and impose the stability rule on the growth rates of output, spending, taxes and federal debts. Specifically, I check the roots of the associated VECM polynomial of the VAR and discard every draw that has more than $k = 4$ roots in or on the unit circle.

Step 2: Covariance states $p\left(\tilde{\alpha}^T | y^T, \beta^T, \sigma^T, s^T, V\right)$. — Starting with the compact form of the structural model (3.5), we can derive the observation equation of the proper state space model from

$$A_t^* \left(y_t - X_t' \beta_t\right) = y_t^* = \tilde{A}_t e_t. \tag{3.27}$$

Conditional on β^T and the matrix of predetermined contemporaneous relations A_t^*, the adjusted residuals y_t^* are observable. As in Primiceri (2005), here is the point where the triangular form of the matrix $\tilde{A}_t$ with ones on the main diagonal can be conveniently used to rewrite (3.27) as

$$\begin{bmatrix} y_{g,t}^* \\ y_{t,t}^* \\ y_{x,t}^* \\ y_{d,t}^* \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ e_{g,t} & 0 & 0 & 0 & 0 & 0 \\ 0 & e_{g,t} & e_{t,t} & 0 & 0 & 0 \\ 0 & 0 & 0 & e_{g,t} & e_{t,t} & e_{x,t} \end{bmatrix} \begin{bmatrix} \tilde{\alpha}_{21,t} \\ \tilde{\alpha}_{31,t} \\ \tilde{\alpha}_{32,t} \\ \tilde{\alpha}_{41,t} \\ \tilde{\alpha}_{42,t} \\ \tilde{\alpha}_{43,t} \end{bmatrix} + \begin{bmatrix} e_{g,t} \\ e_{t,t} \\ e_{x,t} \\ e_{d,t} \end{bmatrix}. \tag{3.28}$$

and (3.12) serves as state equation for $\tilde{\alpha}_t$. Now, the block-diagonality of the covariance matrix S of the innovations ζ_t and block-triangular structure of the 4×6 matrix in (3.28), enables us to use the algorithm of Carter and Kohn (1994), explained in Step 1, in an equation-by-equation fashion. Specifically, given β^T and the triangular form of $\tilde{A}_t$, $e_{g,t}$ is predetermined and thus $\tilde{\alpha}_{21,t}$ can be drawn in the first equation. For the second equation we use the draw of $\tilde{\alpha}_{21,t}$ and predetermine $e_{t,t}$ such that we obtain draws for the block

$[\tilde{\alpha}_{31,t}, \tilde{\alpha}_{32,t}]$. Continuing this procedure of predetermining one structural shock at the time leads to draws for the block $[\tilde{\alpha}_{41,t}, \tilde{\alpha}_{42,t}, \tilde{\alpha}_{43,t}]$ in the third equation and so forth. The triangular structure of predetermined variables in the system of equations and the independence across the blocks of S restores the necessary assumption of a linear state space model in the Carter and Kohn (1994) algorithm.

Table 3.1: Selection of the Mixing Distribution to be $\log\chi^2(1)$

j	p_j	m_j	v_j^2	j	p_j	m_j	v_j^2
1	0.00730	−10.12999	5.79596	5	0.34001	0.61942	0.64009
2	0.10556	−3.97281	2.61369	6	0.24566	1.79518	0.34023
3	0.00002	−8.56685	5.17950	7	0.25750	−1.08819	1.26261
4	0.04395	2.77786	0.16735				

Notes: Replication of Table 4 in Kim, Shephard and Chib (1998).

Step 3: Volatility states $p\left(\sigma^T | y^T, \beta^T, \tilde{\alpha}^T, s^T, V\right)$. — Drawing σ^T relies on the algorithm of Kim, Shephard and Chib (1998), a procedure to transform an otherwise nonlinear and nonnormal state space model into a linear and approximately normal one; consequently, the standard algorithm of Carter and Kohn (1994), as laid out in Step 1, is again available. The observation equation can be written as

$$\tilde{A}_t^{-1} A_t^* \left(y_t - X_t' \beta_t\right) = \Sigma_t \varepsilon_t. \tag{3.29}$$

Given $y^T, \beta^T, \tilde{\alpha}^T$ the right-hand side is observable and is nothing else than the set of identified structural shocks, e_t, of Step 2. Since I have defined the law of motion (3.14) for the diagonal entries of Σ_t as a geometric random walk, we can convert (3.29) into the appropriate form by squaring and taking the logarithm. We obtain the linear state space model

$$e_t^* = 2\log\sigma_t + \xi_t \quad \text{and} \quad \log\sigma_t = \log\sigma_{t-1} + \eta_t, \tag{3.30}$$

in which $e_{i,t}^* = \log\left(e_{i,t}^2 + 0.001\right)$ and $\xi_{i,t} = \log\left(\epsilon_{i,t}^2\right)$ for $i = (g, t, x, d)$; the offset constant 0.001 deals with very small values of $e_{i,t}^2$ as in Kim, Shephard and Chib (1998); and the innovation ξ_t follows a $\log\chi^2(1)$ distribution. While this conversion restores the linearity assumption, the distributional form of ξ_t still precludes direct and simple inference. Kim, Shephard and Chib (1998) show how to accurately approximate the $\log\chi^2(1)$ distribution through a matched mixture of seven normal distributions,

$$f(\xi_{i,t}) \approx \sum_{j=1}^{7} p_j N\left(\xi_{i,t} | m_j - 1.2704,\ v_j^2\right), \qquad i = (g, t, x, d), \tag{3.31}$$

in which $N\big(\xi_{i,t}|m_j - 1.2704,\ v_j^2\big)$ denotes the density function of a normal distribution with mean $m_j - 1.2704$ and variance v_j^2. Values for p_j, m_j and v_j^2 are reproduced in Table 3.1. Conditional on s^T we can draw a value for $\xi_{i,t}|s_{i,t} = j \sim N\big(m_j - 1.2704,\ v_j^2\big)$ and proceed as in Step 1 to draw $\log \sigma_{i,t}$ for all i and t. Given these draws of $\xi_{i,t}$ we independently sample each $s_{i,t}$ from the discrete density $\Pr(s_{i,t} = j|e_t^*, \log \sigma_{i,t})$, a density which is proportionally determined from the normal density $N\big(e_t^*|2\log \sigma_{i,t} + m_j - 1.2704, v_j^2\big)$.

Step 4: Hyperparameters. — The inverse Wishart is a convenient choice for the prior distribution of the innovation variances V in (3.15), i.e. the hyperparameters Q, W and the blocks of S. Since the parameters β^T, $\tilde{\alpha}^T$ and σ^T are mutually uncorrelated draws from a normal distribution the posterior distribution of each hyperparameter is also inverse Wishart. Conditional on β^T, $\tilde{\alpha}^T$, σ^T, s^T and y^T the innovations in (3.15) become observable and it is therefore relatively easy to draw the hyperparameters from the inverse Wishart. The scale matrix and the degrees of freedom, the two factors that fully specify the inverse Wishart, are based on the choice for the prior distribution and take the form

$$\begin{gathered}
\Big(0.0003 \times (\dim(\hat{\beta}) + 1) \times \mathrm{Var}(\hat{\beta}) + \sum_{t=1}^{T} \Delta\beta_t \Delta\beta_t'\Big)^{-1} \quad \text{and} \quad \dim(\hat{\beta}) + 1 + T, \\
\Big(0.001 \times (i + 1) + T \times \hat{S}_i\Big)^{-1} \quad \text{and} \quad i + 1 + T, \quad i = 1 \ldots, k - 1, \\
\Big(0.001 \times (\dim(\hat{\sigma}) + 1) \times I_k + \sum_{t=1}^{T} \Delta\sigma_t \Delta\sigma_t'\Big)^{-1} \quad \text{and} \quad \dim(\hat{\sigma}) + 1 + T,
\end{gathered} \tag{3.32}$$

in which $\hat{S}_i$ denotes the variance of the i-th block of S in (3.15).

For the counterfactual analysis, Step 1 needs to be slightly modified. Everything else being as just laid out, the shocked and shock-free realizations of the impulse response function (3.20) come from draws of β_{t-1}. The sequence of parameters β_{t+h}, $h = 0, 1, \ldots, H$, follows then from (3.13) and (3.19) either with $\tilde{\omega}_t = \delta$ or $\tilde{\omega}_t = 0$.

The Gibbs sampling algorithm is now complete. Iterations on Steps 1 to 4 produce a set of draws from the conditional distributions that converge in the limit to the joint pos-

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terior distribution of all the parameters in the model (see, e.g., Gelfand and Smith 1990). I perform 100,000 iterations from which I discard the first 50,000 and save only every fifth draw of the remaining 50,000 draws. This "thinning" practice breaks the autocorrelation of the draws since draws from a Markov chain are typically not independent.

3.3.3 Convergence Diagnostics of the Markov Chain

From theoretical work such as Gelfand and Smith (1990) we know that the Gibbs sampler converges to the "true" joint posterior distribution as the number of iterations goes to infinity. Whether this property holds in an empirical application with a finite number is an important question which I address here. Intuitively, convergence of the Markov chain slows down the more complicated the conditional distribution gets.

I implement three MCMC convergence diagnostics for the 10,000 saved draws of each parameter and hyperparameter: the sample autocorrelation; the measure of Geweke (1992); and the Raftery and Lewis (1992) diagnostic. Table 3.2 reports the results of the diagnostic checks for each of the 8,732 parameters in the model. Because of the sheer amount of parameters the table shows summary statistics, grouped into hyperparameters V, coefficients β^T, covariances $\tilde{\alpha}^T$ and volatilities σ^T. Moreover, each summary statistic reports two values based on the first and last 1,500 draws from the 10,000 saved iterations. This testing strategy adds another layer to the formal MCMC diagnostics: if the Markov chain is in an equilibrium state the means of these two splits should be roughly equal.

The 20-th-order sample autocorrelations summarized in Panel A of Table 3.2 show a relatively low degree of autocorrelation. Only a few hyperparameters V exhibit statistics higher than 0.2. The draws are therefore almost independent, an indication for the efficiency of the algorithm and for accurate posterior estimates. Related to that is the inefficiency factor, as measured by the inverse of the relative numerical efficiency statistic of Geweke (1992) with a 4% tapered window for the estimation of the spectral density at frequency zero. If the draws come from an independent and identically distributed (iid) sample, drawn directly form the posterior distribution, the inefficiency factor has a value of one. For instance, in Panel B of Table 3.2 the mean value of 10.94 for the last 1,500 draws of the hyperparameters V indicate that about eleven times as many draws are necessary to achieve the same numerical efficiency of an iid set of draws. Since only values above 20 are considered to be critical and 10.94 is the largest one here, Table 3.2 confirms the iid nature of the draws. Finally, Raftery and Lewis (1992) provide a measure of the number of draws actually required to achieve a certain accuracy of the posterior summaries of the Markov chain. I set the parameters for this test such that a nominal reporting based on a 95% interval using the 0.025 and 0.975 quantile points leads to an accuracy of the posterior values of 0.025 to the left and right of the specified quantiles in the cumulative distribution function. The probability of attaining this accuracy is 95%. The maximum number over the whole parameter space for the Raftery and Lewis (1992) diagnostic is 4,818 and thus well below the 10,000 draws used in the analysis. All three MCMC convergence diagnostics do not indicate any problems with the Gibbs sampler.

Table 3.2: Convergence Diagnostics of the Markov Chain

	Median		Mean		Min		Max		10-th		90-th	
A. 20-th-Order Sample Autocorrelations												
V	−0.02	0.04	−0.02	0.04	−0.31	−0.05	0.44	0.49	−0.15	−0.01	0.13	0.08
β^T	0.00	0.00	0.00	0.00	−0.20	−0.03	0.18	0.05	−0.07	−0.01	0.07	0.02
$\tilde{\alpha}^T$	−0.04	0.01	−0.03	0.01	−0.14	−0.02	0.10	0.03	−0.11	−0.01	0.07	0.02
σ^T	−0.02	0.00	−0.02	0.01	−0.17	−0.03	0.11	0.09	−0.07	−0.01	0.05	0.02
B. Inefficiency Factor												
V	5.74	10.67	5.74	10.94	3.79	4.16	9.54	41.34	4.54	7.36	6.86	14.50
β^T	1.11	1.43	1.15	1.50	0.50	0.61	2.49	4.35	0.86	1.04	1.50	2.02
$\tilde{\alpha}^T$	0.94	1.08	0.96	1.30	0.70	0.77	1.36	2.69	0.85	0.83	1.13	2.21
σ^T	1.31	1.66	1.38	1.87	0.74	0.78	3.57	10.28	0.98	1.10	1.87	2.64

Notes: Summary of the distributions of the 20-th-order sample autocorrelations and the inefficiency factors (the inverse of Geweke's (1992) measure of relative numerical efficiency with a 4% tapering of the spectral window at frequency zero) for the whole parameter space. "10-th" and "90-th' denote the 10-th and 90-th percentiles. Each statistic has two entries which refer to statistics based on the first and last 1,500 draws out of the saved 10,000. The discarded burn-in draws are 50,000 and the thinning factor is five.

3.4 Results

I center the discussion of the results, especially the observed changes over the last 40 years, around three topics: the volatility of government spending and tax shocks, the propagation of these shocks and counterfactual fiscal policy scenarios.

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3.4.1 Volatility of the Fiscal Shocks

Figure 3.2 shows the time profile of the median and the interval containing 68% of the posterior distribution of the standard deviation of the estimated fiscal policy shocks. For the government spending shock the median and the 68% interval are fairly stable over time while for tax shocks these statistics are, on average, lower in the 1980s and 1990s than at the beginning and the end of the sample. The picture of a relatively high volatility in the 1970s, with a peak around 1975, and in the 2000s is consistent with Romer and Romer's (2010) narrative analysis of tax shocks. The 1970s and early 1980s were periods of frequent and large tax changes, such as Presidents Ford and Reagan's tax cuts, mainly aimed to boost long-run growth or to counteract economic conditions. Until the Bush tax cuts of the early 2000s and the tax measures included in the 2008-2009 stimulus packages there were only a few and relatively modest deficit-driven tax changes.

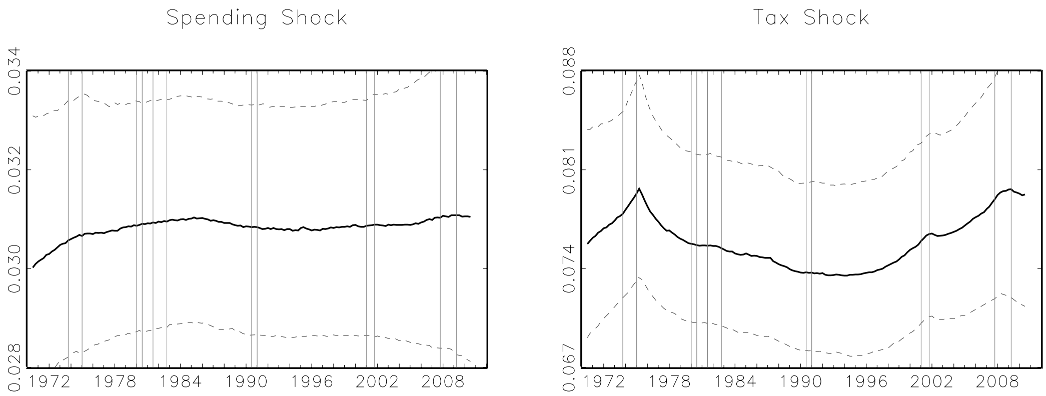

Figure 3.2: Standard Deviation of the Structural Shocks

Notes: The two graphs displays the time-varying volatility parameters $\sigma_{1,t}$ and $\sigma_{2,t}$ in (3.8). Superimposed are NBER-dated U.S. recession episodes.

3.4.2 The Dynamic Responses to Fiscal Shocks

Figures 3.3 and 3.4 display the systematic responses to fiscal shocks. I focus on three specific periods: 1975:2, 1991:2 and 2009:1. Although all of them represent NBER-dated troughs of U.S. recessions the sole objective is to uncover changes in the transmission of fiscal policy shocks over the last 40 years. Since I use smoothed estimates based on the entire set of observations the responses in, say, 1973:4 and 1975:2 are hard to distinguish from each other. Overall, the impulse responses support, perhaps with a few exceptions,

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the common belief about the changing transmission mechanism of fiscal policy. Solow (2005) brings this change to the point: "[t]he use of fiscal policy as a stabilization device has all but vanished [...] in the United States."

The output response to a spending shock (Figure 3.3) was more effective in (and around) 1975:2 when there was considerable slack in the U.S. economy; the general U-shaped pattern is in line with the results of Blanchard and Perotti (2002). While the spending response is relatively persistent and similar over time, tax revenues fall below zero after an initial increase and slowly revert to trend. This U-shape is mainly driven by the automatic adjustment of tax collections to changes in output but the pattern is somewhat different over time, reflecting changes in the Taylor-type rule describing tax-policy making (i.e. the structural tax equation). Around 1975:2, a discretionary increase in spending leads to a faster decline of future tax revenues. This faster decline comes, however, at the cost of higher future debts.

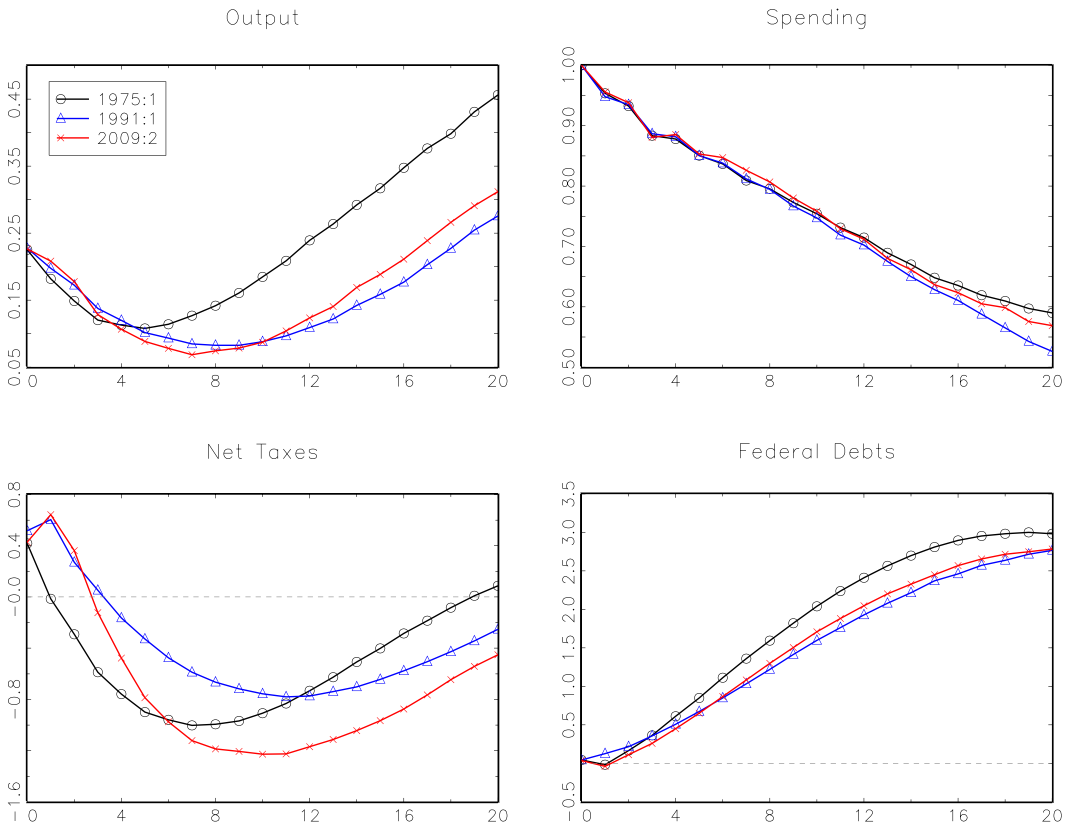

Figure 3.3: Responses to Spending Shocks

Notes: Impulse responses of output, government spending, net taxes and federal debts to spending shocks in 1975:1, 1991:1 and 2009:2. Responses expressed in percentage changes.

In Figure 3.4, the output effects to tax shocks are, perhaps, the exception to the mentioned conventional wisdom of a declining fiscal policy effectiveness. A tax shock leads to a higher (negative) output response in 1991:1 than in 1975:1. The years around 1991 were a period of several deficit-driven tax changes aimed to bring the ever rising debt-to-output ratio to a halt (see right panel in Figure 3.1). More persistent tax revenues and lower spending, although the spending effect is in general quite small, reduce debt levels more effectively than in other periods. This debt reduction motive of the government has, of course, detrimental effects on output.

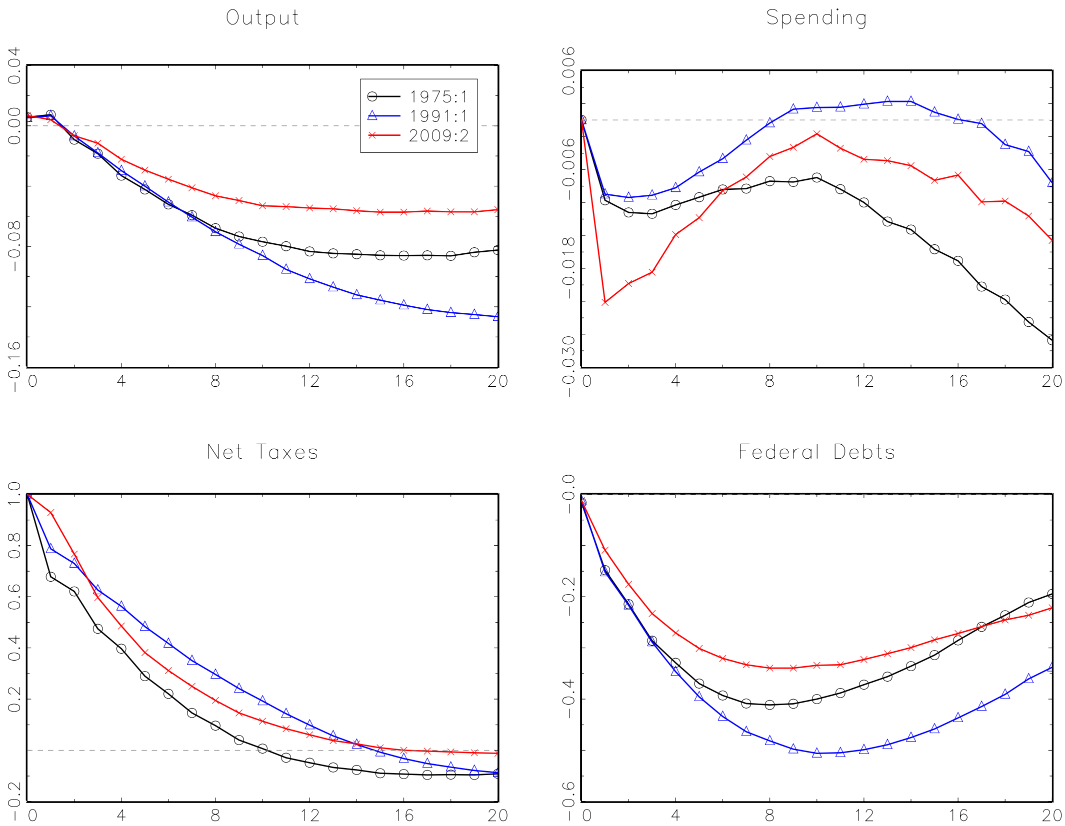

Figure 3.4: Responses to Tax Shocks

Notes: Impulse responses of output, government spending, net taxes and federal debts to tax shocks in 1975:1, 1991:1 and 2009:2. Responses expressed in percentage changes.

Much of the debate about fiscal policy effectiveness centers around the size of spending and tax multipliers. Figure 3.5 displays the response of output in dollars to a one dollar input shock at selected horizons from 1970:3 until 2010:3. To convert the original elasticity estimates from before into dollar-for-dollar changes, I divide the elasticities by the spending-to- and tax-to-output ratio prevailing at time t. These are the ratios plotted in the left panel of Figure 3.1. For better comparison of the two multiplier effects, I compute the tax multipliers based on negative shocks.

Three results stand out from the multiplier analysis. First, the spending multiplier in the 1970s is, on average, more effective in the long-run: with one dollar, the government buys about 1.60 dollars of output four years out. Second, the impact spending multiplier increases almost steadily over time, from one dollar in 1970 to 1.25 dollars in 1998. This effect arises, however, mostly through the declining spending share (see Figure 3.1). In every case, the size of the spending multipliers is reasonable throughout, taking values between 0.50 and 1.60 dollars before 1980 and between 0.50 and 1.25 dollars after 1980. Table 2 in Hall (2009) provides a summary of several time-invariant VAR estimates: there the multipliers range from 0.50 up to 1.20 dollars. Finally, tax multipliers lie consistently below the spending multipliers. Starting with a value of 0.50 dollars in 1970 the effect after four years reaches its peak at roughly 0.80 dollars in 1983 and decreases thereafter until it reaches again the 0.50 dollar mark in 2010. For the other horizons the effects lie between zero and 0.40 dollars with no obvious drifts. The comparison of tax multipliers with other papers is flawed because recent papers such as Romer and Romer (2010) and Perotti (2011) use a narrative approach to identify tax shocks and get much larger effects. For that reason, I plan to incorporate narrative measures of tax shocks in a fiscal TVP-VAR in future work.

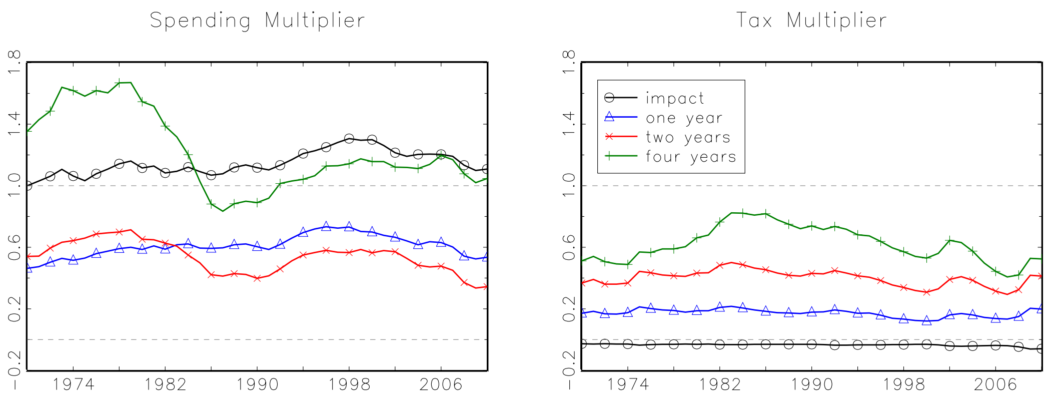

Figure 3.5: Multipliers

Notes: The spending and tax multipliers display the output responses expressed as dollar-for-dollar changes. Conversion from percentage changes into dollar changes based on the spending-to- and tax-to-output ratio prevailing at time t (see ratios in Figure 3.1). For better comparison with the spending multipliers, I use a negative tax shock to compute the tax multipliers.

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3.4.3 Fiscal Policy Counterfactuals

The objective of the counterfactual experiments laid out in Section 3.2.3 is to simulate a government that reduces the level of debts in two different ways, an active and passive one. In the first experiment I let the government cut spending more aggressively whenever we observe rising debts and, in the second one, the government adjusts taxes more swiftly in response to higher expenditures. Scenario one requires the government to directly control the level of debts through tighter spending constraints and has a stronger incentive to increase its own efficiency. Under scenario two, on the other hand, the government just levies enough taxes in order to pay for whatever expenditures they made in the previous periods. The questions is then how the different objectives and incentives the government has in the active and passive stance will spread over the private sector and how, as a result, it will affect output.

The design of the counterfactual follows Canova and Gambetti (2009) and circumvents the Lucas critique by accounting for the effect a change in one or more coefficients has on the whole coefficient structure β_t through the estimated correlation Q. I display the counterfactual responses in Figures 3.6 and 3.7 at four specific dates: the three recession trough dates used above—1975:1, 1991:1, 2009:2—and in addition 1984:1. The impulse response function in (3.20) implies a dependency on the local history of the variables. I add this specific date because it represents a time when all four variables were growing rapidly; it therefore provides a natural counterpart to the three trough dates.

The responses in Figures 3.6 and 3.7 confirm the hunch that the two government stances imply different effects on output. In the active stance the spending cuts have no adverse output effects in the long-run: it positively affects the private sector and outweighs the stresses and strains from the debt reduction. When the government is in the passive stance, output decreases: even though spending increases the government raises taxes swiftly and puts any positive incentives for the private sector on hold. Corsetti et al. (2010) have a standard New Keynesian model that delivers the same qualitative effects. In their model, government spending either responds to the deviation of debts from a target level or is entirely financed by taxes, similar to my active versus passive scenarios. Key to the positive output effect is the private sector's anticipation of prospective spending cuts (i.e. the incentive) rather than higher taxes.

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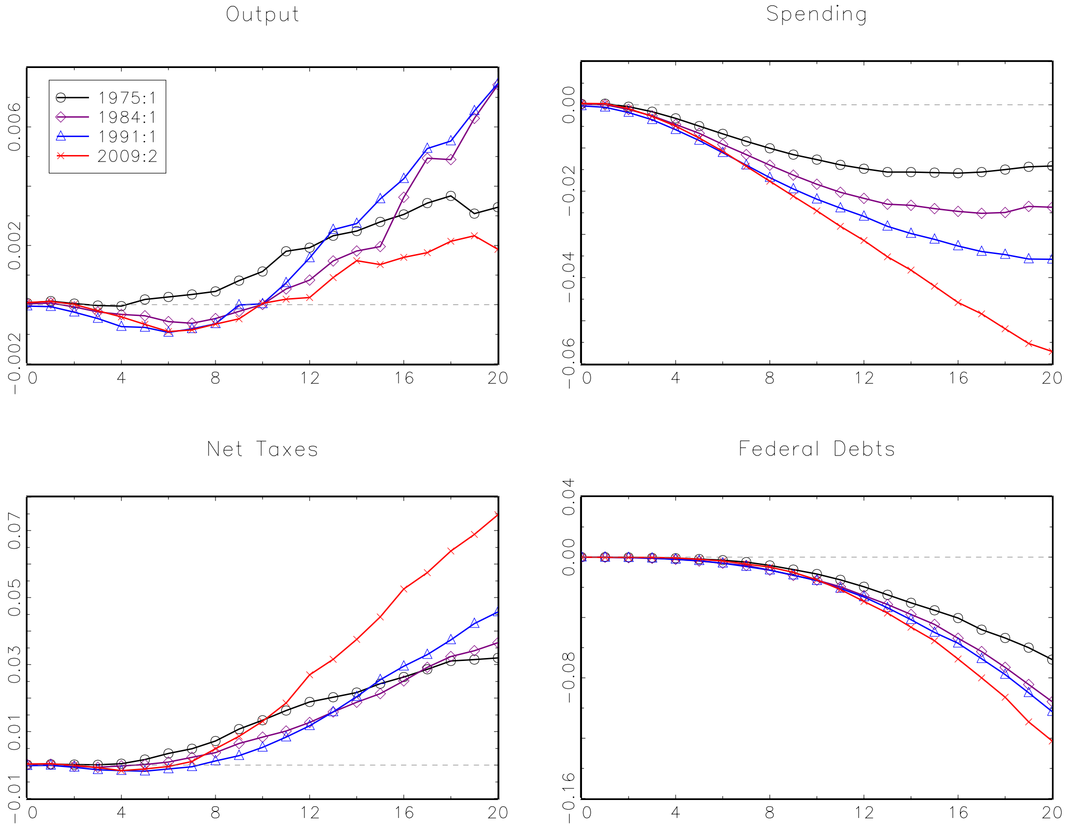

Figure 3.6: Active Government Stance

Notes: Counterfactual responses of output, government spending, net taxes and federal debts in 1975:1, 1984:1, 1991:1 and 2009:2. The experiment simulates a government that reduces debts by means of more aggressive spending cuts. Computed along the lines of Section 3.2.3 and Canova and Gambetti (2009). Responses expressed in percentage changes.

The counterfactual responses in the recent 2009:2 period differ somewhat from other periods. In Figure 3.6 the government reduces spending and, at same time, increases taxes by more than in 1975:1, 1984:1 and 1991:1. This result is emblematic for the severe recession in 2008 and 2009 with extreme changes in all four variables which, in turn, require larger counterfactual responses of the public sector variables in order to achieve a certain goal. Only output lags behind: the counterfactual output response lies below the others at horizons beyond ten quarters. Also in the passive stance in Figure 3.7 one sees a much smaller negative output response in the 2009:2 period. The spending increase is accompanied by a less pronounced rise in taxes and a smaller reduction of debts, thus the subdued effects on output.

The general message here is clear. A government that actively reduces debts by

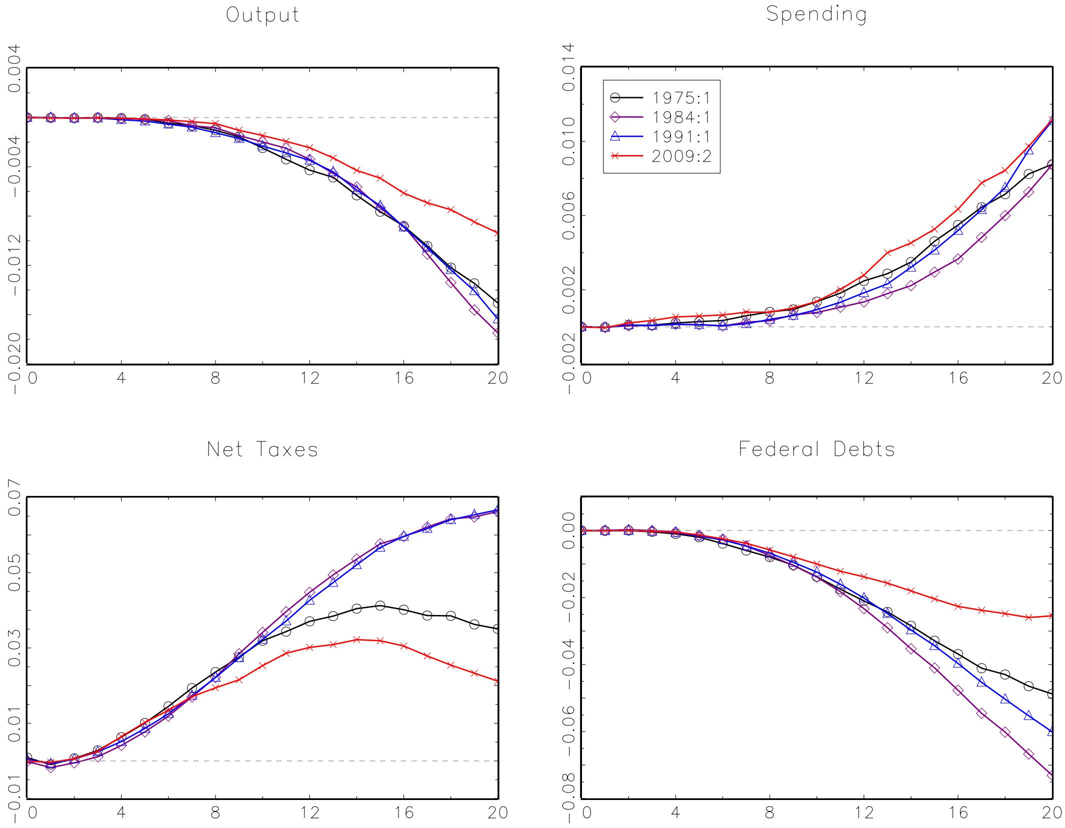

Figure 3.7: Passive Government Stance

Notes: Counterfactual responses of output, government spending, net taxes and federal debts in 1975:1, 1984:1, 1991:1 and 2009:2. The experiment simulates a government that reduces debts by adjusting taxes more quickly in response to higher expenditures. Computed along the lines of Section 3.2.3 and Canova and Gambetti (2009). Responses expressed in percentage changes.

cutting spending in a credible way provides enough incentives for the private sector to pitch in for the government in the long-run. Passively reducing debts by just controlling the deficit through tax adjustments does not seem to be good policy-making.

3.5 Conclusions

In this paper, I contribute to the huge recent literature on the effects of fiscal policy by highlighting the time-variation in the transmission of government spending and tax shocks. My analysis is cast in the time-varying parameter structural VAR framework of Primiceri (2005) which, with a few exceptions, has been mainly used so far to study monetary policy. Specifically, I model fiscal policy and the private sector behavior of the U.S. economy over the last four decades, including data on output, government spending, net taxes and federal debts. Estimation relies on an efficient Markov chain Monte Carlo algorithm, Gibbs sampling in particular, for the numerical evaluation of the posterior distributions.

The main results accord well with the conventional wisdom of a declining effectiveness of changes in fiscal policy, with one qualification for taxes. Unlike other periods, the late 1980s and early 1990s were characteristic for deficit-driven tax changes with the objective to reverse the course of the surging debt-to-output ratio. The TVP-VAR uncovers this mid-period as the one when tax policy was most effective, especially with respect to reducing the level of debts. Overall, the observed pattern of time-variation, makes a TVP-VAR an attractive and natural choice for the empirical characterization of changes in fiscal policy.

From a methodological point of view the paper innovates upon the TVP-VAR literature in one important aspect. It implements the widely used Blanchard and Perotti (2002) method to identifying fiscal policy shocks into a TVP-VAR. The twist is, simply put, that identification requires a non-recursive structure of the contemporaneous impact matrix, whereas Primiceri's (2005) framework relies on a triangular shape of that matrix. While Pereira and Lopes (2010) are the first who provide a solution to this aspect, my reformulation of the problem is more compatible with the estimation algorithm of Primiceri (2005). Whether the method of Blanchard and Perotti (2002) is the best way to identifying the "true" underlying government spending and tax shocks was beyond the scope of this paper. In every case, their is plenty of room for more ingenuity. An immediate extension would be to identify the shocks through sign restrictions as in Mountford and Uhlig (2009), although eliciting better information on impulse responses is by no means guaranteed as the identifying restrictions provide very weak information. On the other hand, combing the new narrative-based tax measures, most notably Romer and Romer (2010), with TVP-VARs is, perhaps, a more promising direction of research for dealing with identification issues. Especially the ones arising through fiscal foresight.

In addition to the methodological contribution, I use the counterfactual policy design of Canova and Gambetti (2009) to study the effects of two different ways to reduce the level of debts: actively by cutting spending and passively through budget surpluses obtained from tax adjustments in response to past expenditure levels. In that respect, the counterfactual analysis also bears on the policy debate about what should follow after the recent, mostly deficit-financed, stimulus packages. As one may perhaps expect, the active government policy stance has hardly any adverse effects on output. In fact, output tends to increase in the long-run. The passive stance, on the other hand, provides no positive spillover effects on the private sector and, consequently, output decreases. The differences arise through the way the government actions affect private incentives and the anticipation of tax changes. A government that reduces the debt burden in a credible and active way and, in the same time, may increase its own efficiency provides enough positive incentives for the private sector to more than compensate for the reduced public expenditures.

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