Essays in Applied Macroeconomics

Alexander Ziegenbein

TESI DOCTORAL UPF / ANY 18

DIRECTOR DE LA TESI
Regis Barnichon i Luca Fornaro
Departament d'Economia i Empresa

Universitat Pompeu Fabra Barcelona

To my parents, Moni and Klaus

Acknowledgements

First of all, I thank my main supervisor Regis Barnichon for all his support, encouragement and time. Regis took me under his wing, made me his research assistant, then co-author, and always encouraged and believed in me even when (or in particular when) things did not go well. He was always available to talk and took an enormous amount of time, allowing me to learn a lot from him over these years.

I am also deeply thankful to my second supervisor Luca Fornaro who provided me with invaluable support and advise during the final year of my PhD studies, in particular in relation to the academic economics job market.

Many people took a considerable amount of time to talk about research, provide me with feedback and listen to my ideas: Edouard Schaal, Christian Brownlees, Jordi Gali, Isaac Bailey, Davide Debortoli, Andrea Caggese, Donghai Zhang, Giacomo Caracciolo, Christoph Hedtrich, Florens Odendahl: I thank you all very much. I would also like to thank all participants at the CREI Macroeconomics Lunch for constructive comments and feedback during and after presentations.

A very big thank you to Marta Araque and Laura Agusti who manage the doctoral program and organize economics teaching at UPF, respectively. The extent of support we PhD students receive from you is absolutely incredible. While I still wonder how you manage to get all that work done, it is safe to say that the program would not be same without you.

I wrote part of this thesis during an internship at the International Monetary Fund in Washinton DC. I would like to thank my hosts, co-authors, and friends Luis Jacome H. and Tahsin Saadi Sedik for their hospitality and guidance during my time there.

Outside of academia, I first of all, thank my family. Mom and Dad: I am sure you did not see this coming during my less than promising high school years! While I know that over these last five years you were not always sure what I am doing and why exactly it is taking so long, you always showed me your unconditional support and love and gave me countless advice. I am forever thankful for that. I thank my brother Matthias, who, during the final stages of my thesis, received one or two hysteric phone calls, listened to my ”problems” with great patience and replied with just what I needed to hear. I also thank my sister Kathi and

my brother(-in-law) Roman for their numerous visits during my time in Barcelona. It is always so good to have you around, and I am excited that we will live closer to each other again soon. I send a special thank you to my departed granddad ”Opi”, who, whenever I felt myself under strong pressure over the last years, showed up in one of my dreams telling me to relax and not take life so seriously. You are of course right, and I did my best to follow your advice.

I would also like to thank my friends. A special thank you goes to Diego who is not only my first and best friend in Barcelona but has also often been required as my primary source of advice and inspiration when I faced a difficult decision. Our friendship is one of the best things I am taking from this time, and I am extremely grateful to have shared many major life events with you over the last years. A big thank you goes to my great friend and six year office mate: Donghai, it was an honour to spend my doctoral studies side by side with you, and I thank you for all our coffee breaks, Taco lunches, drinks, dinners (despite your questionable restaurant choices), your feedback and encouragement, and mostly your friendship. I send a special thank you to my late friend Bryan with whom I first started the idea to move to Barcelona. I miss you, my friend... how much fun it would be to celebrate this occasion with you! A huge thanks to my friends Flo and Christi: we had so much fun together, and I don’t know if and how I would have completed the Master without you! Thanks so much to Abdel, Giacomo, Adil, Miguel, Andrea, Cate, Jared, Giulia, Alice, Kelvin, Sebastian and Niklas G., who were all essential in making the time here such a special one for me. A big thank you to my friends from Zurich with whom I started the journey during my undergraduate studies. Andrea, Janna, Jojo, Marius, Michael: we spent such an important time together, and your friendship and support have only made it possible for me to take this next step.

Finally, and most importantly, I thank Dijana. Over these last years we grew together, learned together and from each other, tried new things together, had a lot of fun together, enjoyed life together, experienced great moments, tough times, and some tragedy together. We also celebrated a great deal of accomplishments together. One of those accomplishments is this moment: us finishing the PhD together. And now, I am happy that we move on, together.

Abstract

The thesis is a collection of three self-contained essays. In the first chapter, I present evidence that the effects of US tax changes on output depend on the level of economic slack. Tax cuts have large effects in good times, but only small effects in bad times. To explain the finding, I develop a search model of unemployment, in which the effect of a tax cut is small when unemployment is high. In the second chapter, we show that adverse financial shocks have large and persistent effects on output, while favorable financial shocks have little effects. Our results help to reconcile contradictory findings from the two leading strands of literature on the effects of financial crises. In the third chapter, we find that credit easing leads to a sharp increase in domestic currency depreciation and inflation and a reduction in economic growth in a sample of emerging and developing economies.

Resum

La tesi és un recull de tres assajos complerts. En el primer capítol, presento proves que els efectes de canvis impositius dels Estats Units en la producció depenen del nivell del *slack* econòmic. Les reduccions d'impostos tenen grans efectes en bons moments, però pocs efectes en mals moments. Per explicar aquesta troballa, desenvolupo un model de cerca de l'atur, en el qual l'efecte d'una baixada d'impostos és baix quan l'atur és alt. En el segon capítol, mostrem que els xocs financers advers tenen efectes grans i persistents en la producció, mentre que els xocs positius tenen efectes petits. Opinem que la nostra troballa ajuda a reconciliar altres troballes contradictòries en dos corrents de la literatura dels efectes de les crisis financeres. En el tercer capítol, mostrem que *credit easing* condueix a un marcat increment en la depreciació de la moneda domèstica i en la inflació, a més d'una reducció en el creixement econòmic, per a una mostra d'economies en desenvolupament i emergents.

Preface

The thesis is a collection of three self-contained essays. In all three chapters, I use state-of-the-art econometric methods to study highly topical macroeconomic policy questions and phenomena: Chapter 1 investigates how the effects of US tax policy vary over the business cycle; Chapter 2 examines the magnitude and persistence of output losses in the aftermath of financial market disruptions; Chapter 3 studies the effects of credit easing policies in emerging and developing economies.

In the first chapter, I present empirical evidence that the effects of US tax changes on output depend on the level of economic slack. Tax cuts have large effects in good times, but only small and statistically insignificant effects in bad times. I show that the finding holds across different identification schemes, many alternative specifications, and when I consider shocks to the two largest tax categories —personal and corporate income taxes— separately. To explain the finding, I develop a simple search model of unemployment, in which the effect of a tax cut is small when unemployment is high. A tax cut raises the utility gain from work and thus stimulates jobseekers' job-search effort. The higher search effort reduces search frictions, which makes it less costly for firms to hire new workers, and therefore raises employment and production. When labor demand is depressed and unemployment is high, however, the number of jobseekers per vacancy is large and recruiting is easy and inexpensive, so search frictions do not matter much. As a result, a tax cut that raises search effort has little effect on employment and output.

In the second chapter, co-authored with Regis Barnichon and Christian Matthes, we first highlight that the two leading strands of literature on the implications of financial market disruptions reach conflicting conclusions. The first studies the behaviour of output around *narratively* identified financial crises and finds large and persistent drops in output in the aftermath of a crisis. The second uses Structural Vector AutoRegressions to identify the *causal* effects of *financial shocks* and finds rather small and short-lived effects on output. We argue that these seemingly contradictory findings are due to the asymmetric effects of financial shocks, which have been predicted theoretically but not considered empirically. We propose and estimate a model designed to identify the (possibly asymmetric) effects of financial market disruptions, and we find that a favorable financial shock —an easing of financial conditions— has little effect on output, but an adverse shock has large and persistent effects. In fact, the financial market disruptions experienced by the US in the 2007-2008 financial crisis can explain two thirds of the 10 percentage points gap between current GDP and its pre-crisis trend. Our results help to reconcile the evidence from narrative accounts and SVARs: SVARs find only mild average effects because the large and persistent effects of adverse shocks are mixed with the close to zero effects of positive shocks. Narrative studies find large effects as they focus solely on crisis episodes, i.e. adverse events.

In the third chapter, co-authored with Luis Jacome H. and Tahsin Saadi Sedik, we study whether credit easing, which has been used extensively in advanced economies since the global financial crisis, is also a suitable policy tool for emerging and developing economies. Credit easing may help to stabilize the financial system, thus avoiding higher output losses. However, theory suggests that using central bank money to bail out the financial system can pave the way for balance-of-payment problems and the large output losses associated with it. We first propose a measure of credit easing, which builds on balance sheet data on central banks' claims on the financial system, and highlight that some emerging economies have used credit easing to a similar extent as advanced economies. Then, we show that an increase in credit easing is followed by a sharp increase in domestic currency depreciation and inflation, and a reduction in economic growth. Our findings suggest that credit easing bears the risk of creating new problems and further output losses in emerging and developing economies.

Contents

List of Figures

List of Tables

Chapter 1

CAN TAX CUTS RESTORE ECONOMIC GROWTH IN BAD TIMES?

1.1 Introduction

The effects of tax changes on economic activity are subject to constant policy analysis and debate. In particular in times of low economic growth and high unemployment, politicians often argue that tax cuts can revive the economy. In the U.S., bringing employment and output back to potential is commonly stated explicitly as a motivating factor behind a tax cut.[1] But is this a viable strategy? Can tax cuts restore economic growth in bad times? While recent empirical work suggests that tax changes have large effects on output *on average*,[2] there is no evidence on how these effects vary with the state of the economy.

In this paper, I present empirical evidence that the effects of U.S. tax changes

[1]Well known examples are the Obama tax cuts in the American Recovery and Reinvestment Act of 2009, the Bush tax cuts in the Job Creating and Worker Assistance Act of 2002 and the Economic Growth and Tax Relief Reconciliation Act of 2001, the Ford tax cuts in the Tax Reduction Act of 1975, and the Nixon tax cut in the Tax Reform Act of 1971.

[2]Perotti (2012) summarizes existing approaches and concludes that the peak effect of a 1 percent reduction in taxes/GDP on real GDP are about halfway between the 2-3 percent estimates of Romer and Romer (2010), and Mertens and Ravn (2011; 2012; 2014) and the 0.5-1 percent estimates of Blanchard and Perotti (2002) and Favero and Giavazzi (2012).

on output depend on the level of economic slack. In good times, tax shocks have large effects on output—much larger than estimates from a linear model suggest. In bad times, on the other hand, tax shocks have small and statistically insignificant effects on output. The finding holds for two leading identification schemes, for a variety of alternative specifications, and when I consider tax shocks to the two largest tax categories—personal and corporate income taxes—separately. In addition, tax shocks have large effects on employment, consumption, and investment only in good times. The effects of a tax shock on the real wage are small, statistically insignificant and do not depend on economic slack.

To explain the results, I develop a simple search model of unemployment, in which the income tax multiplier is small when unemployment is high. I focus on an income tax because it is by far the largest tax category. The effect of a tax change depends on economic slack, because of (i) the presence of search frictions in the labor market and (ii) job rationing, i.e., the labor market does not clear in the absence of search frictions. An income tax cut raises the utility gain from work and thus stimulates jobseekers' job-search effort. The higher search effort reduces search frictions, which makes it less costly for firms to hire additional workers, and hence raises employment and production. When labor demand is depressed and unemployment is high, however, the number of jobseekers per vacancy is large and recruiting is easy and inexpensive, so search frictions do not matter much. As a result, a tax cut that raises search effort has only small effects on employment and output. The same mechanism leads to a large effect on employment and output when unemployment is low and the matching process is congested by vacancies.

In Section 1.2, I present my baseline empirical framework. To identify tax shocks, I build on Romer and Romer's (2010) narrative measure of exogenous tax changes constructed from historical sources. My key identifying assumption is that the narrative measure correlates with the unobserved tax shock, but is uncorrelated with other shocks. Thus, I use the narrative measure as an external instrument for the tax shock. I prefer the narrative approach over a purely statistical one because it addresses more convincingly the possibilities of forward-looking policy or correlations with non-cyclical, non-policy influences on tax revenues and other determinants of output. I use an instrumental variable (IV) approach because the identification assumption is weaker than assuming the narrative account measures the true tax shock without error. To estimate impulse responses, I use Jordà's (2005) local projections method (LP), and I use the lagged unemployment rate as a measure of economic slack. I choose the unemployment rate as it is a widely accepted measure of underutilized resources. The LP method is more robust to arbitrary forms of model misspecification than the more conventional VAR. In addition, with the LP method, one does not have to take a stand on how the shock affects the state of economy.[3]

In Section 1.3, I present the main finding that tax shocks have large effects on output in good times, but only small and statistically insignificant effects in bad times. In fact, estimates from a linear model are approximately a weighted average of large effects when economic slack is low, and small effects when economic slack is high. I show that the same finding emerges with the Blanchard and Perotti (2002) identification strategy that imposes short-run restrictions in a structural VAR. Digging deeper, I examine whether one of the two largest tax categories is driving the result. I consider personal income taxes, which account for on average 74 percent of total federal tax revenues, and corporate income taxes, which account for on average 16 percent. Specifically, I use the decomposition of the narrative measure into the two subcategories by Mertens and Ravn (2013). However, the number of exogenous tax changes per category is small, which generates an efficiency problem when using a method as flexible as LP. To address the issue, I develop a new Bayesian method that allows to flexibly combine the advantages of VARs and LPs. My method allows to maintain much of the efficiency of the VAR while relaxing its strong parametric restrictions. The main idea is to use LPs with informative priors centered around the iterated VAR impulse response function. Applying my new method, I find that both tax categories have large effects in good times, and small and insignificant effects in bad times.

In Section 1.4, I develop a simple search-and-matching model to provide a structural interpretation for the result. I perform a comparative steady-states analysis to highlight the key economic forces at work. I derive an analytical expression for the income tax multiplier and represent the equilibrium diagrammatically. The

[3]In this context, the LP method, therefore, dominates a VAR which requires additional assumptions on the path of the state variable.

steady-state equilibrium is the intersection of a convex and upward-sloping quasi-labor supply and a downward-sloping labor demand in an (employment, labor market tightness) plane. The quasi-labor supply is the employment rate when labor market flows are balanced. The properties of the curves are due to a standard matching function and a production function with diminishing marginal returns to labor. An income tax cut raises the utility gain from work and thereby stimulates jobseekers' job-search effort. In the diagram, the quasi-labor supply shifts outwards. The higher search effort reduces tightness, which makes it less costly for firms to hire new workers, and hence raises employment. I compare a steady-state to another steady-state with lower labor demand and thus higher unemployment. The effect of a tax cut on employment and output is determined by the amplitude of the reduction in tightness. When labor demand is lower, a tax cut has a smaller effect on tightness because the quasi-labor supply is convex. Intuitively, in recessions, jobs are lacking, labor market tightness is low, and search frictions do not matter much. Thus, a tax cut that raises search effort has only little influence on tightness and employment.

To improve realism, I embed the search-and-matching model into a New Keynesian model. Unemployment fluctuates because the economy is subject to technology shocks and real wage rigidities. I compare the effect of a technology shock when it is accompanied by a tax change and when it is not. The peak effect of an income tax cut on output falls from 0.41% to 0.12% when the unemployment rate increases from 5 percent to 8 percent. I conclude the section by discussing some of the model's shortcomings, and the ability of competing explanations to rationalise the patterns I find in the data.

The findings of the paper question whether estimates of the average effects of tax shocks from a linear model can provide meaningful guidance for fiscal policy. My paper is complementary to empirical work that studies whether the government spending multiplier is larger in bad times. Interestingly, these papers find that the government spending multiplier is either larger in bad times (see for example Auerbach and Gorodnichenko 2012a; 2012b; Fazzari et al., 2015), or does not depend on economic slack (Ramey and Zubairy, 2016). I recover the opposite result for the effects of tax shocks. My paper builds on and complements the theoretical work of Michaillat (2014). In his model, a public employment multiplier increases when the unemployment rate is high. I extend the model of Michaillat (2014) to allow for endogenous job-search effort and show that the model can also rationalize the finding that tax shocks have larger effects when unemployment is low. Section 1.5 concludes with some thoughts for future research.

1.2 Empirical Framework

In this section, I first lay out my identification strategy. Then, I present my econometric specification and my baseline measure of economic slack.

1.2.1 Identification

My identification strategy is based on Romer and Romer's (2010, henceforth RR) narrative measure of exogenous U.S. tax changes. RR use historical sources[4] to record 110 U.S. tax code changes between 1947Q1 and 2007Q4 along with their (projected) impact on federal tax liabilities and motivation. Each tax act is classified by its key purpose as either (i) spending driven, (ii) countercyclical, deficit-driven (to reduce an inherited budget deficits), or, to raise long-run growth. RR argue that tax changes that address an inherited budget deficit or aim to increase long-run growth are *exogenous* because they are not motivated by current or short-run economic conditions. Following this definition, 51 tax changes are exogenous. Some are legislated in the same quarter, such that exogenous tax changes occur in 45 quarters. I follow RR and divide tax liability changes by (lagged) nominal GDP. Hence tax changes are expressed in percentage of GDP.[5] Figure 1.1 plots the narrative measure. We see that exogenous tax changes are fairly equally distributed over the sample. The standard deviation is 0.24, and the standard deviation of non-zero observations is 0.55.

My key identification strategy is that the narrative measure correlates with the latent tax shock but is uncorrelated with other structural shocks. Hence, I use

[4]Such as presidential speeches, the Economic Report of the President, and reports of Congressional committees.

[5]I follow Mertens and Ravn (2014) and remove the mean from non-zero observations. The mean is approximately zero.

the narrative measure as an external instrument for the latent tax shock.[6] This identification assumption is weaker than assuming that the narrative measure is equal to the unobserved tax shock.[7] In practice, the construction of the narrative measure from historical sources likely introduces measurement error. Historical records sometimes contradict each other which makes judgment calls impossible to avoid. My strategy takes this into account. I only require that the narrative measure correlates with the unobserved tax shock, but the correlation does not need to be perfect.

The narrative approach has two advantages. First, it addresses the possibilities of forward-looking policy or correlations between non-cyclical, non-policy influences on revenues and other determinants. Purely statistical approaches, on the other hand, typically assume that once one corrects for the impact of output on tax revenues and controls for government spending, changes in revenues are uncorrelated with other determinants of output (see Perotti, 1999 and Blanchard and Perotti, 2002).[8] Second, it allows me to sidestep the VAR and use Jordà's (2005) local projection (LP) method.

1.2.2 Econometric Method

I estimate impulse responses to a tax shock with the LP method. The LP method has two advantages over the more conventional VAR. First, it is more robust to arbitrary forms of model misspecification. This is important in the context of tax shocks as the literature documents that small specification changes, such as number of lags assumed in the VAR or an additional control variable, lead to drastically different results.[9] Second, the LP method can be adapted to allow for state-dependent impulse responses without taking a stand on how the economy transitions from state to state. In a state-dependent VAR, one needs to impose

[6]The approach is related to Mertens and Ravn (2014) who use the narrative measure to identify parameters in a structural VAR.

[7]See for example RR, Mertens and Ravn (2011; 2012), Favero and Giavazzi (2012), Perotti (2012), Cloyne (2013).

[8]Leeper et al. (2011) point out that fiscal foresight could cause a misalignment between the agents' and the econometrician's information set, thus making it impossible to extract meaningful shocks to taxes from statistical innovations in a VAR.

[9]For a detailed discussion, see Perotti (2012).

additional assumptions on how the shock affects the state variable.[10] A common assumption is that the shock does not alter the state over the impulse response horizon.[11] This seems implausible in the context of tax shocks as empirical evidence points to large effects.

1.2.3 Linear Specification

I combine the LP method with the RR narrative measure as an instrumental variable (IV) for the latent tax shock (LP-IV).[12] [13] To establish a benchmark, I first estimate a linear model:

$$x_{t+h} = \alpha_h + \beta_h ATR_t + \gamma_h' z_t + \delta_h' D_t + u_{t+h}. \tag{1.1}$$

ATR_t is the average tax rate, defined as federal tax revenues minus transfers divided by lagged nominal GDP. x_t is the dependent variable of interest. I estimate impulse responses for log real GDP (Y_t), log real federal government spending (G_t) and ATR_t[14], hence $x_t = \{Y_t, G_t, ATR_t\}$. z_t is a vector of control variables. D_t are deterministic terms. I use quarterly data from 1947Q1 to 2007Q4.[15] The impulse response of variable x at horizon $h \in \{0, H\}$ to a tax shock is given by $\theta_h = \beta_h \sigma_\tau$, where σ_τ is the scale of the tax shock. Since ATR_t is endogenous, OLS-estimation of (1.1) is invalid. Instead, with a suitable instrument, (1.1) can be estimated by LP-IV. I propose the RR narrative measure RR_t as an IV for the latent tax shock ϵ_t^τ. RR_t can be used to estimate the causal effects of tax shocks if it satisfies the conditions for instrument validity.

I define $x_t^\perp = x_t - Proj(y_t \mid z_t)$ for some variable y_t and controls z_t. That is $y_t^\perp$ describes the variation in y_t orthogonal to the controls z_t. Moreover, I define the vector of structural shocks $\epsilon_t = [\epsilon^\tau_, \epsilon_t^\bullet]'$. Hence, ϵ_t contains the tax shock and

[10] Appendix 1.A clarifies this point analytically

[11] See for example Auerbach and Gorodnichenko (2012b) and Ramey and Zubairy (2016).

[12] The first to combine the LP method with an instrumental variable approach were Jordà et al. (2015), Jordà and Taylor (2016), and Ramey and Zubairy (2016).

[13] The approach is related to Mertens and Ravn (2014) who use the narrative measure to identify parameters in a fiscal VAR

[14] A detailed description of the data and corresponding sources is given in Table 1.1.

[15] This is the longest time-span for which Y_t, G_t, ATR_t and the narrative measure are all available.

all other structural shocks denoted by $\epsilon_t^{\bullet}$. In the notation of Stock and Watson (2017), the conditions for instrument validity are:

$$E\left(\epsilon_t^{\bullet\perp} RR_t^{\perp}\right) = 0 \qquad \text{(Contemporaneous Exogeneity)}$$
$$E\left(\epsilon_{t+j}^{\perp} RR_t^{\perp}\right) = 0 \text{ for } j \neq 0 \qquad \text{(Lead/Lag Exogeneity)}$$
$$E\left(\epsilon_t^{\tau\perp} RR_t^{\perp}\right) = \mu \neq 0. \qquad \text{(Relevance)}$$

The first condition states that RR_t must be uncorrelated with other shocks. The second condition states that RR_t must be uncorrelated with past and future structural shocks. The third condition states that RR_t must be correlated with the latent structural tax shock.

Exogeneity.—The first condition is likely satisfied. RR specifically employ the narrative approach to avoid that tax changes in RR_t are driven by current or short-term economic conditions. Moreover, legislative lags make it unlikely that other contemporaneous factors affect RR_t. RR, Mertens and Ravn (2012) and Favero and Giavazzi (2012) provide evidence that the second requirement is likely satisfied. They all fail to reject the hypothesis that RR_t is unpredictable by past observations of macroeconomic aggregates. In addition, I can not reject the null of no serial correlation in a regression of RR_t on its own lags.

Relevance.—The third condition can be tested empirically through the first stage of (1.1). I report the first stage regression results in the beginning of the next section.

Controls and deterministic terms.—Because the exogeneity requirements are likely satisfied, I can estimate β_h consistently by LP-IV without controls. However, controls may increase estimator efficiency by reducing the variance of the error term. To that end, I add four lags of Y_t, G_t and ATR_t to the set of controls. D_t includes a quadratic trend and, following Blanchard and Perotti (2002), a dummy for 1975Q2. With this choice of controls, the specification closely resembles the setup in a standard fiscal VAR.[16] I later investigate whether the results

[16]See for example Blanchard and Perotti (2002), Auerbach and Gorodnichenko (2012b), and Mertens and Ravn (2014). Standard fiscal VARs use log real federal tax revenues instead of the average tax rate. I prefer the average tax rate because it corresponds more closely to a policy instrument. Political debates usually evolve around changes in tax rates and less about changes in tax revenues. However, none of the results is sensitive to using log real federal tax revenues

are robust to expanding the set of controls.

Shock scale.—Since the tax shock is unobserved, σ_τ is indeterminate. The scale ambiguity is resolved by adopting, without loss of generality, a normalization for the scale of ϵ_t^τ. My normalization rests on the first stage of (1.1):

$$ATR_t = a + \sigma_\tau RR_t + c'z_t + d'D_t + e_t. \tag{1.2}$$

I define the point estimate of the coefficient on RR_t as the scale of the tax shock. The normalization is convenient because the point estimates of θ_h are now directly comparable to impulse response estimates from studies that treat RR_t as the tax shock.[17]

1.2.4 State-Dependent Specification

I now extend the model to allow for state-dependent impulse responses to a tax shock:

$$\begin{aligned} x_{t+h} &= I_{t-1}\left[\alpha_h^B + \beta_h^B ATR_t + \gamma_h'^B z_t\right] \\ &+ (1 - I_{t-1})\left[\alpha_h^G + \beta_h^G ATR_t + \gamma_h'^G z_t\right] + \delta_h' D_t + u_{t+h}. \end{aligned} \tag{1.3}$$

I_{t-1} is the state variable. The superscript B denotes the *bad* state and G denotes the *good* state of the economy. $I_{t-1} \times RR_t$ serves as an instrument for $I_{t-1} \times \epsilon_t^\tau$, and $(1 - I_{t-1}) \times RR_t$ as an instrument for $(1 - I_{t-1}) \times \epsilon_t^\tau$. The impulse response of variable x at horizon $h \in \{0, H\}$ to a tax shock is given by $\theta_h^B = \beta_h^B \sigma_\tau$ if the shock hits in bad times, and by $\theta_h^G = \beta_h^G \sigma_\tau$ if the shock hits in good times.

I estimate (1.1) and (1.3) by two-stage least squares (TSLS). To construct confidence bands, I follow Ramey and Zubairy (2016) and use the Driscoll and Kraay (1998) method to adjust standard errors for the possibility of correlation in the residuals across dates t and impulse response horizons h. This is akin to estimating the parameters equation by equation and then averaging the moment conditions across horizons h when calculating Newey-West (1987) standard errors. Following Jordà (2005), I set the maximum autocorrelation lag to $h + 1$.

instead.

[17] For example RR, Mertens and Ravn (2011; 2012), Favero and Giavazzi (2012), Perotti (2012).

1.2.5 The State Variable

There are many variables that may describe the state of the economy. Some measure economic slack, such as the unemployment rate, capacity utilization or the output gap. Others capture the state of the business cycle, such as NBER recession dates or output growth. In addition, one has to decide between a discrete thresholds that separates the good from the bad state and a continuous state variable. The literature has used a variety of different combinations.[18]

I interpret bad times as times of high economic slack. Following Owyang et al. (2013) and Ramey and Zubairy (2016), I define the economy to be in a high slack state if the lagged unemployment rate is above 6.5%. Thus, $I_{t-1} = 1$ if $U_{t-1} > 6.5\%$. I use the unemployment rate because it is a widely accepted measure of underutilized resources. The discrete threshold allows for an easy interpretation of the results. I later investigate the robustness of the results to alternative choices. Figure 1.2 plots the unemployment rate together with the RR narrative measure. We see that there is no systematic relationship between the two series. The economy is in the bad state in 66 quarters and in the good state in 178 quarters. 19 tax changes occur in bad times (standard error 0.6) of which 13 are tax increases and 6 tax cuts. 26 tax changes occur in good times (standard error 0.5) of which 12 are tax increases and 14 tax cuts.

1.3 Empirical Results

In this section, I first present the baseline results. I then investigate the robustness of the results to using an alternative identification strategy. I continue with a sensitivity analysis. Next, I study impulse responses of other important macroeconomic aggregates. Lastly, I distinguish between the effects of personal and corporate income tax shocks.

[18]For example, Owyang et al. (2013) and Ramey and Zubairy (2016) use the lagged unemployment rate with a discrete threshold of 6.5%. Fazzari et al. (2015) use lagged capacity utilization with a discrete threshold of 85%. Barro and Redlick (2011) use the standardized lagged unemployment rate. Auerbach and Gorodnichenko (2012b) and Tenreyro and Thwaites (2016) use a smooth transition function of the moving average of output growth.

1.3.1 First Stage

Instrument relevance can be evaluated through the first stage of (1.1) for the linear model, and the first stage of (1.3) for the state-dependent model.[19] The F-statistic for excluding RR_t in the first stage of (1.1) is 11.4.[20] The F-statistic for excluding $I_{t-1} \times RR_t$ in a regression of $I_{t-1} \times ATR_t$ on all variables on the right side of (1.3) is 15.8. The F-statistic for excluding $(1 - I_{t-1}) \times RR_t$ in a regression of $(1 - I_{t-1}) \times ATR_t$ on all variables on the right side of (1.3) is 12.6. Thus, the F-statistic is 15.8 in bad times and 12.8 in good times. To further explore instrument relevance, I consider two tax measures as alternatives for the average tax rate. First, I use the average marginal tax rate (AMTR). This is the income-weighted average of the individual marginal tax rates faced by agents included in the aggregate. Barro and Redlick (2011) construct the AMTR at annual frequency. When I estimate the first stage of (1.3) using annual data and the AMTR, the F-statistic is 26.1 in bad times and 20 in good times. Second, I use log real federal tax revenues. In that case, the F-statistic is 14.7 in bad times and 12.3 in good times.[21]

In all cases, the narrative measure passes Staiger and Stock's (1997) $F > 10$ rule-of-thumb for instrument relevance.[22] However, Olea and Pflueger (2013) show that the threshold can be different when errors are serially correlated. Using the Olea and Pflueger (2013) thresholds, I can not reject that the TSLS bias exceeds 10% of the OLS bias at the 5% level. To address the issue, I also conduct key hypothesis tests using Anderson and Rubin (1949) statistics. These are robust to weak instruments but have low power. In most cases, these statistics point to the same significance level as the Driscoll and Kraay (1998) method described above. Thus, I report statistics based on the Driscoll and Kraay (1998) method and only report Anderson and Rubin (1949) statistics when the two methods point

[19] Since errors may be serially correlated in the first stage, I report F-statistics based on Newey-West (1987) corrected standard errors with automatic lag selection.

[20] Ramey (2016) runs a similar regression and reports a first stage F-statistic of 3.2. However, she only uses a subset of the RR tax changes that removes 18 (out of 45) non-zero observations.

[21] I prefer the ATR over log real tax revenues because it corresponds more closely to a policy instrument. Political discourse usually focuses on changes in tax rates rather than changes in tax revenues. I prefer the ATR over the AMTR as it allows me to use quarterly data. The results are robust to using the alternative tax measures instead.

[22] That is the null hypothesis that the instrument is weak is rejected if $F > 10$.

to different significance levels.

1.3.2 Average Effects of Tax Changes

I first consider the linear model in (1.1). I estimate impulse responses to a tax shock over twelve quarters, i.e. $H = 12$. Figure 1.3 presents the results. The plain line shows the point estimates of θ_h and the shaded areas are 90% confidence bands. I find that a tax shock has no significant impact on output on impact. Over time, output gradually decreases and bottoms out seven quarters after the tax shock 2% below its trend. The result falls in the mid-range of estimated effects of a tax shock on output and is in line with Mertens and Ravn (2011) and Perotti (2012).[23] Importantly, I find that a tax shock has no significant effect on government spending. This suggests that the effect on output is not driven by an endogenous response of government spending to a tax shock. The average tax rate increases on impact by about 0.5 percentage points, remains roughly constant over the next five quarters and then converges slowly back to its trend level.

1.3.3 State-Dependent Effects of Tax Changes

I now estimate the state-dependent model in (1.3). Figure 1.4 presents the results. The left column shows the impulse responses to a tax shock that hits in bad times and the right column the impulse responses to a shock that hits in good times. The plain lines are the point estimates of θ_h^B and θ_h^G and the shaded areas are again 90% confidence bands. To ease orientation, the dashed lines show the point estimates of the linear model θ_h. The effect of a tax shock on output depends crucially on the state of the economy. A tax shock that hits in bad times has no significant effect on output over the entire impulse response horizon. The peak effect is $min(\hat{\theta}_h^B) = -0.5\%$ with a standard error of 1.3. A tax shock that hits in good times, on the other hand, has a much stronger effect on output than the linear model suggests. The point estimate of θ_h^G is consistently below that of θ_h over the entire impulse horizon. The peak effect is $min(\hat{\theta}_h^G) = -3.5\%$ after seven quarters and is significant at the 1% level with a standard error of 1.0. To formally assess

[23] Blanchard and Perotti (2002) and Favero and Giavazzi (2012) find a peak effect on output close to 1% while RR and Mertens and Ravn (2014) report values close to 3%.

whether the effects are different in good times and bad, I test the null hypothesis that the peak effects are the same in both states, i.e. $H_0 : min(\theta_h^B) - min(\theta_h^G)$ = 0. The point estimate of the difference is 3.0 percentage points and is significant at the 5% level with a standard error of 1.5. I find no evidence that the state-dependent effects on output are driven by a state-dependent response of government spending. A tax shock has no significant effect on government spending in both states. The impulse responses of the average tax rate are approximately symmetrical across states. Tax shocks have the same scale in good times and bad. Thus, the effect on impact is identical across states. If the shock hits in bad times, ATR increases further in the two quarters following the tax shock, while it remains roughly constant if the shock hits in good times. These differences are, however, not statistically significant. The impulse responses for the average tax rate, therefore, suggest that the state-dependent effects on output are not driven by larger or more persistent tax shocks in good times.

1.3.4 Alternative Identification Strategy

I now study whether the result is robust to using the Blanchard and Perotti (2002, henceforth BP) identification strategy instead. The specification is identical to BP, but additionally allows for state-dependent effects of tax shocks:

$$\begin{aligned} X_t &= I_{t-1}A^B \boldsymbol{X_{t-1}} + (1 - I_{t-1})A^G \boldsymbol{X_{t-1}} + \delta D_t + u_t \\ u_t &= I_{t-1}C^B \epsilon_t + (1 - I_{t-1})C^G \epsilon_t \\ \Sigma_t &= I_{t-1}\Sigma_u^B + (1 - I_{t-1})\Sigma_u^G. \end{aligned} \tag{1.4}$$

$X_t = [T_t, G_t, Y_t]'$, where T_t are log real federal government revenues. $\boldsymbol{X_{t-1}} = [X'_{t-1}, ..., X'_{t-4}]$. D_t contains a quadratic trend and a dummy for 1975Q2. ϵ_t is the vector of structural shocks with E$(\epsilon_t) = 0$ and $E(\epsilon_t \epsilon'_s) = 0$ for $s \neq t$. $u_t = [u_t^T, u_t^G, u_t^Y]'$ are the reduced form residuals with $u_t \sim N(0, \Sigma_t)$. BP argue that taxes and output have no contemporaneous effect on government spending, because the government is unable to adjust its spending in response to changes in fiscal and macroeconomic conditions in the short run. Thus, $c_{21}^j = c_{23}^j = 0$ for $j = \{B, G\}$. BP follow the approach of Giorno et al. (1995) to estimate the within-quarter elasticity of net taxes with respect to output. I adapt the approach and estimate the elasticity for two subsamples. To obtain an estimate for c^B_{13}, I use the subset of periods in which $U_{t-1} > 6.5$. To obtain an estimate for c^G_{13}, I use the subset of periods in which $U_{t-1} \leq 6.5$. The remaining parameters are estimated from (1.4). To construct impulse responses from a state-dependent VAR, one needs to impose additional assumptions on how the shock affects the state.[24] I follow the standard approach in the literature and assume that the state is constant over the impulse response horizon.[25]

I estimate $c^G_{13} = 2.8$ in good times, and $c^B_{13} = 0.7$ in bad times.[26] Thus, automatic stabilizers lead to a stronger adjustment in taxes in response to a change in output in good times. A possible explanation is that the regular income tax applies to fewer agents in bad times, due to lower levels of employment and the alternative minimum tax (AMT).[27] Figure 1.5 presents the impulse responses estimates. Shaded areas are 90% confidence bands, that I compute with a recursive wild bootstrap using 10.000 replications, see Gonçalves and Kilian (2004). Following Mertens and Ravn (2014), I scale the size of the tax shock such that the initial increase in tax revenues equals 1% of GDP. To ease orientation, the dashed lines show the estimates from a linear VAR. The results are similar to those of the baseline specification. I find that a tax shock has no significant effect on output in bad times. The peak effect is $min(\hat{\theta}^B_h) = -0.5\%$ with a standard error of 0.8. In good times, on the other hand, a tax shock has much stronger effects on output than the linear model suggests. I estimate a peak effect of $\hat{\theta}^G_h$ = -2.7% which is significant at the 1% level with a standard error of 0.7. The difference in peak

[24] Appendix 1.A clarifies this point analytically.

[25] See for instance Auerbach and Gorodnichenko (2012b) and Ramey and Zubairy (2016).

[26] I estimate a value of 2.3 over the full sample, which is slightly larger than BP's 2.1. The discrepancy is due to different sample horizons. The elasticity is increasing over time and my sample is longer. A higher estimate of the elasticity translates into larger effects of a tax shock on output, see the discussion in Caldara and Kamps (2017).

[27] The classic automatic stabilizers are the personal and the corporate income tax system. Because they are progressive in the U.S., a decline in income should be accompanied by a more than proportionate decline in taxes. Importantly, taxpayers pay the higher of the regular income tax or the AMT. The AMT is imposed at a nearly flat rate on taxable income. In bad times a higher fraction of taxpayers pays the AMT instead of the regular income tax. Moreover, more people are unemployed and do not pay taxes. Hence, the regular income tax rate applies to fewer agents. Intuitively, any automatic adjustment in regular income tax rates thus has a smaller effect on tax revenues in bad times.

effects is $min(\hat{\theta}_h^B) - min(\hat{\theta}_h^G) = 2.2$ percentage points, and is significant at the 10% level with a standard error of 1.2. A tax shock has no significant effect on government spending in both states and the impulse responses of the average tax rate are approximately symmetrical across states.

Table 1.2 collects the estimated peak effects of a tax shock on output using the baseline specification (LP-IV) and the BP VAR. Both approaches suggest that tax shocks have large effects on output only in good times. While the results are qualitatively similar, the VAR estimates are a degree of magnitude smaller. A possible explanation for this is the tight dynamic structure VARs impose on the shape of the impulse response function relative to LPs.

1.3.5 Sensitivity Analysis

This section performs a sensitivity analysis. Appendix 1.B describes the robustness checks in detail. I discuss them here in a compressed manner.

State Variable.—I explore whether the results are robust to using alternative state variables. First, I allow for a time-varying threshold and consider deviations from the Hodrick-Prescott filtered unemployment rate, using three different smoothing parameters. Second, I use the continuous unemployment rate. Third, I consider two business cycle indicators: NBER recessions and Auerbach and Gorodnichenko's (2012) smooth transition function of output growth. The peak effects of a tax shock on output are summarized in Table 1.3. The main finding is robust to using alternative state variables. In all cases, the peak effect of a tax shock on output is larger in good times. The difference in peak effects $min(\hat{\theta}_h^B) - min(\hat{\theta}_h^G)$ is significant at the 5% in five out of seven cases, and significant at the 10% level in six out of seven cases.

Controls.—I check that the results are robust to adding additional controls. First, I add four lags of real federal government debt to the public. Second, I aim to control for monetary policy and add four lags of the federal funds rate, the log CPI price level, and log non-borrowed reserves. Third, I follow Mertens and Ravn (2014) to address the possibility of fiscal foresight. I add contemporaneous values and four lags of (i) *the implicit tax rate*, a measure of expected future taxes that is implied by tax exempt municipal bond yields and perfect arbitrage, constructed by

Leeper et al. (2011); (ii) *defense stock returns*, a series for the accumulated excess returns of large U.S. military contractors constructed by Fisher and Peters (2010); (iii) *defense news*, a variable which contains professional forecasters' projections of the path of future military spending, constructed by Ramey (2011). The results are summarized in Table 1.4. Expanding the set of controls has little effect on the estimates.

Trend Assumption.—I switch to a stochastic trend assumption and express variables in annual growth rates. The impulse responses confirm the findings of the baseline specification. Table 1.4 reports that the difference in peak effects is significant at the 5% level.

Econometric method.—I study whether the findings are robust to using alternative econometric methods. I consider three alternatives: (i) the proxy SVAR proposed by Mertens and Ravn (2014), (ii) a VAR augmented with the RR narrative measure[28], and (iii) the truncated moving average representation proposed by RR. Table 1.5 summarizes the results. In all cases, tax shocks have significantly larger effects in good times.

Outliers.—I check that the results are not driven by large and rare tax changes. I re-estimate the LP-IV in (1.3) excluding the largest tax changes in the RR narrative measure one at a time.[29] In all cases, the estimates barely change.

Sign-Dependence.—I examine whether tax shocks have sign-dependent effects, that is whether tax increases and reductions have different effects on output. I estimate sign-dependent impulse responses with the LP method. I find that the effects of tax increases and reductions on output are approximately symmetrical. The estimation details are laid out in Appendix 1.B.5.

[28]Many authors interpret the narrative measure as the tax shock and introduce it as an exogenous regressor in a reduced form VAR. See for example Mertens and Ravn (2011; 2012), Favero and Giavazzi (2012), Perotti (2012).

[29]These are the exogenous parts of the 1948 tax cuts passed by the congress over Truman's veto, the 1964 Kennedy-Johnson tax cuts, the 1981 Reagan tax cuts, the 2001 and 2003 Bush tax cuts, the Social Security Amendments of 1977 and 1983 (tax increases), the Tax Equity and Fiscal Responsibility Act of 1982 (tax increase), and the Omnibus Budget Reconciliation Acts of 1990 and 1993 (tax increases).

1.3.6 State-Dependent Effects on Other Macro Variables

In order to better understand the state-dependent effects of tax shocks on output, I now study the effects on other important macroeconomic aggregates. I estimate impulse responses for log real consumption expenditures C_t, log real private investment I_t, log hours worked L_t, and log average hourly earnings of private employees W_t.[30] More precisely, I estimate the state-dependent LP-IV in (1.3) and add one additional variable at a time. In each step, I also add four lags of the additional variable to the set of controls. For instance, when I estimate the impulse responses for log real consumption expenditures, I set $x_t = C_t$ and add four lags of C_t to z_t.

Figure 1.6 presents the results. To ease orientation, the dashed lines show the point estimates from the linear LP-IV. I find that tax shocks have strongly state-dependent effects on consumption, investment, and employment. In each case, a tax shock has much larger effects in good times. The effects of a tax shock on the average hourly wage are small, statistically insignificant, and do not depend on the state. This finding is interesting because, in standard models of the business cycle, taxes affect the economy through adjustments in the real wage.

1.3.7 Personal and Corporate Income Tax Changes

In this section, I examine whether the finding is driven by one of the two largest U.S. tax categories. I consider personal income taxes, which account for on average 74% of federal tax revenues, and corporate income taxes, which account for on average 16%.[31] Specifically, I use Mertens and Ravn's (2013) decomposition of the RR narrative measure into the two categories. They identify 16 corporate income tax changes of which 11 occur in good times and 5 in bad times, and 14 personal income tax changes of which 6 occur in good times and 8 in bad times. Figure 1.7 plots the narrative measures together with the unemployment rate. While the distribution of tax changes over the states is satisfactory, their small number generates an efficiency problem when using a method as flexible as LP. To address the issue, I develop a new econometric method.

[30] See Table 1.1 for a detailed description of the variables and corresponding sources.

[31] I use data from 1950 to 2006 to compute the averages.

The proposed methodology allows to flexibly combine the advantages of VARs and LPs. A VAR is more efficient when the model is correctly specified. The LP method is more robust to model misspecification. In addition, it can be adapted to allow for state-dependent impulse responses, without taking a stand on how the economy transitions from state to state. In a VAR, one needs to make strong assumptions about how the shocks affect the state variable.[32] My method allows to maintain much the efficiency of the VAR, while relaxing its strong assumptions. Its main idea is to use LPs with informative priors centered around the VAR impulse response function. I refer to the method as VAR-LP.[33]

I first illustrate the method's main idea through a simple example. Assume we have reason to believe that the economy can be approximated by a VAR(1):

$$X_t \ = AX_{t-1} + u_{t+1}. \tag{1.5}$$

X_t is a $n \times 1$ vector of macro variables. Impulse responses can be calculated by iterating forward on the VAR. Alternatively, they can be estimated via LPs:

$$X_{t+h} = \beta_h X_{t-1} + v_{t+h} \tag{1.6}$$

$$v_{t+h} \sim N(0, \Sigma_h) \tag{1.7}$$

The corresponding impulse responses from a VAR (VAR-IR) and LPs (LP-IR) are

$$VAR - IR(h) \ = \ A^{h+1} \tag{1.8}$$

$$LP - IR(h) \ = \ \beta_h \tag{1.9}$$

Note that the two methods are equivalent for $h = 0$. To flexibly combine both approaches, I propose the following Bayesian procedure. First, the model is estimated for $h = 0$ using uniform priors. Then, for each draw of β_0, the prior for β_h is set such that

$$\beta_h \mid \beta_0, \lambda_h \sim N(\beta_0^{h+1}, V_h), \text{ for } h > 0. \tag{1.10}$$

[32]Appendix 1.A clarifies this point analytically.

[33]In independent research, Miranda-Agrippino and Ricco (2017) propose a similar approach to study the of monetary policy shocks. However, they do not consider state-dependent models.

λ_h is a hyperprior at horizon h that I discuss shortly. If $V_h \rightarrow 0$, the method recovers the VAR-IR. If $V_{\beta_h} \rightarrow \infty$, the method recovers the LP-IR. For each horizon h, I use a standard Minnesota prior:[34]

$$V_{h,i,j} = \lambda_h^2 \frac{\sigma_{h,i}^2}{\sigma_{h,j}^2}. \tag{1.11}$$

$V_{h,i,j}$ is the variance of the coefficient for variable j in equation i at horizon h. The hyperprior λ_h determines V_h. λ_h can be understood as describing the confidence we have about the model specification. If we believe the VAR is a good approximation of the DGP, we use a low λ_h. The more uncertain we are about the DGP, the higher we set λ_h. Finally, I follow Kadiyala and Karlsson (1997) and set the prior for Σ_h to

$$\Sigma_h \mid \lambda_h \sim IW(\Phi_h, n+2) \tag{1.12}$$
$$\Phi_h = diag(\sigma_{h,1}^2, ..., \sigma_{h,n}^2). \tag{1.13}$$

$\sigma_{h,i}^2$ is the Newey-West corrected variance of a univariate local projection of variable i on itself at horizon h. It is straightforward to extend the VAR-LP approach to allow for state-dependent effects. The details are laid out in Appendix 1.C. The main difference is that a higher λ_h also relaxes the assumption that the shock does not cause the economy to transition to another state. The larger λ_h, the more we relax the parametric restrictions of the VAR and the closer we move to the LP-IR.

To allow for different effects of corporate and personal income tax shocks, I split the average tax rate (ATR_t) into an average corporate tax rate ($ACITR_t$) and an average personal income tax rate ($APITR_t$).[35] I estimate following the VAR-LP:

$$\begin{aligned} X_{t+h} &= I_{t-1} A_h^B \boldsymbol{X_{t-1}} + (1 - I_{t-1}) A_h^G \boldsymbol{X_{t-1}} + \delta_h D_t + u_{t+h} \quad (1.14) \\ v_{t+h} &\sim N(0, \Sigma_{h,t}) \\ \Sigma_{h,t} &= I_{t-1} \Sigma_{h,B} + (1 - I_{t-1}) \Sigma_{h,G}. \end{aligned}$$

[34]For simplicity, I focus on a VAR(1) here. In case of a higher order autoregressive process, this becomes $V_{h,i,j} = \frac{\lambda_h^2}{l^2} \frac{\sigma_{h,i}^2}{\sigma_{h,j}^2}$, where l denotes the lag.

[35]A detailed description of the data and corresponding sources is given in Table 1.1.

$X_t = [APITR_t, ACITR_t, G_t, Y_t]$. $\boldsymbol{X}_{t-1} = [X_{t-1}, ..., X_{t-4}]'$. The corporate income tax narrative measure serves as an instrument for the unobserved corporate income tax shock. The personal income tax narrative measure serves as an instrument for the personal income tax shock.[36] I use quarterly data from 1950Q1 to 2006Q4.[37] I propose a simple and transparent manner for choosing λ_h. Once λ_h reaches some value κ, the estimated impulse response coincides with the LP-IR (up to a small error). I set $\lambda_H = \kappa$ such that the VAR-LP-IR coincides with the LP-IR at horizon $h = H$. Recall that, at horizon $h = 0$, the VAR-LP-IR coincides with the VAR-IR. At intermediate horizons, I let λ_h increase gradually:

$$\lambda_h = \kappa \frac{h}{H}. \tag{1.15}$$

The setup follows a simple logic. At short horizons, iterated forecasts (VAR-IR) perform well. We can benefit from its high estimator efficiency by setting a low λ_h. As the horizon grows, the VAR-IR suffers from an increasingly large bias.[38] Thus, I increase λ_h such that the VAR-LP-IR gradually approaches the LP-IR. The setup also implies that I relax the assumption that the shock does not alter the state of the economy as the horizon grows. This is an intuitive feature. A tax shock likely does not change the state on impact but can unfold dynamics that cause the economy to transition to another state over time.

Figure 1.8 presents the impulse responses of output to the two types of tax shocks. The plain lines are the mean impulse response estimates. The shaded areas cover 90% of the posterior probability. To ease orientation, the dashed lines show the mean impulse response estimates from a linear version of (1.14). The top panels show the effects of a personal income tax shock and the bottom panels show the effects of a corporate income tax shock. I use the same scale for the tax shocks as in the baseline specification.[39] I find that both types of tax shocks have

[36]The approach is similar to Mertens and Ravn (2013) who use the narrative measures as proxy variables for the tax shocks in a VAR.

[37]This is the longest time span for which the decomposition of the narrative measure is available.

[38]This can be appreciated by returning to Equation 1.8: a bias in the estimate of A leads to biased impulse response estimates. This error is compounded at longer horizons.

[39]I again verify that the $APITR$ and $ACITR$ impulse responses are approximately symmetrical across states. This suggests that the state-dependent effects on output are not driven by larger or more persistent tax shocks in good times.

strongly state-dependent effects on output. They have a small and insignificant effect on output when they hit in bad times, and large and significant effects when they hit in good times.

1.4 Theory

This section provides a structural interpretation of the results. I study a simple search model of unemployment with endogenous job-search effort. The model closely follows the work of Michaillat (2014) and extends it to allow for endogenous job-search effort. In the model, the effect of an income tax cut is low when unemployment is high. I focus on income taxes because it is by far the largest tax category. An income tax cut raises the utility gain from being employed and therefore stimulates jobseekers' job-search effort. The higher search effort reduces search frictions, which makes it less costly for firms to hire additional workers, and hence raises employment and production. When labor demand is depressed and unemployment is high, however, the number of jobseekers per vacancy is large and recruiting is easy and inexpensive, so search frictions do not matter much. As a result, a tax cut that raises search effort has only small effects on employment and output. The same mechanism leads to a large effect on employment and output when unemployment is low and the matching process is congested by vacancies.

The search-and-matching approach is supported by the empirical evidence. Barro and Redlick (2011) find that tax changes affect output mainly through substitution effects, rather than wealth effects. Consistent with that finding, Keane (2011) surveys the literature on the relationship between taxes and labor supply and concludes that tax cuts have a positive effect on hours worked. However, a well established empirical fact is that most cyclical variations in hours are due to variations in the number of employed workers and not variations in hours per worker (Shimer, 2010). In the textbook real business cycle model and the textbook New Keynesian model, the labor supply decision amounts to choosing hours directly. In a search-and-matching-framework with endogenous job-search effort, on the other hand, workers can only choose the intensity with which they search for a job. Once matched, they do not decide on hours, which is consistent with the empirical evidence. Thus, a tax cut raises labor supply by increasing workers' job search effort. This is again consistent with the empirical evidence (Gentry and Hubbard, 2004).

First, I perform a comparative steady-states analysis, because it is transparent. It allows for an analytical expression of the income tax multiplier and can be studied in a diagram. Second, I embed the model into a standard New Keynesian model to quantify the degree of state-dependence the model can generate. In the last part, I discuss the model's key assumptions and its empirical support.

1.4.1 A Search Model with Endogenous Job-search Effort

Labor Market.— A measure 1 of identical workers participate in the labor market. A measure 1 of identical firms employ L_t workers. At the beginning of period t, a fraction λ of the L_{t-1} established worker-job matches is destroyed exogenously. Workers who lose their job start to search for a job in the same period. Thus, at the beginning of period t, $u_t = 1 - (1-\lambda)L_{t-1}$ workers search for a job. Each unemployed worker searches for a job with effort s_t. Job seekers who find a job start working in period t. The representative firm posts v_t vacancies to hire workers. The number of matches in period t is determined by a Cobb-Douglas matching function $m_t = m\left(s_t u_t\right)^{\eta}\ v_t^{1-\eta}$. The parameter m measures matching effectiveness and $\eta \in (0,1)$ is the elasticity of the matching function with respect to unemployment. Let $\theta_t \equiv \frac{v_t}{s_t u}$ be the labor market tightness. Job seekers who exert search effort $s_t = 1$ find a job with probability $f(\theta_t) = \frac{m_t}{s_t u_t} = m\theta_t^{1-\eta}$. The firm can fill a vacancy with probability $q(\theta_t) = \frac{m_t}{v_t} = m\theta^{-\eta}$. All workers have the same time discount factor $\beta < 1$. Given the matching process on the labor market, the employment rate is

$$L_t = (1-\lambda)\cdot L_{t-1} + (1-(1-\lambda)\cdot L_{t-1})\cdot s_t \cdot f(\theta_t). \tag{1.16}$$

In steady-state employment is constant. Therefore, we can express the employment rate as a function of labor market tightness and search effort:

$$L^s(\theta, s) = \frac{s\cdot f(\theta)}{\lambda + (1-\lambda)\cdot s\cdot f(\theta)}. \tag{1.17}$$

Following Michaillat (2014), I refer to this function as quasi-labor supply. The quasi-labor supply describes how workers' job search decision affects the steady-state employment rate. It is akin to a standard labor supply function in that it translates workers' optimal choices—usually the choice between leisure and work; here, the choice between leisure and job-search—into the quantity of labor supplied. However, there is an important difference. A conventional labor supply indicates directly the workers's employment choice which is the result of workers' optimal choice between leisure and work. In the search-and-matching framework, on the other hand, workers can not choose directly how much they work.[40] They can only choose the intensity with which they search for a job while they are unemployed. Thus, the quasi-labor supply gives the steady-state employment rate when workers' search effort is optimal. Lemma 1 establishes a few properties of the quasi-labor supply:

LEMMA 1: $L^s(\theta, s)$ is strictly increasing and strictly concave in θ and s, $\lim_{\theta\to 0} L^s(\theta, s) = 0$, $\lim_{\theta\to\infty} L^s(\theta, s) = 1$.

This follows from the properties of $f(\theta)$. The lemma says that, in steady-state, employment is high when labor market tightness is high. The reason is that job seekers find jobs quickly when tightness is high. Moreover, if search effort is high, employment is high. The reason is that job seekers find jobs quickly when they exert high search effort.

Firms.—Firms use labor L_t to sell a final good Y_t on a perfectly competitive market. The final good is produced according to the production function $Y_t = A_t \cdot L_t^{\alpha}$. $\alpha \in (0, 1)$ measures diminishing marginal returns to labor and A_t is the firms' level of technology. A risk neutral entrepreneur, with the same discount factor $\beta < 1$ as workers, owns the firm and consumes all profits. Thus, $C_t^f = \phi_t$. The firm pays its workers a real wage w_t. Moreover, in period t, the firm hires

[40]Workers do not choose hours worked directly. This is consistent with the empirical evidence: (i) most cyclical variation in total hours can be attributed to variation in number of employed workers, and not to variation in hours per worker; and (ii) most cyclical variation in unemployment is due to variation in the number of employed workers, and not variation in the number of labor force participants (Shimer, 2010).

$H_t = L_t - (1-\lambda) \cdot L_{t-1}$ new workers. The cost of posting a vacancy for one period is $A_t r > 0$ of the final good. [41] r measures resources spent recruiting workers. A firm can hire a worker with certainty by opening $\frac{1}{q(\theta_t)}$ vacancies and spending $\frac{A_t \cdot r}{q(\theta_t)}$. Hence, the firm's real profits ϕ_t at time t are

$$\phi_t = A_t \cdot L_t^\alpha - w_t \cdot L_t - \frac{A_t \cdot r}{q(\theta_t)} \cdot H_t. \tag{1.18}$$

The firm chooses $\{L_t\}_{t=0}^\infty$ to maximize the discounted sum of real profits, taking $\{\theta_t\}_{t=0}^\infty$ and $\{w_t\}_{t=0}^\infty$ as given. In steady-state, the optimal employment choice fulfills

$$\alpha \cdot A \cdot L^{\alpha-1} = w + [1 - \beta \cdot (1-\lambda)] \cdot \frac{r \cdot A}{q(\theta)}. \tag{1.19}$$

Rearranging (1.19), we obtain steady-state labor demand as a function of tightness and the real wage:

$$L^d(\theta, w) = \left[\frac{1}{\alpha} \cdot \left(\frac{w}{A} + [1 - \beta \cdot (1-\lambda)] \cdot \frac{r}{q(\theta)} \right) \right]^{\frac{-1}{1-\alpha}}. \tag{1.20}$$

Lemma 2 establishes a few properties of the aggregate labor demand.

LEMMA 2: The function $L^d(\theta, w)$ is strictly decreasing in θ and w, and strictly increasing in A, $\lim_{\theta \to \infty} L^d(\theta, w) = 0$, and $\lim_{\theta \to 0} L^d(\theta, w) = L^*$, where $L^* = \left[\frac{w}{\alpha \cdot A}\right]^{\frac{-1}{1-\alpha}}$.

This follows from the properties of $q(\theta)$. The lemma says that, in steady-state, labor demand is low when the real wage is high, labor market tightness is high, or technology is low. Intuitively, when the real wage is high, labor market tightness is high or technology is low, the marginal cost of labor is high. $\min(L^*, 1)$ is the employment rate when the recruiting cost is $r = 0$. If $L^* < 1$, the labor market does not converge to full employment when the recruiting cost converges to 0. Jobs are rationed if $w > \alpha \cdot A$. In equilibrium, firms are always on their demand

[41] Following Pissarides (2000), the cost of posting a vacancy is proportional to A_t. This is equivalent to assuming that the recruiting technology uses labor as unique input (Shimer, 2010) and is independent of technology. The approach is sensible because recruiting is time-intensive.

curve, that is $L = L^d(\theta, w)$. Since labor demand is strictly decreasing in θ and w and strictly increasing in A, steady-state profits ϕ are strictly decreasing in θ and w and strictly increasing in A.

Workers.—Employed workers receive a real wage w_t and lump-sum transfers T_t, and pay an income tax τ_t. Unemployed workers receive lump-sum transfers T_t. Workers cannot borrow or save. Thus, an employed worker consumes $C_t^e = w_t - \tau_t + T_t$. An unemployed worker consumes $C_t^u = T_t$. The utility from consumption is $U(C_t) = C_t$.[42] The utility gain from being employed is $\Delta U_t \equiv U(C_t^e) - U(C_t^u)$.Each unemployed worker searches for a job with effort s_t.[43] The disutility from job search is $\Psi(s_t) = \delta \cdot \frac{\kappa}{1+\kappa} \cdot s_t^{\frac{1+\kappa}{\kappa}}$. The parameter δ governs the level of disutility, and $\kappa < 1$ governs the convexity of the disutility function. Thus, the worker's utility at time t is:

$$(1 - L_t^s) \cdot U(C_t^u) + L_t^s \cdot U(C_t^e) - [1 - (1 - \lambda) \cdot L_{t-1}^s] \cdot \Psi(s_t). \tag{1.21}$$

Taking $\{\theta_t\}_{t=0}^{\infty}$, $\{w_t\}_{t=0}^{\infty}$, and $\{\tau_t\}_{t=0}^{\infty}$ as given, the worker choses $\{s_t\}_{t=0}^{\infty}$ to maximize utility subject to the probability of being employed in the next period: $L_t^s = (1 - \lambda) \cdot L_{t-1}^s + (1 - (1 - \lambda) \cdot L_{t-1}^s) \cdot s_t \cdot f(\theta_t)$. In steady-state, the optimal search effort satisfies

$$[1 - \beta \cdot (1 - \lambda)] \cdot \frac{\Psi'(s)}{f(\theta)} + \frac{1 + \kappa}{\kappa} \cdot \beta \cdot (1 - \lambda) \cdot \Psi(s) = \Delta U. \tag{1.22}$$

This equation implicitly defines the optimal supply of search effort $s^s(\theta, \tau)$. $s^s(\theta, \tau)$ is strictly increasing and concave in θ and ΔU. Search effort is increasing in labor market tightness, because a higher θ implies a higher job-finding probability $f(\theta)$. Search effort is decreasing in income taxes, because a higher τ implies a lower utility gain from work ΔU. Moreover, we have that $-\partial s^s(\theta, \tau)/(\partial \tau \partial \theta) > 0$.

[42] The linear utility function simplifies derivations. I relax the assumption and use a concave utility function in the numerical analysis of the model.

[43] The model closely follows Landais et al. (2016b). Another approach is to give households control over future employment through the allocation of non-employed workers between unemployment plus job-search and inactivity out of the labor force, which provides leisure (see for example Brückner and Pappa, 2012). The two approaches yield widely similar results in this application.

Thus, the effect of a tax cut on search effort is larger when labor market tightness is high. The reason is that workers internalize the job-finding probability when choosing the optimal search effort. Combining $s^s(\theta, \tau)$ with (1.17) defines the aggregate quasi-labor supply with endogenous search effort.

$$L^s(\theta, \tau) = \frac{s^s(\theta, \tau) \cdot f(\theta)}{\lambda + (1 - \lambda) \cdot s^s(\theta, \tau) \cdot f(\theta)}. \tag{1.23}$$

Lemma 3 establishes a few properties of the aggregate quasi-labor supply.

LEMMA 3: The function $L^s(\theta, \tau)$ is strictly increasing and strictly concave in θ and $-\tau$, $\lim_{\theta \to \infty} L^s(\theta, \tau) = 1$, and $\lim_{\theta \to 0} L^s(\theta, \tau) = 0$.

This follows from the properties of $f(\theta)$ and $s^s(\theta, \tau)$. The lemma says that, employment is high when labor market tightness is high. Intuitively, job seekers search more for jobs and find jobs more quickly when tightness is high. Moreover, if income taxes are high, employment is low. The reason is that job seekers search less for jobs when the utility gain from work is low.

Real Wage.—As in Hall (2005), I assume that the real wage w_t is exogenous.[44]

Government.—The government maintains a balanced budget. It distributes lump-sum transfers T_t. To finance this, the government levies a labor income tax that yields $\tau_t \cdot L_t$. Thus, $T_t = \tau_t \cdot L_t$. Combining the government's, the entrepreneur's, and workers' budget yields the aggregate resource constraint $C_t = w_t \cdot L_t + \phi_t = Y_t - \frac{r \cdot A_t}{q(\theta_t)}$. The final good is consumed or allocated to hiring workers.

The Steady-state Equilibrium

Taking the real wage w and government tax policy τ as given, I solve for the steady-state equilibrium of the model economy. The model has two endogenous variables: the employment rate L and labor market tightness θ. Equilibrium labor

[44] A high degree of real wage rigidity is consistent with the empirical evidence (Card and Hyslop, 1997; Blanchard and Katz, 1997).

market tightness is such that labor demand equals labor supply

$$L^s(\theta, \tau) \;\; = \;\; L^d(\theta, A). \tag{1.24}$$

Once we know equilibrium labor market tightness, equilibrium employment can be obtained from labor supply:

$$L \;\; = \;\; L^s(\theta, \tau). \tag{1.25}$$

where θ satisfies (1.24). Lemma 1 and 2 assure that the equilibrium exists and is unique. Figure 1.9 Panel (a) shows the steady-state equilibrium in a diagram with employment L on the horizontal axis and tightness θ on the vertical axis. The aggregate labor demand curve is downward sloping and convex. The quasi-labor supply is upward-sloping and convex. In equilibrium, the two curves intersect. The labor demand curve intersects the x-axis at L^*. Vacancy posting assures that the equilibrium is achieved. For instance, if quasi-labor supply is greater than labor demand, firms start posting fewer vacancies. In turn, less jobseekers find a job, the unemployment rate increases and labor market tightness falls. This reduces the marginal cost of labor which increases labor demand and thus reduces the gap between labor supply and demand. The process continues until the gap is closed.

Comparative Statics

I compare steady-state equilibria that differ by the value of technology A. This exercise is useful because it closely resembles the analysis of business cycles that are driven by technology shocks, or driven by demand shocks in the presence of real wage rigidities. I interpret a steady-state with a low value of A as bad times, and a steady-state with a high A as good times. Lemma 4 summarizes how variables change over different steady-state equilibria.

LEMMA 4: $\frac{d\theta}{dA} > 0$, $\frac{dL}{dA} > 0$, and $\frac{du}{dA} < 0$.

Lemma 4 states that in bad times, labor market tightness and employment are low, and unemployment is high. In Appendix 1.D, I provide a proof of the lemma. However, the main forces at work can be appreciated graphically by comparing comparing a steady-state with a low A as shown in Figure 1.9 Panel (a) to a steady-state with a high A as shown in Figure 1.9 Panel (b). In the low A steady-state, aggregate labor labor is lower because the marginal cost of labor is high. Thus, the labor demand is located further inward and the intersection of quasi-labor supply and labor demand occurs at a point with lower labor market tightness, lower employment and higher unemployment.

Income Tax Multiplier

Starting from a steady-state, I cut the income tax, compute the new corresponding steady-state and compare employment in the two steady-states. I then check how the effect of a tax cut on employment depends on the value of A. I measure the effect of the tax cut on employment through the multuplier

$$M \equiv -\frac{\partial L}{\partial \tau}. \tag{1.26}$$

Proposition 1 describes some of the tax multiplier's properties.[45]

PROPOSITION 1: The income tax multiplier M satisfies

(i) $M > 0$;

(ii) $\frac{dM}{dA} > 0$.

Part (i) shows that the multiplier is positive. An income tax cut increases employment. The result is illustrated in Figure 1.9 Panel (c). A tax cut increases the utility gain from work. This increases job-search effort by jobseekers and the quasi-labor supply curve shifts outwards. At the current tightness, labor demand falls short of quasi-labor supply. To reach a new equilibrium, tightness decreases. Thus, the vacancy-filling rate rises and hiring cost falls. As a consequence, firms increase employment and produce more of the final good. The effect of a tax

[45] I focus on an employment multiplier instead of an output multiplier to reduce notation. The output multiplier is $M^Y = -dY/d\tau = \alpha \cdot M \cdot L^{\alpha-1}$. Proposition 1 also applies to M^Y. Hence, (i) $M^Y > 0$ and (ii) $dM^Y/dA > 0$. I proof this in Appendix 1.D.

cut on employment and output is determined by the amplitude of the reduction in tightness and hiring cost. Appendix 1.D proofs part (i).

Part (ii) shows that the multiplier is higher in steady-states in which A is high. This is illustrated by comparing the low A steady-state in Figure 1.9 Panel (c) to the high A steady-state in Figure 1.9 Panel (d). The effect of a tax cut on employment depends on A for three reasons: (i) the curvature of the quasi-labor supply; (ii) the curvature of the labor demand; (iii) the effect of a tax cut on jobseekers' search effort.

In the low A steady-state (bad times), the quasi-labor supply is flatter at the equilibrium point. Hence, a shift in the quasi-labor supply curve following a tax cut has a smaller effect on labor market tightness. In addition, the labor demand curve is steeper at the equilibrium point in the low A steady-state. Thus, any change in labor market tightness has a smaller effect on firm hiring. Moreover, the effect of a tax cut on search effort is smaller because workers internalize that the job finding probability is low in the low A steady-state. Consequently, the effect of the tax cut on labor market tightness, employment and output is small. Intuitively, in the low A steady-state, when labor demand is depressed, the number of jobseekers per vacancy is large and recruiting is easy and inexpensive. Thus, search frictions do not matter much and the effect of a tax cut that raises search effort is small.

In the high A steady-state (good times), the quasi-labor supply is steeper at the equilibrium point. Thus, a shift in the quasi-labor supply curve following a tax cut has a large effect on labor market tightness. In addition, the labor demand curve is flatter at the equilibrium point in the high A steady state. Hence, any change in labor market tightness has a larger effect on firm hiring. Also, the effect of a tax cut on search effort is larger because workers internalize that the job finding probability is high in the high A steady-state. Consequently, the effect of the tax cut on labor market tightness, employment and output is large.

The proof of proposition 1 is in Appendix 1.D and I only provide a brief sketch here. Let $\epsilon^s \equiv (\partial L^s/\partial\theta) \cdot (\theta/L^s) > 0$ and $\epsilon^d \equiv -(\partial L^d/\partial\theta) \cdot (\theta/L^d) > 0$ be the elasticities of quasi-labor supply and labor demand with respect to tightness. Through implicit differentiation of the equilibrium conditions (1.24) and (1.25), I obtain the multiplier:

$$M = -\frac{\partial L^s}{\partial \tau} \cdot \frac{1}{1 + (\epsilon^s/\epsilon^d)}, \tag{1.27}$$

The multiplier is positive because $\partial L^s/\partial \tau < 0$, and ϵ^s and ϵ^d are both finite. A tax cut raises the utility gain from work and thus stimulates jobseekers' job-search effort and quasi-labor supply. The proof shows that ϵ^d and $-\partial L^s/\partial \tau$ are increasing in A, and ϵ^s is decreasing in A. Hence, M is increasing in A. The multiplier is high when the quasi-labor supply is steep and the labor demand is flat. In addition, the multiplier is high when the effect of a tax cut on jobseekers search effort is high, which is the case when labor market tightness is high because this implies a high job-finding probability.

1.4.2 Dynamic Multiplier

The goal of this part is to quantify the degree of state-dependence the model can generate. Through a series of simulations, I explore the effect of a tax cut at different states of the business cycle. To create a more realistic dynamic environment, I embed the search-and-matching model into a New Keynesian model. Simulations of the model calibrated to US data conform the steady-state results. The income tax multiplier is positive and strongly procylical.

I start from the New Keynesian model with search-and-matching frictions laid out by Michaillat (2014). I depart from his model in two ways. First, I abstract from government employment policies and focus on tax policy. Second, I adapt the model to allow for endogenous job-search effort.

The model departs from the textbook New Keynesian model in two ways. First, monopolistic firms are subject to the quadratic price adjustment cost of Rotemberg (1982) instead of the price-setting friction of Calvo (1983). Thus, the model admits a closed-form expression for the Philips-curve, which simplifies simulations of the nonlinear model. Second, the labor market is not perfectly competitive but is subject to search frictions. This changes the standard New Keynesian model in four ways: (i) the conventional labor supply is replaced by the quasi-labor supply; (ii) firms' profit maximization—and hence labor demand—account for hiring cost; (iii) labor market tightness is an additional variable; (iv) the model features an additional equation, a rule that determines the real wage.

Second, the labor market is not perfectly competitive but adopts the search-and-matching structure described above. This introduces four modifications to the standard New Keynesian model. First, the labor supply is replaced by the quasi-labor supply. Second, firms' labor demand accounts for hiring cost. Third, the model counts one more variable, labor market tightness, which is determined by the equality of labor demand and quasi-labor supply. Fourth, the model counts one more equation, a rule that determines the real wage. I relegate the model derivations to Appendix 1.E. Here, I focus on key features and differences to the small search-and-matching model.

Business Cycle.—Business cycles are driven by technology which is driven by a stochastic process $\{A_t\}_{t=0}^{\infty}$.

Labor Market.—Workers are employed by intermediate good firms indexed by $i \in [0, 1]$. Firm i employs $L_t(i)$ workers and aggregate employment is $L_t = \int_0^1 L_t(i)di$.

Large Household.—All workers are part of a large household. In addition to job-search effort, the household chooses between consumption and saving to maximize utility, subject to a budget constraint and a no-Ponzi-game condition. The household saves by investing in risk-free government bonds. Labor income is subject to a proportional income tax τ_t. The household's intertemporal consumption decision satisfies the Euler equation:

$$C_t = \beta \cdot \mathbb{E}_t \left[\frac{R_t}{1 + \pi_{t+1}} \cdot C_{t+1} \right], \tag{1.28}$$

where $\pi_t \equiv (P_t/P_{t-1}) - 1$ is inflation at time t. The household's optimal search path is given by:

$$\frac{\Psi'(s_t)}{f(\theta_t)} - \beta \cdot (1 - \lambda) \cdot \mathbb{E}_t \frac{\Psi'(s_{t+1})}{f(\theta_{t+1})} \cdot [1 - s_{t+1} \cdot f(\theta_{t+1})] = \Delta U_t. \tag{1.29}$$

This equation implicitly defines optimal search effort as an increasing function of labor market tightness θ_t and the utility gain from work ΔU_t. The search path $\mathbb{E}_t s_{t+1}/s_t$ is increasing in the expected job-finding probability in the future relative to today $\mathbb{E}_t f(\theta_{t+1})/f(\theta_t)$.

Final Good Firms.—A measure 1 of identical firms sell a final good in a perfectly competitive market. The representative final good firm uses $y_t(i)$ units of each intermediate good $i \in [0, 1]$ to produce Y_t units of final good.

Intermediate Good Firms.—In the intermediate good sector, there is no entry or exit. Each intermediate good is produced by a monopolist which uses $L_t(i)$ units of labor to produce $y_t(i)$ units of intermediate good i according to $y_t(i) = A_t \cdot L_t(i)^\alpha$. In addition to the hiring cost of the search-and-matching model, the monopolist faces a cost to adjusting its nominal price, following Rotemberg (1982)

$$\frac{\gamma}{2} \cdot \left(\frac{p_t(i)}{p_{t-1}(i)} - 1\right)^2 \cdot C_t, \tag{1.30}$$

where γ describes the amount of resources devoted to adjusting prices. The price-adjustment cost is denoted in units of the final good and is proportional to the size of the economy, measured by C_t.

Real Wage.—Following Blanchard and Galí (2010), the real wage is a function of A_t

$$w_t = \omega \cdot A_t^\nu. \tag{1.31}$$

ω is the level of the real wage, and ν governs the degree of wage rigidity. I assume that the real wage is somewhat rigid. Thus, $\nu < 1$.

Monetary Policy.—The central bank sets the nominal interest rate according to a standard Taylor rule:

$$R_t = \beta^{-1} \cdot (1 + \pi_t)^{\phi_\pi(1-\rho_R)} \cdot (\beta \cdot R_{t-1})^{\rho_R}. \tag{1.32}$$

ρ_R governs the degree of interest-rate smoothing, $\phi_p i > 1$ governs the response of monetary policy to inflation. I assume that steady-state inflation is $\pi = 0$ such that the steady-state nominal interest rate is β^{-1}.

Government.—The government distributes lump-sum taxes T_t and services debt from the previous period, which costs $R_{t-1}D_{t-1}$. To finance this, it collects proportional labor income taxes, which yields $w_t \cdot \tau_t \cdot L_t$ and issues new debt D_t. Thus, the budget constraint is

$$T_t + R_{t-1} \cdot D_{t-1} = w_t \cdot \tau_t \cdot L_t + D_t. \tag{1.33}$$

Plugging in the household's budget constraint and the firm profits, I obtain the aggregate resource constraint

$$Y_t = C_t \cdot \left(1 + \frac{\gamma}{2} \cdot \pi_t^2\right) + \frac{r \cdot A_t}{q(\theta_t)} \cdot H_t. \tag{1.34}$$

The aggregate resource constraint states that the final good is either consumed, used to changing prices or used to hiring new workers.

Symmetric Equilibrium.—All intermediate good firms are identical in a symmetric equilibrium. Thus, $L_t(i) = L_t$, $y_t(i) = Y_t$, $p_t(i) = P_t$, and $\mu_t(i) = \mu_t$, where $\mu_t(i)$ is the marginal revenue of producing one good of intermediate good i in period t. Using the symmetry assumption, I derive aggregate labor from monopolists' labor demand:

$$\mu_t \cdot \alpha \cdot L_t^{\alpha-1} = \frac{w_t}{A_t} + \frac{r}{q(\theta_t)} - \beta \cdot (1-\lambda) \cdot \mathbb{E}_t\left[\frac{C_t}{C_{t+1}} \cdot \frac{A_{t+1}}{A_t} \cdot \frac{r}{q(\theta_{t+1})}\right]. \tag{1.35}$$

The Philips curve is derived from monopolists' optimal price setting equation:

$$\pi_t \cdot (\pi_t + 1) = \frac{1}{\gamma} \cdot \frac{Y_t}{C_t} \cdot [\epsilon \cdot \mu_t - (\epsilon - 1)] + \beta \cdot \mathbb{E}_t[\pi_{t+1} \cdot (\pi_{t+1} + 1)]. \tag{1.36}$$

The aggregate production function is derived from the monopolists' production function:

$$Y_t = A_t \cdot L_t^{\alpha}. \tag{1.37}$$

The zero-inflation steady-state of the New Keynesian model is very similar to the steady-state of the simple search-and-matching model laid out in the previous section. In steady-state, the optimal search effort is still given by (1.22). The quasi-labor supply is still given by (1.23). Firms' labor demand satisfies (1.20) except that now the marginal cost of labor is multiplied by the markup $1/\mu = \epsilon/(\epsilon - 1) > 1$ because the New Keynesian model assumes that intermediate good firms have monopoly power. Taken together, the steady-state of the New Keynesian model is still given by the intersection of the quasi-labor supply curve and the labor demand curve. When the real wage is rigid, i.e., $\nu < 1$, the ratio $w/a = \omega A^{\nu-1}$ decreases when technology increases. Therefore, a steady-state with high A still corresponds to a steady-state with high labor demand and low unemployment.

The model has two shocks. A technology shock and a tax shock. I assume the stochastic processes.

$$\begin{aligned} log(A_t) &= \rho_A \cdot log(A_{t-1}) + \epsilon_t^A && (1.38) \\ \tau_t - \tau &= \rho_\tau \cdot (\tau_{t-1} - \tau) + \epsilon_t^\tau, && (1.39) \end{aligned}$$

where τ is the steady-state level of taxes. $\mid \rho_A \mid < 1$, and $\mid \rho_\tau \mid < 1$ describe the persistence of the shocks. I assume that technology shocks and tax shocks are uncorrelated. A technology shock has the scale σ_A. A tax shock has the scale σ_τ.

Calibration

I calibrate the model to US data. To enhance transparency, I use the exact same parameter values as Michaillat (2014). To calibrate the parameters relating to job-search effort, I follow Landais et al. (2016a). Thus, I set the parameter governing the convexity of the disutility from search to $\kappa = 0.22$. I set the level of disutility to $\delta = 0.33$ to match a steady-state search effort of $s = 1$. I set $\tau = 0.26$, which matches the estimate of the average effective labor income tax rate from Mendoza et al. (1994). Michaillat (2014) calibrates the model to weekly data and sets $\rho_A = 0.992$. I set ρ_τ to match the empirical impulse response of the average tax rate to a tax shock. This implies a value of 0.896 at quarterly frequency, so I set the weekly autocorrelation to $\rho_\tau = 0.992$. Thus, the persistence of the two shocks is identical. Table 1.6 summarizes the calibration of all parameters.

Simulations

I use a shooting algorithm to simulate an approximation of the model in which the household and firms have perfect foresight. First, I simulate the effect of a technology shock. In period $t-1$, the economy is in the steady-state. In period t an unexpected technology shock $\epsilon_t^A = \sigma_A$ hits the economy. No other shock occurs after that. The impulse response at horizon h is given by

$$IRF^A(h) = \left[x_{t+h} \mid \epsilon_t^A = \sigma_A, \epsilon_t^\tau = 0\right] - \left[x_{t+h} \mid \epsilon_t^A = 0, \epsilon_t^\tau = 0\right], \qquad (1.40)$$

where x_{t+h} is the variable of interest. Second, I simulate an expansion that is accompanied by a tax shock. In period $t-1$, the economy is in the steady-state. In period t an unexpected technology shock hits $\epsilon_t^A = \sigma_A$ hits the economy. At the same time, an unexpected tax shock $\epsilon_t^\tau = \sigma_\tau$ hits. No other shock occurs after that. The impulse response function is given by

$$IRF^{A+\tau}(h) = \left[x_{t+h} \mid \epsilon_t^A = \sigma_A, \epsilon_t^\tau = \sigma_\tau\right] - \left[x_{t+h} \mid \epsilon_t^A = 0, \epsilon_t^\tau = 0\right], \qquad (1.41)$$

The difference between (1.41) and (1.40) is the impulse response function of the tax shock given the state of the economy:

$$IRF^\tau(h) = \left[x_{t+h} \mid \epsilon_t^A = \sigma_A, \epsilon_t^\tau = \sigma_\tau\right] - \left[x_{t+h} \mid \epsilon_t^A = \sigma_A, \epsilon_t^\tau = 0\right]. \qquad (1.42)$$

I simulate impulse responses to a 1 percentage point reduction in the tax rate τ_t. Thus, $\sigma_\tau = 0.01$.[46] I repeat the simulations for a collection of 16 technology shocks ranging from $\sigma_A = -0.036$ to $\sigma_A = +0.054$. I compute impulse responses for three variables: log output, labor market tightness, and the unemployment rate. For each technology shock, I compute the peak effect of a tax cut, and I measure the extremum of the unemployment rate without a tax cut. I link each peak effect to the associated unemployment rate and plot the 16 peak effect-unemployment pairs in Figure 1.10. The peak effects of a tax cut are strongly procyclical. The peak effect on log output increases from 0.14% when the unemployment rate is

[46] The impulse responses to a tax cut and a tax increase are approximately symmetrical. This is in line with the empirical evidence presented in Section 1.3. Thus, I only show results for a tax cut.

8% to 0.41% when the unemployment rate is 5%. The peak effect on labor market tightness moves from -0.07 to 0.38. The peak effect on unemployment moves from 0.4 percentage points to 1.1 percentage points. These results highlight that the model can account for a high degree of state-dependence in the effects of tax shocks.

1.4.3 Alternative Theories and Empirical Evidence

In this part, I discuss additional evidence that supports (i) the mechanism through which a tax cut affects labor market tightness and employment in the model and (ii) the models' key assumptions.

The effect of search effort on employment and tightness

In the model, a tax cut increases the job-search effort of jobseekers. This is consistent with the empirical evidence of Gentry and Hubbard (2004). An increase in job-search effort lowers labor market tightness and increases employment. Consistent with the predictions of the model, Crépon et al. (2013) provide micro-evidence from a large randomized experiment in France: some young educated jobseekers receive a treatment in the form of job-search assistance. Crépon et al. (2013) randomize which areas are treated and who receives the treatment within treated areas. They obtain two main results: (i) treated jobseekers have a higher job-finding probability than control jobseekers in the same area; (ii) control jobseekers in control areas have a higher job-finding probability than control jobseekers in treated areas. Gautier et al. (2012) obtain similar results from an experiment in Denmark. Thus, both studies provide evidence that an increase in search effort reduces the job-finding probability of other jobseekers in the same labor market. This evidence supports a model in which an increase in search effort has a negative effect on tightness.

In the model, the effect of an increase in search effort is smaller in bad times. Toohey (2017) exploits variations in job-search requirements across US states and over time and finds evidence in support of the models' prediction. He finds that when search requirements are more stringent, unemployment insurance recipients search more and find jobs faster. However, increasing search effort has a smaller effect on the unemployment rate in bad times than in good times.

Alternative Theories

The model has two key assumptions: (i) diminishing marginal returns to labor and (ii) a rigid wage. I discuss the importance of these assumptions by considering two well-known alternatives. I again focus on steady-state equilibria as described in Section 1.4.1. I then argue that the empirical evidence supports my assumptions.

Hall (2005).—In Hall (2005), the wage is fixed and firms produce with constant returns to scale ($\alpha = 1$). The firm's optimal employment choice solely determines equilibrium labor market tightness. Figure 1.11 Panel (a) shows the effect of a tax cut in the in bad times and Figure 1.11 Panel (b) shows the effect of a tax cut in good times. In the diagram, the labor demand is a horizontal line. An increase in A in shifts the labor demand upwards. In the high A steady-state, employment and labor market tightness are higher. A tax cut increases the utility gain from work. In the diagram, the quasi-labor supply shifts outwards. In the new steady-state, employment is higher. Labor market tightness is unchanged because the labor demand is flat. In the model with constant returns to scale, labor demand is perfectly elastic, so $\epsilon^d = +\infty$. Thus, the multiplier in (1.27) simplifies to

$$M = -\frac{\partial L^s}{\partial \tau}. \tag{1.43}$$

The multiplier is still higher when A is high because $-\partial L^s/\partial \tau > 0$ is increasing in A.

Pissarides (2000).—In the standard search-and-matching model of Pissarides (2000), firms produce with constant returns to scale ($\alpha = 1$) and the wage is flexible. When a worker and firm are matched, they bargain over the wage. The workers bargaining power is $\chi \in (0, 1)$. The surplus from each match is shared. The worker keeps a fraction χ of the surplus. The worker's surplus from a match is the utility gain from work ΔU. The firm's surplus is the amount of produced goods by a worker A minus the real wage w. Worker and firm split the total surplus. Thus, the wage satisfies

$$w = A - \frac{1-\chi}{\chi} \cdot \Delta U. \tag{1.44}$$

Figure 1.11 Panel (c) shows the effect of a tax cut in bad times and Figure 1.11 Panel (d) shows the effect of a tax cut in good times. Following an increase in A, the labor demand shifts upwards. In the flexible wage model, A raises the wage, which leads to an increase in the utility gain from work. Thus, the quasi-labor supply shifts outwards. In the high A steady-state, employment and labor market tightness are higher. A tax cut increases the utility gain from work. In the diagram, the quasi-labor supply shifts outwards. With a flexible wage, an increase in ΔU reduces the wage. Therefore, the labor demand shifts upwards. I derive the multiplier of the model in Appendix 1.F. It equals

$$M = -\frac{\partial L}{\partial \tau} = -\frac{\partial L^s}{\partial \tau} + (1-\chi) \cdot \epsilon^s \cdot \frac{L}{w}, \tag{1.45}$$

The proof in Appendix 1.F shows that $-\partial L^s / \partial \tau > 0$ is increasing in A. ϵ^s and L/w are decreasing in A. Thus, whether M increases when A is high is ambiguous. In the diagram, a tax cut shifts both the labor demand and the quasi-labor supply. Importantly, the quasi-labor supply is convex. Thus, the effect of a shift in the labor demand on employment is higher when A is low. The effect of a shift in the quasi-labor supply is higher when A is high. Which effect dominates depends on the parameters. An extreme case arises when workers have full bargaining power ($\chi = 1$). Then, $w = A$ at all times. The multiplier is $M = -\partial L^s/\tau$ and does not depend on A.

I now discuss additional evidence to contrast the alternative models. The evidence on the effects of unemployment insurance (UI) on employment supports the assumptions of the model I propose. A reduction in UI is comparable to a tax cut because it increases the utility gain from work. Landais et al. (2016a) summarize the evidence. They define two elasticities. The *microelasticity* $\epsilon^m = (\partial L^s / \partial \Delta U) \cdot (\Delta U / L^s) \mid_\theta$ measures the percentage increase in labor supply when the utility gain from work increases by 1 percent, given the level of labor market tightness. The *macroelasticity* $\epsilon^M = (dL/d\Delta U) \cdot (\Delta U / L)$ measures the percentage increase in employment when the utility gain from work increases by 1 percent after labor demand has adjusted. Therefore, the macroelasticity accounts for both the change in jobseekers' search effort and the equilibrium adjustment of tightness. Landais et al. (2016a) conclude that estimates of the microelasticity are larger than estimates of the macroelasticity. Thus, the empirical evidence supports $\epsilon^M < \epsilon^m$. In addition, the ratio ϵ^M/ϵ^m is higher in good times. I use the multiplier M to obtain an expression for the macroelasticity. I replace a tax cut $-d\tau$ with an increase in the utility gain from work $d\Delta U$ and multiply by $\Delta U/L$. Figure 1.12 represents the elasticities in the competing models diagrammatically.

For my model with a rigid wage and diminishing marginal returns to labor, I derive the macroelasticity from the multiplier (1.26). I obtain $\epsilon^M = \frac{\epsilon^m}{1+(\epsilon^s/\epsilon^d)}$. Because ϵ^s and ϵ^d are both finite, we have that $\epsilon^M < \epsilon^m$. Moreover, the ratio ϵ^M/ϵ^m is larger in good times, because the quasi-labor supply is convex. Thus, the model is consistent with the empirical evidence of Landais et al. (2016a). Figure 1.12 Panel (a) represents the microelasticity and the macroelasticity of my model in a diagram. The model predicts that an increase in job-search effort lowers labor market tightness. This is in with the micro evidence of Crépon et al. (2013) discussed above. In the diagram, we see that an increase in job-search effort lowers tightness because the labor demand is downward-sloping.

Hall (2005).—From the multiplier in (1.43), I obtain the macroelasticity $\epsilon^M = \epsilon^m$. In the model with a fixed wage and diminishing marginal returns to labor, the microelasticity is equal to the macroelasticity. This is at odds with the empirical evidence of Landais et al. (2016a). Figure 1.12 Panel (b) represents the microelasticity and the macroelasticity of the model in a diagram. The model predicts that an increase in job-search effort has no effect on labor market tightness. This is at odds with the evidence of Crépon et al. (2013). In the diagram, we see that an increase in job-search effort has no effect on tightness because the labor demand is a horizontal line.

Pissarides (2000).—From the multiplier in (1.45), I obtain the macroelasticity $\epsilon^M = \epsilon^m + (1-\chi)\cdot\epsilon^s\cdot(\Delta U/w)$. The macroelasticity is larger than the microelasticity. Therefore, the model with a flexible wage and constant returns to labor is inconsistent with the evidence of Landais et al. (2016a). Figure 1.12 Panel (c) represents the microelasticity and the macroelasticity of the model in a diagram.

The model predicts that an increase in job-search effort leads to an increase in labor market tightness. In the diagram, we see that this is the case because the wage falls and the labor demand shifts upwards. This is at odds with the evidence of Crépon et al. (2013).

These results highlight that both diminishing marginal returns to labor and a rigid wage are crucial for the model's ability to account for the empirical evidence.

1.5 Concluding Remarks

This paper has presented empirical evidence that the effects of U.S. tax changes on output depend strongly on the amount of slack in the economy. Tax cuts have large effects on output only in good times. In bad times, however, the effects on output are small. The finding questions whether estimates of the average effects of tax shocks from a linear model can provide meaningful guidance for fiscal policy.

To explain the result, I have proposed a simple search model of unemployment in which the effect of an income tax cut is low when unemployment is high. I have focussed on a simple version of the model to keep the analysis transparent. Quantitative DSGE models of distortionary taxation are much larger and include features such as habit formation, investment adjustment costs, durable goods and variable capacity utilization.[47] An interesting path for future research is to embed the search-and-matching structure of the labor market into a quantitative DSGE model. Specifically, it would be interesting to see whether such a model can adequately match the state-dependent empirical impulse responses to tax shocks.

Another interesting path is to consider other types of tax and government spending policies in the search model of unemployment. The model can also be used to study interdependent effects of fiscal policies.

[47] See for example Baxter and King (1993), Burnside et al. (2004) and Mertens and Ravn (2011).

Tables and Figures

Table 1.1: Variable description

Variable	**Description**	**Source**
Output (Y)	Nominal GDP divided by its implicit price deflator	FRED
Government spending (G)	Federal government consumption expenditures and gross investment divided by the GDP deflator.	FRED
Average tax rate (ATR)	Nominal federal tax revenues minus transfers divided by nominal GDP.	FRED
Narrative tax measure (RR)	Narrative measure of exogenous tax changes.	Romer and Romer (2010)
Average personal income tax rate ($APITR$)	Federal personal income tax revenues including contributions to government social insurance divided by personal income tax base.	Mertens and Ravn (2013)
Average corporate income tax rate ($ACITR$)	Federal corporate income tax revenues divided by corporate income tax base.	Mertens and Ravn (2013)
Narrative personal income tax measure (RR^P)	Narrative measure of exogenous personal income tax changes.	Mertens and Ravn (2013)
Narrative corporate income tax measure (RR^C)	Narrative measure of exogenous corporate income tax changes.	Mertens and Ravn (2013)
Tax revenues (T)	Nominal federal tax revenues minus transfers divided by the GDP deflator.	FRED
Consumption (C)	Consumers nominal expenditure divided by its deflator.	FRED
Investment (I)	Private sector gross investment divided by its deflator.	FRED
Hours (L)	Product of hours per worker and civilian non-farm employment divided by population. Combined with Francis and Ramey (2002) hours worked series.	Mertens and Ravn (2012)
Wage (W)	Average hourly earning of private employees.	FRED
Unemployment rate (U)	Civilian unemployment rate.	FRED
Public Debt	Federal government debt held by the public divided by the GDP deflator.	Favero and Giavazzi (2012)
Nonborrowed reservers	Nonborrowed reserves.	FRED
Federal funds rate	Effective federal funds rate.	FRED
Price level (CPI)	Consumer price index for all urban consumers.	FRED
Implicit tax rate	Expected future tax rate implied by tax exempt municipal bond yields and perfect arbitrage. Based on bonds with maturity of one year.	Leeper et al. (2011)
Defense stock returns	Accumulated excess returns of large U.S. military contractors.	Fisher and Peters (2010)
Defense news	Professional forecasters' projections of the path of future military spending	Ramey (2011)

Table 1.2: Peak effect of a tax shock on output (in percent)

	Romer & Romer Narrative Approach Local Projections-IV	**Blanchard & Perotti Structural VAR**
	(1)	**(2)**
Linear Model	-2.03***	-1.61**
$\min(\hat{\theta}_h)$	(0.68)	(0.62)
Bad Times	-0.52	-0.47
$\min(\hat{\theta}_h^B)$	(1.34)	(0.75)
Good Times	-3.54***	-2.68***
$\min(\hat{\theta}_h^G)$	(1.00)	(0.73)
Difference	3.02**	2.21*
$\min(\hat{\theta}_h^B)$ - $\min(\hat{\theta}_h^G)$	(1.54)	(1.19)

Peak effects of a tax shock on real GDP (in percent). Standard errors in parentheses. *, **, *** indicates statistical significance at the 10%, 5% and 1% level, respectively. (1) is the baseline specification: the Romer and Romer (2010) narrative measure is an instrumental variable (IV) for the latent tax shock. Estimates from the local projections-IV in Equation 1.3. (2) uses the Blanchard and Perotti (2002) identification strategy. Estimates from the VAR model in Equation 1.4. Estimation using quarterly data from 1947Q1 to 2007Q4.

Table 1.3: Peak effect of a tax shock on output (in percent): alternative state variables

	U **6.5%**	**U HP** $\boldsymbol{\lambda = 10^3}$	**U HP** $\boldsymbol{\lambda = 10^5}$	**U HP** $\boldsymbol{\lambda = 10^7}$	**NBER Dates**	**Smooth Trans.**	**U Cont.**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Linear Model	-2.03***	-2.03***	-2.03***	-2.03***	-2.03***	-2.03***	-2.03***
min($\hat{\theta}_h$)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)	(0.68)
Bad Times	-0.52	-0.78	-0.90	-1.31**	0.25	-1.34*	-0.71
min($\hat{\theta}_h^B$)	(1.34)	(0.75)	(0.78)	(0.64)	(0.84)	(0.79)	(1.43)
Good Times	-3.54***	-4.37***	-3.46**	-4.84***	-3.40***	-3.96***	-3.75***
min($\hat{\theta}_h^G$)	(1.00)	(1.35)	(1.35)	(1.09)	(0.90)	(1.31)	(1.12)
Difference	3.02**	3.59**	2.55	3.53**	3.65**	2.62*	3.04**
min($\hat{\theta}_h^B$) - min($\hat{\theta}_h^G$)	(1.54)	(1.55)	(1.75)	(1.26)	(1.23)	(1.53)	(1.55)

Peak effects of a tax shock on real GDP (in percent). Standard errors in parentheses. *, **, *** indicates statistical significance at the 10%, 5% and 1% level, respectively. (1) uses the baseline state variable. The discrete threshold that separates bad and good times is an unemployment rate of 6.5%. (2) The threshold is the HP-filtered trend unemployment rate using a smoothing parameter of $\lambda = 10^3$. (3) The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^5$. (4) The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^7$. (5) Bad times are NBER recession periods. (6) The state variable is the smooth transition function of past output growth. Estimates in column (1) to (6) are from the local projections-IV in Equation 1.3. (7) The state variable is the continuous unemployment rate. Estimates from the local projections-IV in Equation 1.B.1. Estimation using quarterly data from 1947Q1 to 2007Q4.

Table 1.4: Peak effect of a tax shock on output (in percent): additional control variables

	Baseline	**Control for Public Debt**	**Control for Mon. Policy**	**Control for Foresight**	**Vars in Growth Rates**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Linear Model	-2.03***	-2.52**	-2.07**	-2.51***	-1.57**
$\min(\hat{\theta}_h)$	(0.68)	(1.02)	(0.60)	(0.64)	(0.69)
Bad Times	-0.52	-0.74	-0.64	-0.68	-0.82
$\min(\hat{\theta}_h^B)$	(1.34)	(1.29)	(0.64)	(1.09)	(0.64)
Good Times	-3.54***	-3.67***	-3.05***	-3.59***	-3.28***
$\min(\hat{\theta}_h^G)$	(1.00)	(1.12)	(0.99)	(0.96)	(1.01)
Difference	3.02**	2.93*	2.41**	2.91**	2.46**
$\min(\hat{\theta}_h^B)$ - $\min(\hat{\theta}_h^G)$	(1.54)	(1.71)	(1.72)	(1.45)	(1.20)

Peak effects of a tax shock on real GDP (in percent). Standard errors in parentheses. *, **, *** indicates statistical significance at the 10%, 5% and 1% level, respectively. (1) uses the baseline set of controls. (2) uses four lags of log real federal government debt as additional controls. (3) uses four lags of the federal funds rate, the log CPI price level and log-non-borrowed reserves as additional controls. (4) uses contemporaneous values and four lags of the implicit tax rate, defense stock returns and defense stock news as additional controls. (5) uses the baseline specification but with variables expressed in annual growth rates instead of log levels. Estimates from the local projections-IV in Equation 1.3. Estimation using quarterly data from 1947Q1 to 2007Q4. (4) uses quarterly data from 1953Q2 to 2007Q4.

Table 1.5: Peak effect of a tax shock on output (in percent): alternative methods

	Baseline	Proxy SVAR	Augmented VAR	Truncated MA
	(1)	**(2)**	**(3)**	**(5)**
Linear Model	-2.03***	-1.22**	-1.61**	-1.95*
$\min(\hat{\theta}_h)$	(0.68)	(0.60)	(0.67)	(1.02)
Bad Times	-0.52	-0.34	-0.75	-0.54
$\min(\hat{\theta}_h^B)$	(1.34)	(0.82)	(0.87)	(1.02)
Good Times	-3.54***	-2.52***	-2.70***	-3.06***
$\min(\hat{\theta}_h^G)$	(1.00)	(0.73)	(0.72)	(0.78)
Difference	3.02**	2.18*	1.95*	2.52**
$\min(\hat{\theta}_h^B)$ - $\min(\hat{\theta}_h^G)$	(1.54)	(1.10)	(1.13)	(1.28)

Peak effects of a tax shock on real GDP (in percent). Standard errors in parentheses. *, **, *** indicates statistical significance at the 10%, 5% and 1% level, respectively. (1) is the baseline specification. Estimates from the local projections-IV in Equation 1.3. (2) Estimates from proxy SVAR in Equation 1.B.2. (3) Estimates from the augmented VAR in Equation 1.B.3. (4) Estimates from the truncated MA in Equation 1.B.4. Estimation using quarterly data from 1947Q1 to 2007Q4.

Table 1.6: Calibration of the New Keynesian model

Parameter	Value	Description	Target/Source
steady-state Targets			
A	1.00	Steady-state technology	Michaillat (2014)
u	0.064	Steady-state unemployment	Michaillat (2014)
θ	0.43	Steady-state labor market tightness	Michaillat (2014)
s	1	Steady-state job-search effort	Michaillat (2014)
Parameters			
η	0.7	Elasticity of matching to unemployment	Michaillat (2014)
r	0.21	Recruiting cost	Michaillat (2014)
λ	0.01	Job-destruction rate	Michaillat (2014)
ν	0.5	Elasticity of real wage to technology	Michaillat (2014)
ϕ_π	1.5	Elasticity of monetary rule to inflation	Michaillat (2014)
ρ_r	0.96	Elasticity of monetary rule to lagged interest rate	Michaillat (2014)
γ	61	Price adjustment cost	Michaillat (2014)
ρ_A	0.992	Autocorrelation of technology	Michaillat (2014)
ρ_τ	0.992	Autocorrelation of taxes	Matches empirical impulse response function of the average tax rate to a tax shock
α	0.66	Marginal returns to labor	Michaillat (2014)
β	0.999	Discount factor	Michaillat (2014)
ϵ	11	Elasticity of substitution across goods	Michaillat (2014)
m	0.17	Matching effectiveness	Matches steady-state targets (Michaillat, 2014)
ω	0.64	Real wage level	Matches steady-state targets (Michaillat, 2014)
κ	0.22	Disutility from job search: convexity	Landais et al. (2016a)
δ	0.33	Disutility from job search: level	Matches steady-state targets (Landais et al., 2016a)
τ	0.26	steady-state labor income tax rate	Matches estimate of the average effective labor income tax rate by Mendoza et al. (1994)

Figure 1.1: Romer & Romer (2010) narrative measure of exogenous tax changes

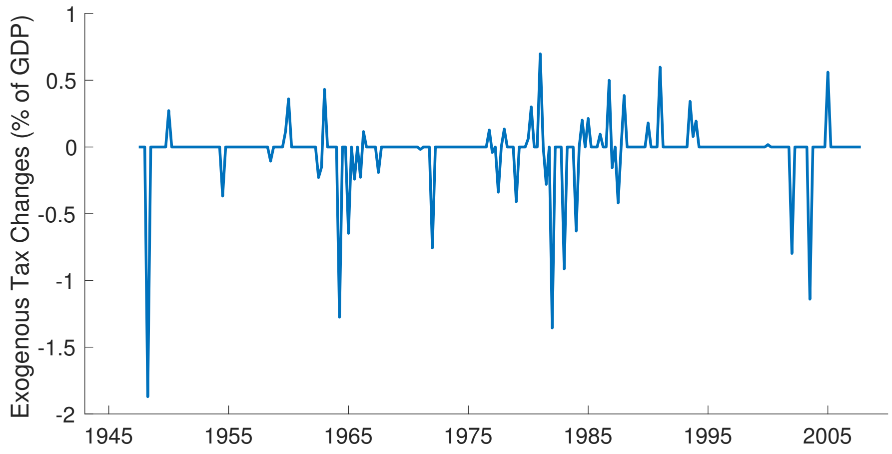
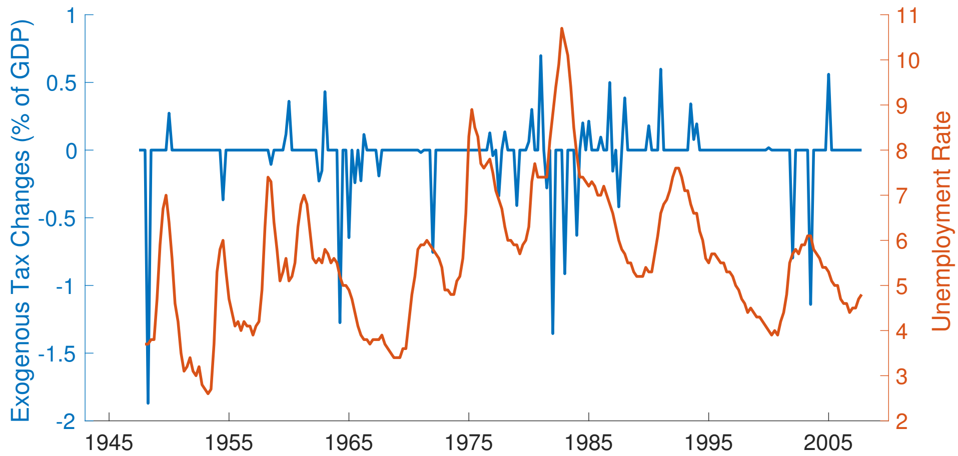
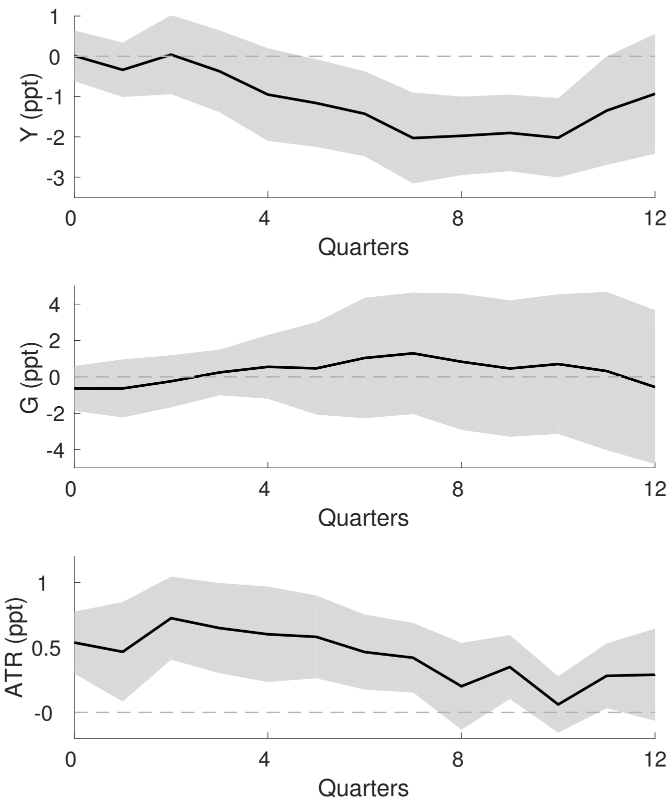


Figure 1.2: Romer & Romer (2010) narrative measure and the unemployment rate



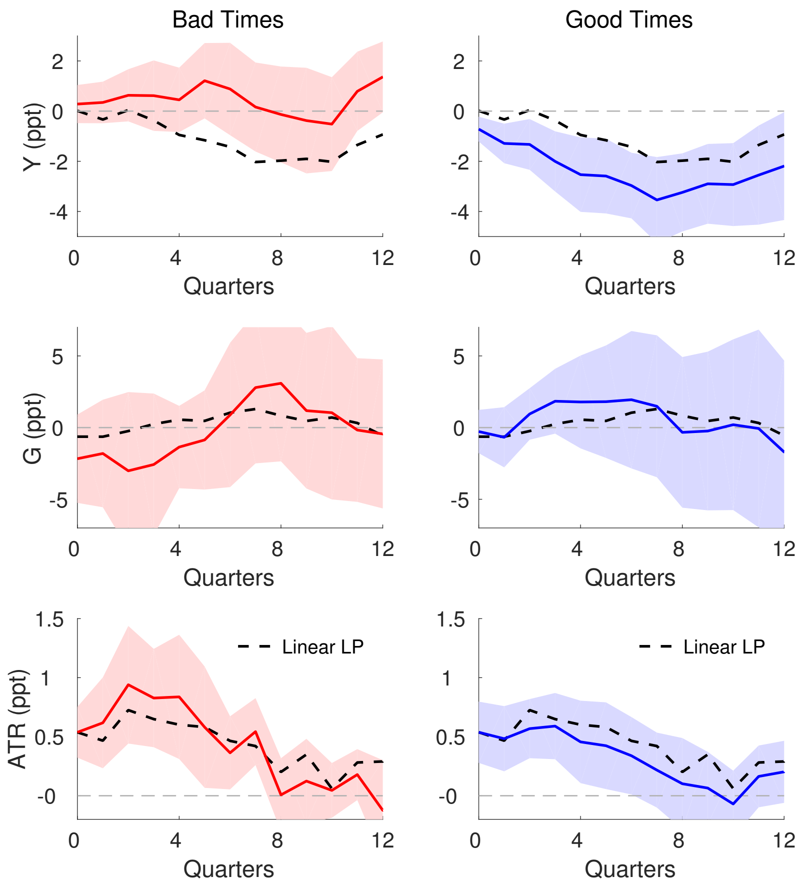
Romer & Romer (2010) narrative measure of exogenous tax changes (blue line) and the unemployment rate (red line)

Figure 1.3: Impulse responses to a tax shock — symmetric benchmark



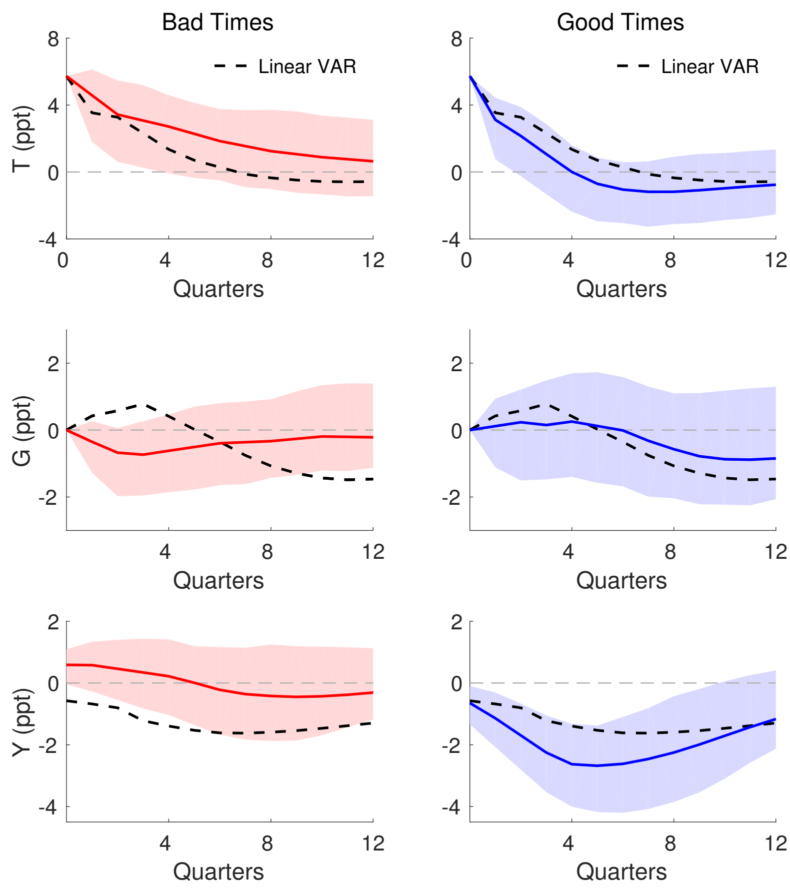
Impulse responses of real GDP (Y), real federal government spending (G) and the average tax rate (ATR) to a tax shock. Estimates from the linear local projections-IV in Equation 1.1 using quarterly data from 1947Q1 to 2007Q4. Shaded areas are 90% confidence bands using Newey-West standard errors.

Figure 1.4: The state-dependent effects of tax shocks



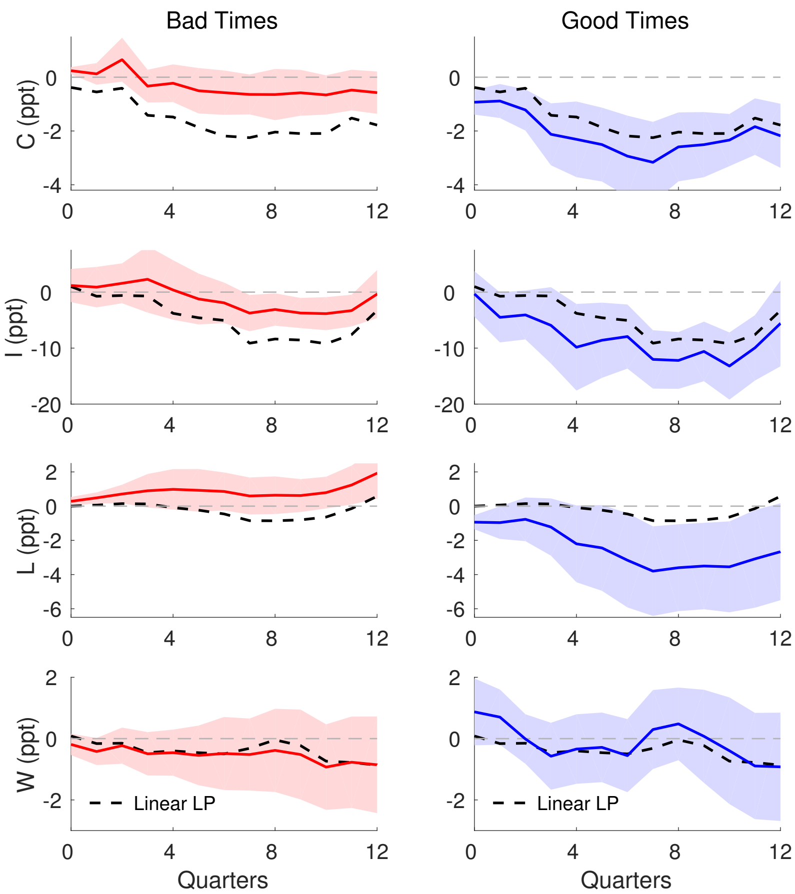
Impulse responses of real GDP (Y), real federal government spending (G) and the average tax rate (ATR) to a tax shock. Estimates from the linear local projections-IV in Equation 1.1 (dashed line) or from the state-dependent local projections-IV in Equation 1.3 (plain line). Shaded areas are 90% confidence bands using Newey-West standard errors. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.5: Robustness check — estimates from a state-dependent VAR



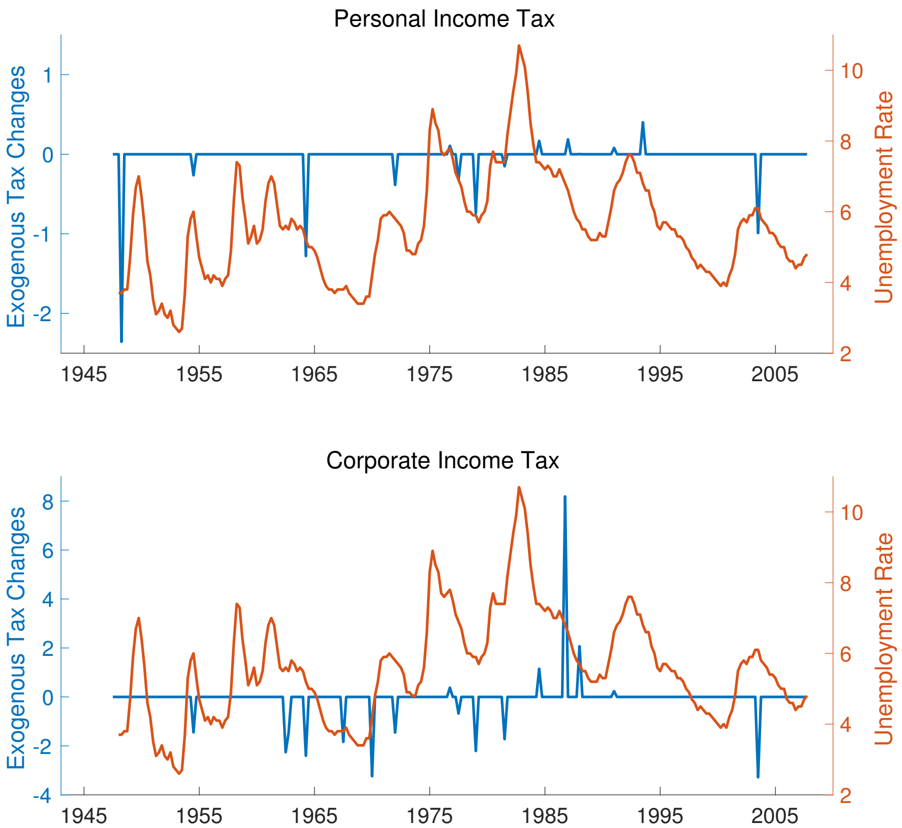
Impulse responses of real federal tax revenues (T), real federal government spending (G) and real GDP (Y) to a tax shock. Estimates from a linear VAR (dashed line) or from the state-dependent VAR in Equation 1.4 (plain line). Shaded areas are 90% confidence bands calculated with a recursive wild bootstrap using 10.000 replications. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.6: The state-dependent effects of tax shocks II



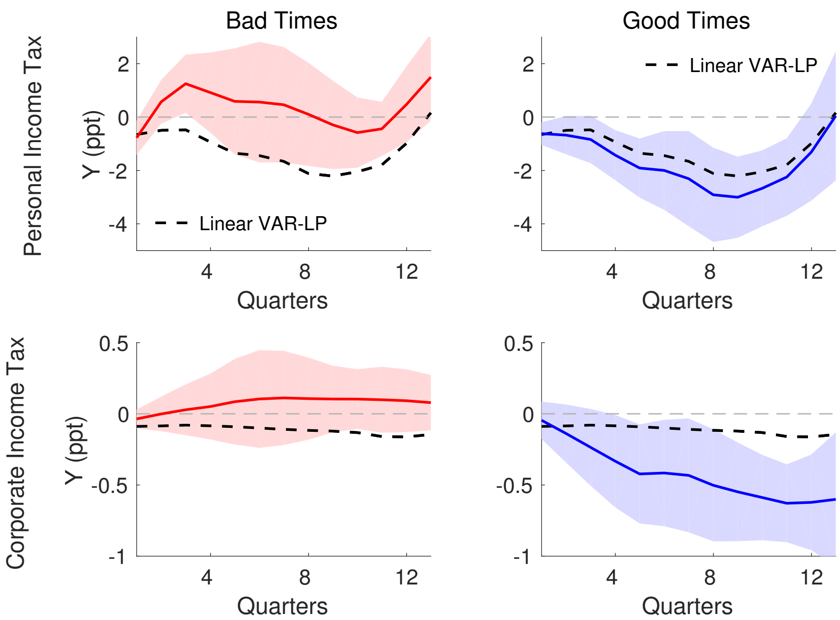
Impulse responses of real consumption expenditures (C), real private investment (I), hours worked (L), average hourly earnings (W) to a tax shock. Estimates from the linear local projections-IV in Equation 1.1 (dashed line) or from the state-dependent local projections-IV in Equation 1.3 (plain line). Shaded areas are 90% confidence bands using Newey-West standard errors. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.7: Narrative exogenous personal and corporate income tax changes



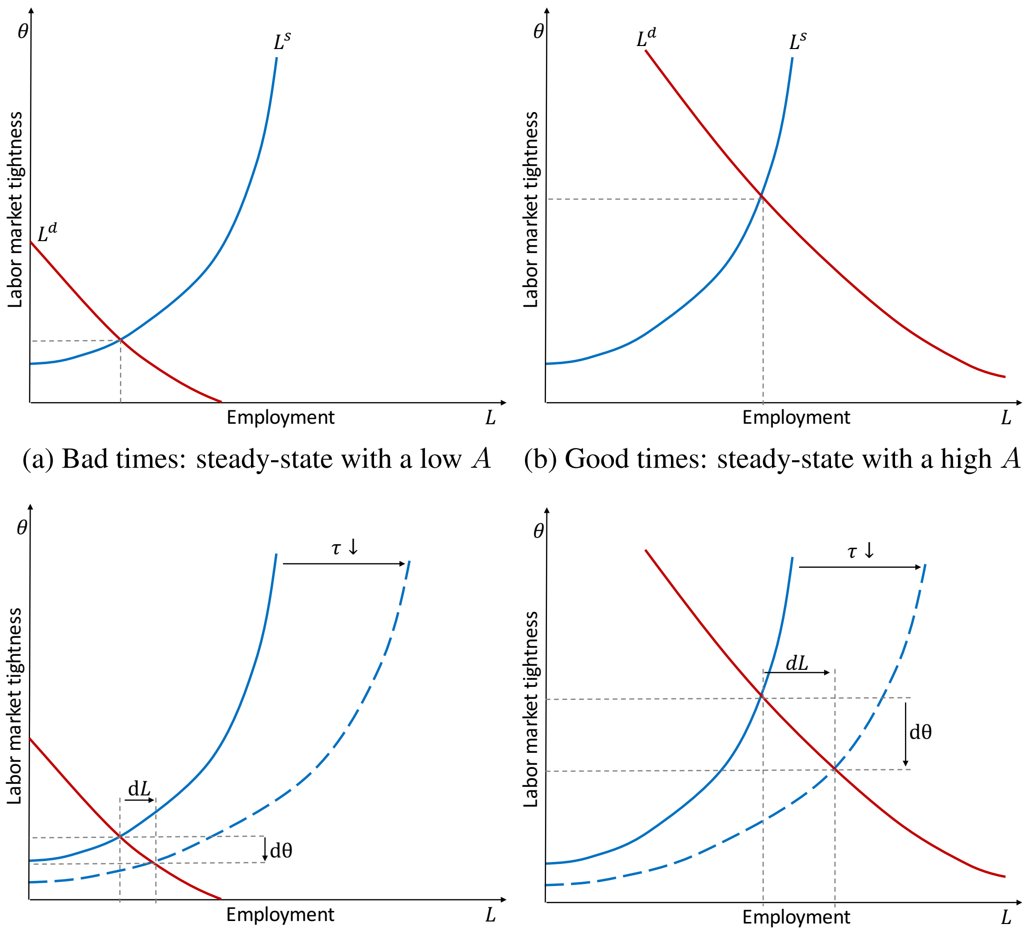
Mertens and Ravn (2013) narrative measures of exogenous personal income tax changes (top panel) and exogenous corporate income tax changes (bottom panel). Exogenous tax changes are expressed in percent of GDP.

Figure 1.8: The state-dependent effects of personal & corporate income tax shocks



Impulse responses of real GDP (Y) to a personal income tax shock (top panels). Impulse responses of real GDP (Y) to a corporate income tax shock (bottom panels). Estimates from a linear VAR-LP (dashed line) or from the state-dependent VAR-LP in Equation 1.14 (plain line). Shaded areas cover 90% of the posterior probability. Estimation using quarterly data from 1950Q1 to 2006Q4.

Figure 1.9: Steady-state equilibria in the search-and-matching model



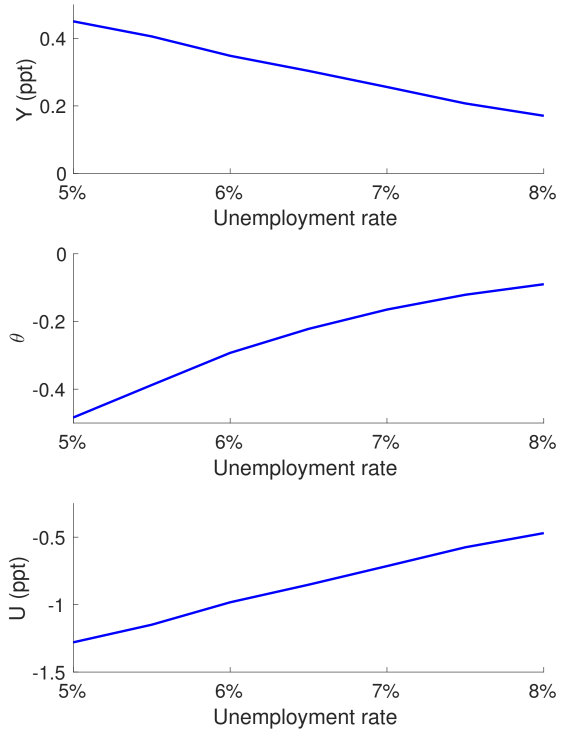
(a) Bad times: steady-state with a low A

(b) Good times: steady-state with a high A

(c) Effect of an income tax cut in bad times

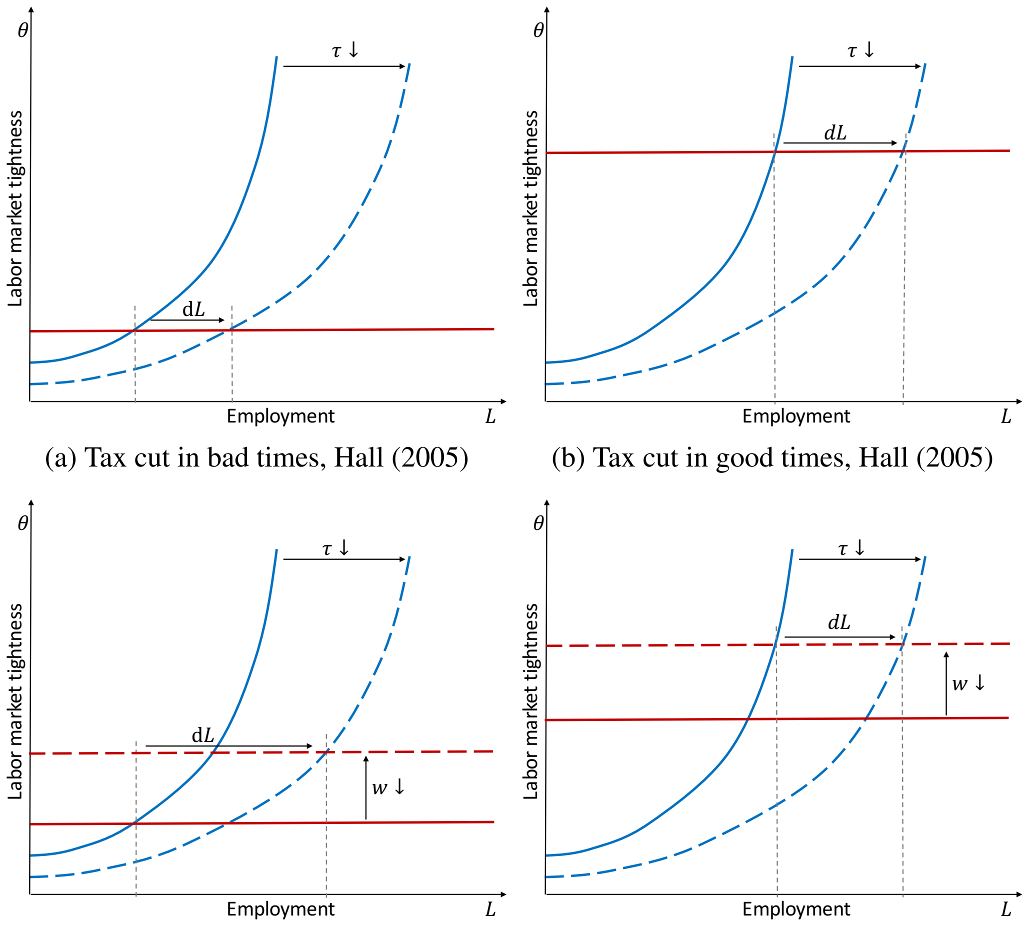
(d) Effect of an income tax cut in good times

Figure 1.10: Responses to a tax shock in the New Keynesian / search model



Peak effects of a 1 percentage point reduction of the labor income tax rate on log output (Y), labor market tightness (θ) and the unemployment rate (u). Results from simulations of the calibrated New Keynesian model with search-and-matching frictions in Section 1.4.2. The peak effect is the extremum effect of a tax cut in response to 1 of 16 technology shocks ranging from -3.6 percent to +5.4 percent. The unemployment rate on the x-axis is the extremum of the unemployment rate after the technology shock, without a tax cut.

Figure 1.11: Steady-state equilibria in Hall (2005) and Pissarides (2000)



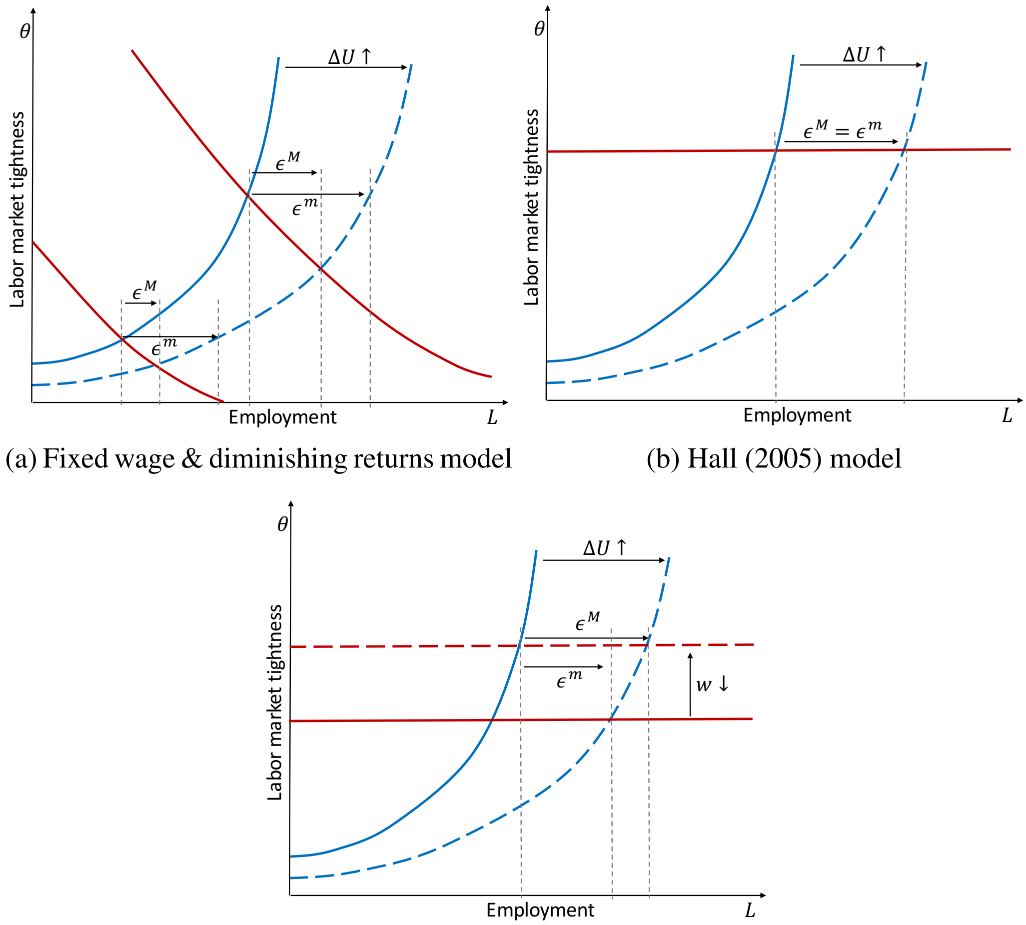
(a) Tax cut in bad times, Hall (2005)

(b) Tax cut in good times, Hall (2005)

(c) Tax cut in bad times, Pissarides (2000)

(d) Tax cut in good times, Pissarides (2000)

Figure 1.12: Microelasticity and macroelasticity in competing models



(a) Fixed wage & diminishing returns model

(b) Hall (2005) model

(c) Pissarides (2000) model

1.A Estimating State-Dependent Impulse Responses: VAR vs. Local Projections

I show that calculating state-dependent impulse responses from a VAR instead of LPs requires an additional assumption about how the shock affects the state variable.

State-Dependent VAR.—Consider the state-dependent VAR(1)[48]

$$X_t = I_t \left[A^B X_{t-1} + C^B \epsilon_t\right] + (1 - I_t) \left[A^G X_{t-1} + C^G \epsilon_t\right] + u_t.$$

X_t is a vector of endogenous variables. I_t is the state variable. ϵ_t is a structural shock. The superscript B denotes the *bad* state and G the *good* state. I denote the impulse response of X to a unit shock to ϵ_t at horizon $h \in \{0, H\}$ by β_h^j, where $j = \{B, G\}$. Then, the impulse response to a unit shock at horizon $h = 0$ is given by $\beta_0^B = C^B$ if the shock hits in bad times, and, by $\beta_0^G = C^G$ if the shock hits in good times. To calculate the impulse responses at $h = 1$, I am iterating forward the VAR by one period

$$X_{t+1} = I_{t+1} \left[A^B X_t + C^B \epsilon_{t+1}\right] + (1 - I_{t+1}) \left[A^G X_t + C^G \epsilon_{t+1}\right] + u_{t+1}.$$

I plug in X_t from above to get

$$\begin{aligned} X_{t+1} &= I_{t+1} \left[A^B \left(I_t \left[A^B X_{t-1} + C^B \epsilon_t\right] + (1 - I_t) \left[A^G X_{t-1} + C^G \epsilon_t\right] + u_t\right) + C^B \epsilon_{t+1}\right] \\ &+ (1 - I_{t+1}) \left[A^G \left(I_t \left[A^B X_{t-1} + C^B \epsilon_t\right] + (1 - I_t) \left[A^G X_{t-1} + C^G \epsilon_t\right] + u_t\right) + C^G \epsilon_{t+1}\right] \\ &+u_{t+1}. \end{aligned}$$

Note that it is impossible to pin down the response of X_{t+1} to ϵ_t without making an assumption about how the shock affects the state of the economy in $t + 1$. The standard assumption is that the structural shock does not alter the state of the economy over the impulse response horizon.[49] This implies $I_t = I_{t+1} + I_{t+2} + ... + I_{t+H}$. Using this assumption, the impulse response to a unit shock at horizon $h = 1$ is given by $\beta_1^B = A^B C^B$ if the shock hits in bad times, and, by $\beta_1^G = A^G C^G$

[48]For simplicity of exposition, I assume a VAR(1) representation. It is straightforward to generalize the results to a VAR(p) and writing it in companion form.

[49]See for instance Auerbach and Gorodnichenko (2012b) and Ramey and Zubairy (2016).

if the shock hits in good times.

State-Dependent Local Projections.—To allow for an easy comparison between methods, I assume that we use the same data as for the VAR, that we want to generate impulse responses for all variables in X_t, and that we use a lag of X_t as control:

$$X_{t+h} = I_t \left[\gamma^B X_{t-1} + \beta_h^B \epsilon_t\right] + (1 - I_t) \left[\gamma^G X_{t-1} + \beta_h^G \epsilon_t\right] + u_{t+h},$$

The impulse response at $h = 0$ is estimated from

$$X_t = I_t \left[\gamma^B X_{t-1} + \beta_h^B \epsilon_t\right] + (1 - I_t) \left[\gamma^G X_{t-1} + \beta_h^G \epsilon_t\right] + u_t,$$

A comparison with the state-dependent VAR representation reveals that the estimated impulse responses are identical at horizon $h = 0$. The impulse response at $h = 1$ is estimated from

$$X_{t+1} = I_t \left[\gamma^B X_{t-1} + \beta_h^B \epsilon_t\right] + (1 - I_t) \left[\gamma^G X_{t-1} + \beta_h^G \epsilon_t\right] + u_t,$$

Note that, other than in the state-dependent VAR, the impulse response at horizon $h = 1$ does not depend on the state-variable at time $t + 1$. Hence, no additional assumption is required.

1.B Sensitivity Analysis

This section performs a sensitivity analysis. In B.1, I explore alternative state variables. In B.2, I study whether the results are robust to using additional controls. In B.3, I use an alternative trend assumption. In B.4, I study robustness to alternative econometric methods. In B.5, I examine whether tax shocks have sign-dependent effects.

1.B.1 State Variable

I investigate whether the findings are robust to using alternative state variables. This robustness check is important because alternative measures change the distribution of tax shocks over the states of the economy. Table 1.7 summarizes the distribution of tax shocks for the state variables I consider.

Alternative Thresholds.—First I keep the focus on the unemployment rate with a discrete threshold that separates the good state from the bad. I now allow for a time-varying threshold and consider deviations from the Hodrick-Prescott filtered unemployment rate. I use three alternative smoothing parameters: $\lambda = 10^3$, $\lambda = 10^5$ and $\lambda = 10^7$. Table 1.3 summarizes the peak effect of a tax shock on real GDP in good times $min(\hat{\theta}_h^G)$, and bad times $min(\hat{\theta}_h^B)$, and reports the test statistic for the null hypothesis $min(\theta_h^G) - min(\theta_h^B) = 0$ for the alternative thresholds. In three out of four cases, the difference in peak effects is significant at the 5% level. For $\lambda = 10^5$ the difference falls marginally short of significance at the 10% level.

Continuous State Variable.—I now use the continuous unemployment rate as a state variable. To implement this change, I adapt (1.3):

$$\begin{aligned} x_{t+h} &= a_h + \beta_h^1 ATR_t + \beta_h^2 U_{t-1} \times ATR_t + \gamma_h'^{\,1} z_t \\ &+ \gamma_h'^{\,2} U_{t-1} \times z_t + \delta' D_t + \kappa U_{t-1} + u_{t+h}. \end{aligned} \tag{1.B.1}$$

I use RR_t as an instrument for ϵ_t^τ, and $U_{t-1} \times RR_t$ as an instrument for $U_{t-1} \times \epsilon_t^\tau$. I assume that the economy is in a bad state if the unemployment rate is one standard error (σ_U) above its median ($\tilde{U}$), and in a good state if the unemployment rate is one standard error below its median. The benchmark impulse response at horizon h is now given by $\theta_h = \left(\beta_h^1 + \beta_h^2 \times \tilde{U}\right) \sigma_\tau$. The impulse response in the good state is given by $\theta_h^G = \left(\beta_h^1 + \beta_h^2 \times (\tilde{U} - \sigma_U)\right) \sigma_\tau$ and in the bad state by $\theta_h^B = \left(\beta_h^1 + \beta_h^2 \times (\tilde{U} + \sigma_U)\right) \sigma_\tau$. Table 1.3 reports that the estimated peak effects are remarkably close to the baseline specification. The difference in peak effects $min(\theta_h^G) - min(\theta_h^B) = 2.6$ percentage points and significant at the 5% level.

State of the Business Cycle.—Until now I used measures of economic slack as the state variable. However, the effect of tax shocks might also depend on the state of the business cycle. Note that the two concepts have important differences. Measures of the state of the business cycle indicate periods in which the economy is moving from its peak to its through. A typical recession encompasses periods in which unemployment is rising from its low point to its high point. Therefore periods that are marked as recessions are not necessarily periods of high economic slack. Only about half of the quarters that are official recessions are also periods of high unemployment. I consider two business cycle indicators: NBER recession dates and Auerbach and Gorodnichenko's (2012b) smooth transition function of output growth. To use the NBER recession dates as a state variable I simply set $I_t = NBER_t$. To implement the approach of Auerbach and Gorodnichenko (2012b) I set

$$I_t = F(s_t) = \frac{exp(-\nu s_t)}{1 + exp(-\nu s_t)}.$$

s_t is the standardized seven-quarter moving average of output growth. I follow Auerbach and Gorodnichenko (2012b) and set $\nu = 1.5$ which implies that the economy spends about 20% of time in recession. Other than Auerbach and Gorodnichenko (2012b) I use a lagged moving average instead of a centered one. Table 1.3 reports that the difference in peak effects is 3.6 percentage points and significant at the 5% level when using NBER recession dates, and 2.6 percentage points and significant at the 10% level when using the smooth transition function of output growth. I conclude from this section that the main results are robust to using alternative state variables. For a quick comparison, Figure 1.13 plots the point estimates of the state-dependent LP-IV using the alternative state variables.

1.B.2 Controls

I investigate whether the results are robust to introducing additional controls. First, I add four lags of log of real federal government debt to the public to the set of controls. Government debt is a potentially important variable since any change in taxes must eventually lead to adjustments in fiscal instruments, see Leeper (2010) and Favero and Giavazzi (2012).

Second, I aim to control for monetary policy and add four lags of variables used in standard monetary VARs to the set of controls. These are the federal funds rate, the log CPI price level, and log non-borrowed reserves.

Third, I address the possibility of fiscal foresight. To address this issue, I follow Mertens and Ravn (2014) and make use of three variables. These are (i) *the implicit tax rate*, a measure of expected future taxes that is implied by tax exempt municipal bond yields and perfect arbitrage, constructed by Leeper et al. (2011); (ii) *defense stock returns*, a series for the accumulated excess returns of large U.S. military contractors constructed by Fisher and Peters (2010); (iii) *defense news*, a variable which contains professional forecasters' projections of the path of future military spending, constructed by Ramey (2011). I use the contemporaneous values and four lags of the three variables as controls.[50]

Figure 1.14 presents the point estimates of the LP-IVs using additional controls. Expanding the set of controls has little effect on the estimated coefficients. Table 1.4 reports the peak effects in good times and bad for the specifications using additional controls variables. The difference between peak effects is significant at the 5% level using controls for monetary policy and fiscal foresight, and significant at the 10% level using controls for public debt.

1.B.3 Trend Assumption

In the baseline specification, I use variables in log levels and allow for a quadratic deterministic trend. Instead, I now switch to a stochastic trend assumption and express output and government spending in annual growth rates. Table 1.4 reports that the difference in peak effects for the growth specification is 2.5 percentage points and significant at the 5% level.

1.B.4 Econometric Methods

I investigate whether the results are robust to using alternative methodologies that have been proposed in the literature. I discuss results for three alternatives. These are (i) the *Proxy SVAR* proposed by Mertens and Ravn (2014), (ii) the *Augmented VAR*[51], (iii) the *Truncated MA* proposed by Romer and Romer (2010).

Proxy SVAR.—Mertens and Ravn (2014, henceforth MR) propose to use the RR narrative measure as an external instrument for the latent tax shock in a standard fiscal VAR. The specification is identical to MR, but additionally allows for

[50] I use the implicit tax rate variable based on bonds with maturity of one year. Since this data is only available since 1953Q2, the same was shortened correspondingly in this case.

[51] Many authors interpret the narrative measure as the tax shock and introduce it as an exogenous regressor in a reduced form VAR. See for example Mertens and Ravn (2011; 2012), Favero and Giavazzi (2012), Perotti (2012).

state-dependent effects of tax shocks:

$$\begin{aligned} X_t &= I_{t-1}A^B\boldsymbol{X_{t-1}} + (1-I_{t-1})A^G\boldsymbol{X_{t-1}} + \delta D_t + u_t \qquad (1.B.2)\\ u_t &= I_{t-1}C^B\epsilon_t + (1-I_{t-1})C^G\epsilon_t \\ \Sigma_t &= I_{t-1}\Sigma_u^B + (1-I_{t-1})\Sigma_u^G. \end{aligned}$$

$X_t = [T_t, G_t, Y_t]'$. $\boldsymbol{X_{t-1}} = [X'_{t-1}, ..., X'_{t-4}]$. D_t contains a quadratic deterministic trend and a dummy for 1975Q2. ϵ_t is a vector of structural shocks with $\mathrm{E}(\epsilon_t) = 0$, $E(\epsilon_t\epsilon'_t) = I$ and $E(\epsilon_t\epsilon'_s) = 0$ for $s \neq t$. $u_t = [u_t^T, u_t^G, u_t^Y]'$ are the reduced form residuals with $u_t \sim N(0, \Sigma_t)$. The narrative measure RR_t serves as an external instrument for the latent tax shock ϵ_t^T. Hence, $I_{t-1} \times RR_t$ serves as an instrument for $I_{t-1} \times \epsilon_t^T$, and $(1 - I_{t-1}) \times RR_t$ as an instrument for $(1 - I_{t-1}) \times \epsilon_t^T$. Since we are only interested in the effects of a tax shock, it is sufficient to identify the parameters in the first column of C^G and C^B. I get consistent estimates of the first column by running a regression of u_t on $(1 - I_{t-1}) \times RR_t$ and $I_{t-1} \times RR_t$. In a state-dependent VAR, one needs to impose additional assumptions on how the shock affects the state variable. I follow the standard approach in the literature and assume that the state is constant over the impulse response horizon.[52]

Figure 1.15 presents the impulse responses. The dashed lines serve as a benchmark and depict impulse response estimates from a linear version of (1.B.2). Shaded areas are 90% confidence bands that I compute with a recursive wild bootstrap using 10.000 replications, see Gonçalves and Kilian (2004). Following Mertens and Ravn (2014), the impulse responses are scaled by the inverse of the average tax revenue to GDP ratio. The results are similar to those of the baseline specification. Tax shocks have no statistically significant effect on output in bad times. In good times, on the other hand, tax shocks have much stronger effects on output than the linear model suggests. Importantly, the impulse responses for tax revenues and government spending exhibit no state-dependence.[53]

Augmented VAR.—Some authors treat the narrative measure as the tax shock

[52] See for example Auerbach and Gorodnichenko (2012b) and Ramey and Zubairy (2016).

[53] In the linear model, I find a peak effect on output of -1.2%. This result is close to Figure 5 in MR. In their baseline specification, they use a subset of RR tax changes that removes 18 non-zero observations and find a larger peak effect. Once they use all RR tax changes, their estimates are very close to mine.

and introduce it as an exogenous regressor in a reduced form VAR. I augment a standard fiscal VAR with the RR narrative measure:

$$\begin{aligned} X_t &= I_{t-1}\left[C^B \boldsymbol{RR_t} + A^B \boldsymbol{X_{t-1}}\right] \\ &+ (1 - I_{t-1})\left[C^G \boldsymbol{RR_t} + A^G \boldsymbol{X_{t-1}}\right] + \delta D_t + u_t. \end{aligned} \tag{1.B.3}$$

$\boldsymbol{RR_t} = [RR_t', ..., RR_{t-4}']$. I again assume that the state remains constant over the impulse response horizon. Figure 1.16 presents the results. I find that the estimates are very close to the ones obtained from the proxy SVAR.

Truncated MA.—RR estimate the effects of the narrative measure on output from a truncated moving average representation. Other than RR, I use the log level of output instead of its growth rate to allow for an easy comparison between methods.The state-dependent version of the truncated MA is

$$Y_t = \alpha + \sum_{h=0}^{12} \left[I_{t-1-h}\theta_h^B RR_{t-h} + (1 - I_{t-1-h})\theta_h^G RR_{t-h}\right] + \delta' D_t + u_t. \tag{1.B.4}$$

The results from the truncated MA model are shown in Figure 1.17. The peak effects are larger than in the VAR specifications and are instead very close to the LP-IV estimates.

Table 1.4 collects the peak effects for the three alternative econometric methods. The peak effects in the VAR specification are a degree of magnitude smaller than in the LP-IV and truncated MA specifications. A possible explanation for this is the tighter dynamic structure VARs impose on the shape of the impulse response function. Nevertheless, the main result is robust to using any of the alternative methods. In all specifications, a tax shock that hits the economy in good times has larger effects on output than the corresponding linear model suggests. A tax shock that hits in bad times has small and statistically insignificant effects.

1.B.5 Sign-Dependence

I study whether tax increases have different effects on output than tax reductions.[54] To that end, I estimate the sign-dependent LPs:

$$x_{t+h} = a_h + \theta_h^+ RR_t^+ + \theta_h^- RR_t^- + \gamma_h' z_t + \delta_h' D_t + u_{t+h}. \tag{1.B.5}$$

where RR_t^+ are narratively identified exogenous tax increases and RR_t^- tax reductions. I use the same set of deterministic terms and controls as in the baseline specification. The impulse response of x at horizon h to a positive tax shock is given by θ_h^+, and to a negative tax shock by θ_h^-. Figure 1.18 presents the results. The plain lines are the point estimates of θ_h^+ and θ_h^-. The shaded areas are 90% confidence bands. The dashed lines are the point estimates from the linear model in (1.1). For ease of comparison, the impulse responses to a tax reduction are multiplied by -1. I find no evidence that tax shocks have sign-dependent effects on output. The effects of tax increases and reductions appear to be fairly symmetrical as the point estimates of the sign-dependent model are close to the point estimates of the linear model over the entire impulse response horizon.

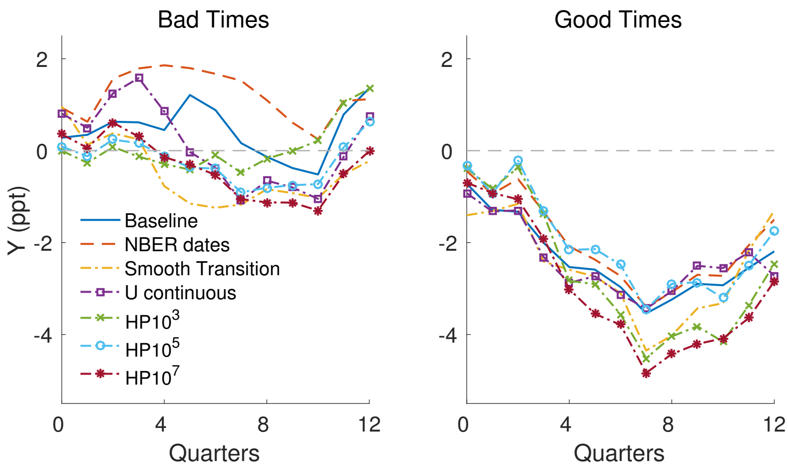
[54] Recent evidence suggests that many macroeconomic shocks have sign-dependent effects. For instance, Barnichon and Matthes (2016) find that contractionary monetary policy is more powerful than its expansionary counterpart. Barnichon and Matthes (2017) find that a reduction in government spending has a stronger effect on economic activity than an increase. Barnichon et al. (2016) show that credit supply contractions have larger effects on output than credit supply expansions.

Table 1.7: Distribution of tax shocks using alternative state indicators

	U **6.5%**	**U HP** $\boldsymbol{\lambda = 10^3}$	**U HP** $\boldsymbol{\lambda = 10^5}$	**U HP** $\boldsymbol{\lambda = 10^7}$	**NBER Dates**	**Smooth Transition**	**U Continuous**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
All Tax Shocks							
Periods	244	244	244	244	244	244	244
N Shocks	45	45	45	45	45	45	45
Mean	0	0	0	0	0	0	0
Std. Dev.	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Positive	25	25	25	25	25	25	25
Negative	20	20	20	20	20	20	20
Bad Times							
Periods	66	104	110	118	36	66	122
N Shocks	19	21	23	30	8	10	31
Mean	.09	-.06	-.10	.09	-.18	-.40	.06
Std. Dev.	.49	.62	.58	.51	.65	.79	.49
Positive	13	12	12	19	4	4	19
Negative	6	9	11	11	4	6	12
Good Times							
Periods	178	140	134	126	206	178	122
N Shocks	26	24	22	15	37	35	14
Mean	-.06	.05	.10	-.19	.04	.11	-.14
Std. Dev.	.59	.48	.50	.60	.53	.40	.66
Positive	12	13	13	6	21	21	6
Negative	14	11	9	9	16	14	8

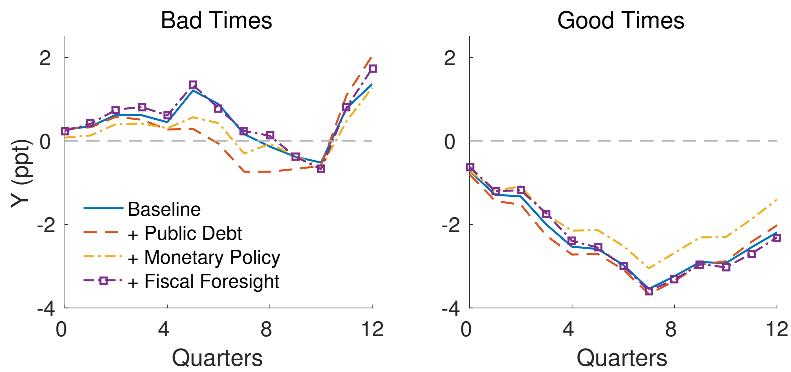
Summary statistics are for non-zero observations of the tax shocks. (1) is the baseline state variable. The discrete threshold that separates bad and good times is an unemployment rate of 6.5%. (2) The threshold is the HP-filtered trend unemployment rate using a smoothing parameter of $\lambda = 10^3$. (3) The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^5$. (4) The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^7$. (5) Bad times are NBER recession periods. (6) The state variable is the smooth transition function of past output growth. Bad times are periods in which $F(s_t) > 0.8$. (7) The state variable is the continuous unemployment rate. Bad times are periods in which the unemployment rate is below its median.

Figure 1.13: Robustness check — alternative state-variables



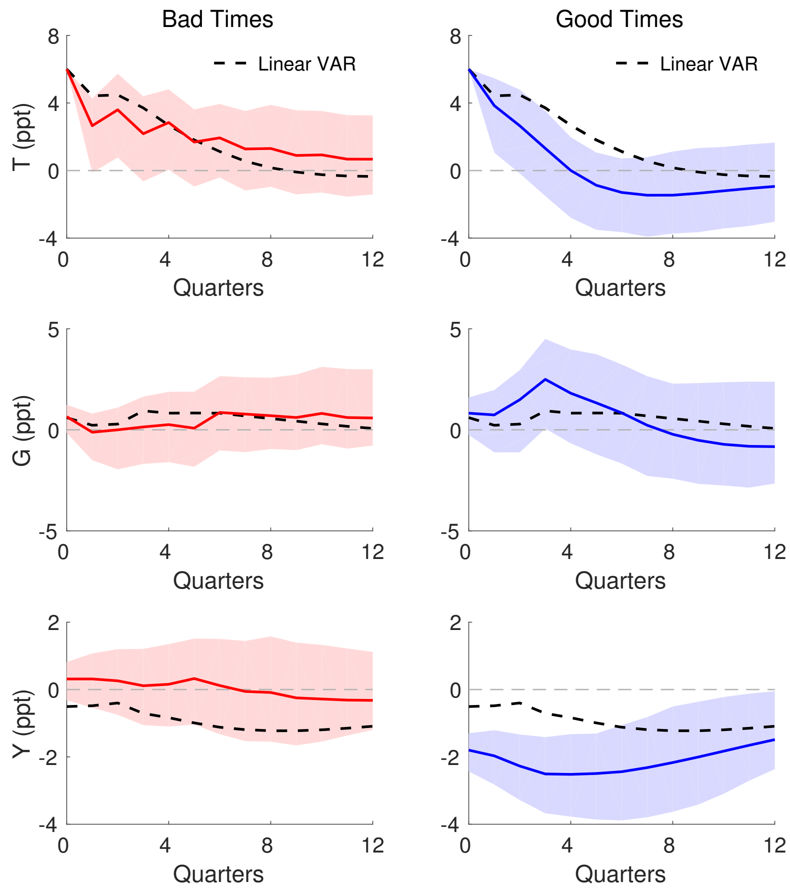
Impulse responses of real GDP (Y) to a tax shock using alternative state variables. *Baseline*: the discrete threshold that separates bad and good times is an unemployment rate of 6.5%. *HP* 10^3: The threshold is the HP-filtered trend unemployment rate using a smoothing parameter of $\lambda = 10^3$. *HP* 10^5: The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^5$. *HP* 10^7: The threshold is the HP-filtered trend unemployment rate using $\lambda = 10^7$. *U continuous*: the state variable is the continuous unemployment rate. *Smooth Transition*: the state variable is the smooth transition function of past output growth. *NBER dates*: bad times are NBER recession periods. Estimates from the local projections-IV in Equation 1.3 (plain line). For *U continuous*: Estimates from the local projections-IV in Equation 1.B.1. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.14: Robustness check — additional controls



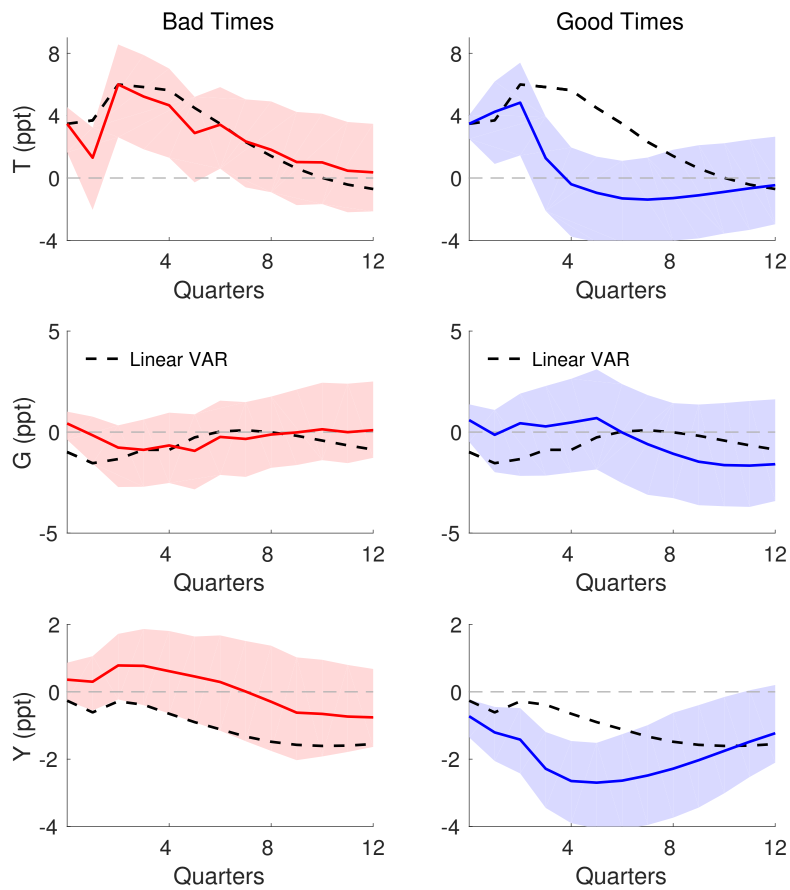
Impulse responses of real GDP (Y) to a tax shock. *Baseline*: uses the baseline set of controls. + *Public Debt*: uses four lags real federal government debt as additional controls . + *Mon. Policy*: uses four lags of the federal funds rate, the CPI price level and non-borrowed reserves as additional controls . + *Fiscal Foresight*: uses contemporaneous values and four lags of the implicit tax rate, defense stock returns and defense stock news as additional controls. Estimates from the linear local projections-IV in Equation 1.1 (dashed line) or from the state-dependent local projections-IV in Equation 1.3 (plain line). Shaded areas are 90% confidence bands using Newey-West standard errors. Estimation using quarterly data from 1947Q1 to 2007Q4. + *Fiscal Foresight*: uses quarterly data from 1953Q2 to 2007Q4.

Figure 1.15: Robustness check — estimates from a proxy SVAR



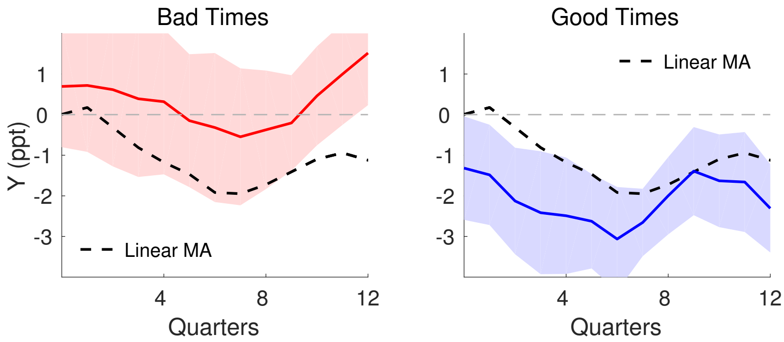
Impulse responses of real federal tax revenues (T), real federal government spending (G) and real GDP (Y) to a tax shock. Estimates from a linear proxy SVAR (dashed line) or from the state-dependent proxy SVAR in Equation 1.B.2 (plain line). Shaded areas are 90% confidence bands calculated with a recursive wild bootstrap using 10.000 replications. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.16: Robustness check — estimates from an augmented VAR



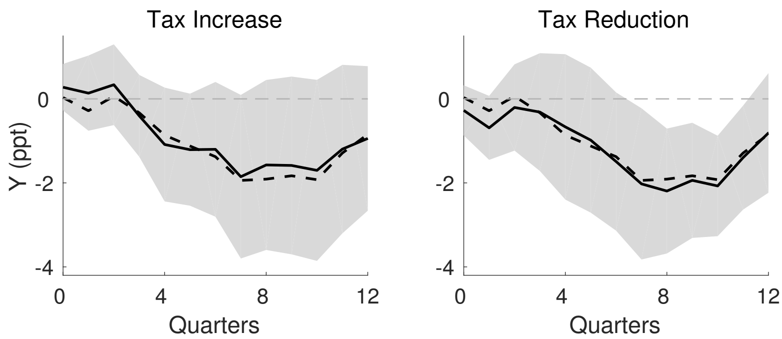
Impulse responses of real federal tax revenues (T), real federal government spending (G) and real GDP (Y) to a tax shock. Estimates from a linear augmented VAR (dashed line) or from the state-dependent augmented VAR in Equation 1.B.3 (plain line). Shaded areas are 90% confidence bands calculated with a recursive wild bootstrap using 10.000 replications. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.17: Robustness check — estimates from a moving average model



Impulse responses of real GDP (Y) to a tax shock. Estimates from a linear truncated MA (dashed lined) or from the state-dependent truncated MA in Equation 1.B.4 (plain lines). Shaded areas are 90% confidence bands calculated with a recursive wild bootstrap using 10.000 replications. Estimation using quarterly data from 1947Q1 to 2007Q4.

Figure 1.18: Robustness check — sign-dependent local projections



Impulse responses of real GDP (Y) to a positive tax shock (left panel) and to a negative tax shock (right panel). Estimates from the linear local projections in Equation 1.1 (dashed line) or from the sign-dependent local projections in 1.B.5 (plain line). Shaded areas are 90% confidence bands using Newey-West standard errors. Estimation using quarterly data from 1947Q1 to 2007Q4. For ease of comparison the responses to a tax reduction are multiplied by -1.

1.C State-Dependent VAR-LP

I extent the VAR-LP to allow for state-dependent impulse response functions. Assume we have reason to believe that the economy can be approximated by a state-dependent VAR(1):

$$X_t \ = I_{t-1}A^B X_{t-1} + (1 - I_{t-1})A^G X_{t-1} + u_t$$

The state-dependent local projections are

$$\begin{aligned} X_{t+h} &= I_{t-1}\beta_h^B X_{t-1} + (1 - I_{t-1})\beta_h^G X_{t-1} + v_{t+1} \\ v_{t+h} &\sim N(0, \Sigma_{h,t}) \\ \Sigma_{h,t} &= I_{t-1}\Sigma_{h,B} + (1 - I_{t-1})\Sigma_{h,G}. \end{aligned}$$

In a state-dependent VAR, one needs to impose additional assumptions on how the shock affects the state variable. A common assumption is to impose that the shock of interest can not alter the state within the impulse response horizon.[55] Using this assumption the state-dependent impulse response functions of the two approaches are given by

$$\begin{aligned} VAR - IR^s(h) &= {A^j}^{h+1} \\ LP - IR^s(h) &= \beta_h^j. \end{aligned}$$

$s = \{B, G\}$ denotes the state of the economy. As in the linear setup, the two approaches are identical at horizon $h = 0$. Again, the coefficients β_h^j are centered around the impulse responses implied by the VAR:

$$\beta_h^s \mid \beta_0^s, \lambda_h \sim N((\beta_0^s)^{h+1}, V_{h,s}), \text{ for } h > 1.$$

For each horizon h and state s, I use a standard Minnesota prior such that

$$V_{h,i,j,s} = \lambda_h^2 \frac{\sigma_{h,i,s}^2}{\sigma_{h,j,s}^2}$$

[55] See for example Auerbach and Gorodnichenko (2012b) and Ramey and Zubairy (2016).

As discussed above, the larger λ_h, the closer the impulse response estimates are to the LP-IR. Thus, in a state-dependent model, a higher λ_h also relaxes the assumption that the shock does not cause the economy to transition to another state. Following Kadiyala and Karlsson (1997), I set the prior for $\Sigma_{h,j}$ to

$$\begin{aligned}\Sigma_{h,s} \mid \lambda_h &\sim IW(\Phi_{h,s}, n+2)\\ \Phi_{h,s} &= diag(\sigma^2_{h,s,1}, ..., \sigma^2_{h,s,n}).\end{aligned}$$

$\sigma^2_{h,s,i}$ is the Newey-West corrected variance of a univariate local projection of variable i starting in state s on itself at horizon h.

1.D Proofs

PROOF OF LEMMA 4:
Implicit differentiation of the first equilibrium condition in (1.24) yields

$$\frac{d\theta}{dA} = \underbrace{\frac{\partial L^d}{\partial A}}_{(+)} \cdot \left[\underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} - \underbrace{\frac{\partial L^d}{\partial \theta}}_{(-)}\right]^{-1}. \tag{1.D.1}$$

The signs of $\partial L^d/\partial\theta$ and $\partial L^s/\partial\theta$ are from Lemma 2 and Lemma 3. The sign of $\partial L^d/\partial A$ comes from the labor demand in (1.20). Thus, $d\theta/dA > 0$. The other results follow because $L = L^s(\theta, \tau)$ and $u = 1 - (1-\lambda)L$.

PROOF OF PROPOSITION 1:

I first proof part (i). Implicit differentiation of the first equilibrium condition in (1.24) yields

$$\frac{d\theta}{d\tau} = -\underbrace{\frac{\partial L^s}{\partial \tau}}_{(-)} \cdot \left[\underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} - \underbrace{\frac{\partial L^d}{\partial \theta}}_{(-)}\right]^{-1}. \tag{1.D.2}$$

The signs of the derivatives are from Lemma 2 and Lemma 3. Thus, $d\theta/d\tau > 0$.

Implicit differentiation of the second equilibrium condition in (1.25) yields

$$\frac{\partial L}{\partial \tau} = \underbrace{\frac{\partial L^d}{\partial \theta}}_{(-)} \cdot \underbrace{\frac{d\theta}{d\tau}}_{(+)} . \tag{1.D.3}$$

Thus, $\frac{\partial L}{\partial \tau} < 0$. It follows that $M > 0$, and $M^Y = \alpha \cdot M \cdot L^{\alpha-1} > 0$.

I now prove part (ii). I plug (1.D.2) into (1.D.3) and rearrange

$$M \equiv -\frac{\partial L}{\partial \tau} = -\frac{\partial L^s}{\partial \tau} \cdot \frac{1}{1 + (\epsilon^s/\epsilon^d)}, \tag{1.D.4}$$

where $\epsilon^s \equiv (\partial L^s/\partial\theta) \cdot (\theta/L^s) > 0$, $\epsilon^d \equiv -(\partial L^d/\partial\theta) \cdot (\theta/L^d) > 0$. The next step is to express ϵ^s and ϵ^d as functions of endogenous variables. The definition of $L^s(\theta, \tau)$ implies

$$\epsilon^s = (1-\eta) \cdot u + \frac{\lambda \cdot \epsilon^e}{\lambda + (1-\lambda) \cdot s(\theta, \tau) \cdot f(\theta)}, \tag{1.D.5}$$

where $\epsilon^e = (\partial s/\partial\theta) \cdot (\theta/s)$. The definition of the search function $s(\theta, \tau)$ implies that ϵ^e is constant and $\partial s/\partial\theta > 0$. From Lemma 4 we have that $d\theta/dA > 0$ and $du/dA < 0$. Thus, $\epsilon^s/dA < 0$.

The definition of labor demand in (1.20) implies

$$\epsilon^d = \frac{\eta}{(1-\alpha)} \cdot \left(\frac{[1-\beta \cdot (1-\lambda)] \cdot r/q(\theta)}{[1-\beta \cdot (1-\lambda)] \ \cdot r/q(\theta) + w/A} \right). \tag{1.D.6}$$

Lemma 4 and the fact that q is decreasing in θ imply that $d\epsilon^d/dA > 0$.

The definition of labor supply and the search function imply

$$-\frac{\partial L^s}{\partial \tau} \equiv -\frac{\partial L^s}{\partial s} \cdot \frac{\partial s}{\partial \Delta U} \cdot \frac{\partial \Delta U}{\partial \tau} = -\Omega \cdot u \cdot L, \tag{1.D.7}$$

where Ω is a constant. The last expression is increasing in A as long as $L > [2 \cdot (1-\lambda)]^{-1}$. This condition is always satisfied for a reasonable parametrization.[56] We have that $d(-\partial L^s/\partial\tau)/dA > 0$, $d\epsilon^s/dA < 0$ and $d\epsilon^d/dA > 0$. Thus,

[56] A separation rate λ of 3 percent implies that the condition is satisfied as long as the employment rate L is above 51% percent. The condition even holds for an unrealistically high separation

$dM/dA > 0$.

$M^Y = \alpha \cdot M \cdot L^{\alpha-1}$. Thus, M^Y is increasing in A as long as $L > [(1+\alpha) \cdot (1-\lambda)]^{-1}$. This condition is always satisfied for a reasonable parametrization.[57]

1.E Derivation of the New Keynesian Model

Large Household.—A measure 1 of identical workers are part of a large household with expected utility[58]

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \cdot \Big[ln(C_t) - (1-(1-\lambda) \cdot L^s_{t-1}) \cdot \Psi(s_t) \Big]. \tag{1.E.1}$$

$\mathbb{E}_0$ is the expectation in period $t = 0$. Workers aggregate their income before choosing between consumption and saving. Employed workers pay a proportional labor income tax τ_t. The household's budget is

$$P_t \cdot C_t + D_t = P_t \cdot w_t \cdot (1-\tau_t) \cdot L_t + R_{t-1} \cdot D_{t-1} + P_t \cdot \phi_t + P_t \cdot T_t. \tag{1.E.2}$$

P_t is the price level. D_t is the quantity of one-period government bonds purchased at time t. R_t is the one-period gross nominal interest rate that pays in period t. The law of motion of the probability of being employed in period t is

$$L^s_t = (1-\lambda) \cdot L^s_{t-1} + (1-(1-\lambda) \cdot L^s_{t-1}) \cdot s_t \cdot f(\theta_t). \tag{1.E.3}$$

The household chooses consumption $\{C_t\}_{t=0}^{\infty}$ and search effort $\{s_t\}_{t=0}^{\infty}$ to maximize utility subject to (1.E.2), (1.E.3) and the no-Ponzi-game constraint

$$\mathbb{E}_0 \left[\lim_{t\to\infty} \frac{D_t}{\prod_{i=0}^{t} R_{i-1}} \right] \geq 0. \tag{1.E.4}$$

rate: a separation rate of 20% implies that the condition is satisfied as long as the employment rate L is above 63%.

[57] A separation rate λ of 3 percent implies that the condition is satisfied as long as the employment rate L is above 62% percent. The condition even holds for an unrealistically high separation rate: a separation rate of 20% implies that the condition is satisfied as long as the employment rate L is above 75%.

[58] Without government bonds, the setup is identical to search-and-matching model in Section 1.4.1.

$\pi_t \equiv (P_t/P_{t-1}) - 1$ is inflation at time t. The household's intertemporal consumption decision satisfies the Euler equation

$$C_t = \beta \cdot \mathbb{E}_t \left[\frac{R_t}{1+\pi_{t+1}} \cdot C_{t+1} \right]. \tag{1.E.5}$$

The household's optimal search path is given by:

$$\frac{\Psi'(s_t)}{f(\theta_t)} - \beta \cdot (1-\lambda) \cdot \mathbb{E}_t \frac{\Psi'(s_{t+1})}{f(\theta_{t+1})} \cdot [1 - s_{t+1} \cdot f(\theta_{t+1})] = \Delta U_t. \tag{1.E.6}$$

This equation implicitly defines optimal search effort as an increasing function of labor market tightness θ_t and the utility gain from work ΔU_t. The search path $\mathbb{E}_t s_{t+1}/s_t$ is increasing in the expected job-finding probability in the future relative to today $\mathbb{E}_t f(\theta_{t+1})/f(\theta_t)$.

Final Good Firms.—A measure 1 of identical final good firms sell the final good on a perfectly competitive market. The representative final good firm uses $y_t(i)$ units of each intermediate good $i \in [0, 1]$ to produce Y_t units of final good according to the production function

$$Y_t = \left[\int_0^1 y_t(i)^{(\epsilon-1)/\epsilon} di \right]^{\epsilon/(\epsilon-1)}. \tag{1.E.7}$$

$\epsilon > 1$ is the elasticity of substitution between intermediate goods. Taking the nominal price $p_t(i)$ of each intermediate good and the nominal price p_t of the final good as given, the representative final good firm chooses $y_t(i)$ to maximize its profits

$$P_t \cdot Y_t - \int_0^1 p_t(i) \cdot y_t(i) di. \tag{1.E.8}$$

The first-order condition is

$$y_t(i) = Y_t \cdot \left(\frac{p_t(i)}{p_t} \right)^{-\epsilon}. \tag{1.E.9}$$

The equation gives the demand for $y_t(i)$ as a function of the intermediate good's relative price $p_t(i)/P_t$. Perfect competition in the final good market assures that the final good price is equal to its marginal production cost, i.e.,

$$P_t = \left(\int_0^1 p_t(i)^{1-\epsilon} di \right)^{1/(1-\epsilon)}. \tag{1.E.10}$$

Intermediate Good Firms.—In the intermediate good sector, there is no entry or exit. Each intermediate good is produced by a monopolist which uses $L_t(i)$ units of labor to produce $y_t(i)$ units of intermediate good i using the production function

$$y_t(i) = A_t \cdot L_t(i)^{\alpha}. \tag{1.E.11}$$

Following Rotemberg (1982), the monopolist faces a cost when adjusting its nominal price:

$$\frac{\gamma}{2} \cdot \left(\frac{p_t(i)}{p_{t-1}(i)} - 1 \right)^2 \cdot C_t, \tag{1.E.12}$$

where γ describes the amount of resources devoted to adjusting prices. The price-adjustment cost is denoted in units of the final good and is proportional to the size of the economy, measured by C_t. Upholding a vacancy for one period costs $r \cdot A_t$. In period t, the monopolist hires $H_t(i) = L_t(i) - (1-\lambda) \cdot L_{t-1}(i)$ new workers. Thus, total hiring cost in period t is $r \cdot A_t / q(\theta_t) \cdot H_t$. The hiring cost is proportional to A_t and measured in units of the final good. The monopolist chooses $\{L_t(i)_{t=0}^{\infty}$ and $\{p_t(i)_{t=0}^{\infty}$ to maximize the expected sum of discounted real profits

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \frac{\beta^t}{C_t} \cdot \left[\left(\frac{p_t(i)}{P_t} \right)^{1-\epsilon} \cdot Y_t - w_t \cdot L_t(i) - \frac{\gamma}{2} \cdot \left(\frac{p_t(i)}{p_{t-1}(i)} - 1 \right)^2 \cdot C_t - \frac{r \cdot A_t}{q(\theta)} \cdot H_t \right]. \tag{1.E.13}$$

Denote $\mu_t(i)$ the Lagrange multiplier on constraint (1.E.11) in period t. The first-order condition with respect to $L_t(i)$ is

$$\mu_t(i) \cdot \alpha \cdot L_t(i)^{\alpha-1} = \frac{w_t}{A_t} + \frac{r}{q(\theta_t)} - \beta \cdot (1-\lambda) \cdot \mathbb{E}_t \left[\frac{C_t}{C_{t+1}} \cdot \frac{A_{t+1}}{A_t} \cdot \frac{r}{q(\theta_{t+1})} \right]. \tag{1.E.14}$$

The first order conditions with respect to $p_t(i)$ is

$$\frac{p_t(i)}{p_t} = \frac{\epsilon}{\epsilon-1} \cdot \mu_t(i) + \frac{\gamma}{\epsilon-1} \cdot \frac{C_t}{Y_t} \cdot \left(\frac{p_t(i)}{p_t}\right)^{\epsilon} \cdot \left[\beta \cdot \mathbb{E}_t\left[\left(\frac{p_{t+1}(i)}{p_t(i)} - 1\right) \cdot \frac{p_{t+1}(i)}{p_t(i)}\right] - \left(\frac{p_t(i)}{p_{t-1}(i)} - 1\right) \cdot \frac{p_t(i)}{p_{t-1}(i)}\right] \tag{1.E.15}$$

$\mu_t(i)$ is the real marginal revenue of producing one unit of intermediate good i in period t.

Symmetric Equilibrium.—All intermediate good firms are identical in a symmetric equilibrium. Thus, $L_t(i) = L_t$, $y_t(i) = Y_t$, $p_t(i) = P_t$, and $\mu_t(i) = \mu_t$. Using the symmetry assumption, I rewrite aggregate labor demand from (1.E.14):

$$\mu_t \cdot \alpha \cdot L_t^{\alpha-1} = \frac{w_t}{A_t} + \frac{r}{q(\theta_t)} - \beta \cdot (1-\lambda) \cdot \mathbb{E}_t\left[\frac{C_t}{C_{t+1}} \cdot \frac{A_{t+1}}{A_t} \cdot \frac{r}{q(\theta_{t+1})}\right]. \tag{1.E.16}$$

The Philips curve is derived from (1.E.15):

$$\pi_t \cdot (\pi_t + 1) = \frac{1}{\gamma} \cdot \frac{Y_t}{C_t} \cdot [\epsilon \cdot \mu_t - (\epsilon - 1)] + \beta \cdot \mathbb{E}_t[\pi_{t+1} \cdot (\pi_{t+1} + 1)]. \tag{1.E.17}$$

The aggregate production function is derived from (1.E.11):

$$Y_t = A_t \cdot L_t^{\alpha}. \tag{1.E.18}$$

1.F Tax Multipliers in Hall (2005) and Pissarides (2000)

Hall (2005).—With constant returns to scale $\alpha = 1$. Other than that, the model is identical to the model in Section 1.4.1. Implicit differentiation of the first equilibrium condition in (1.24) yields

$$\frac{d\theta}{dA} = \underbrace{\frac{\partial L^d}{\partial A}}_{(+)} \cdot \left[\underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} - \underbrace{\frac{\partial L^d}{\partial \theta}}_{(-)}\right]^{-1} = \frac{\theta}{A}, \tag{1.F.1}$$

where I have used that $\epsilon^d = +\infty$ and $(\partial L^d / \partial A) \cdot (A / L^d) = +\infty$. The signs of the derivatives are from Lemma 2 and Lemma 3. Thus, $d\theta/dA > 0$. The other results follow, because $L = L^s(\theta, \tau)$ and $u = 1 - (1 - \lambda)$.

I now calculate the effect of a tax cut. Implicit differentiation of the first equilibrium condition in (1.24) yields

$$\frac{d\theta}{d\tau} = -\underbrace{\frac{\partial L^s}{\partial \tau}}_{(-)} \cdot \left[\underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} - \underbrace{\frac{\partial L^d}{\partial \theta}}_{(-)}\right]^{-1} = 0, \tag{1.F.2}$$

where I have used that $\epsilon^d = +\infty$. The signs of the derivatives are from Lemma 2 and Lemma 3. Thus, $d\theta/d\tau > 0$. Implicit differentiation of the second equilibrium condition in (1.25) yields

$$\frac{\partial L}{\partial \tau} = \underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} \cdot \underbrace{\frac{d\theta}{d\tau}}_{=0} + \underbrace{\frac{\partial L^s}{\partial \tau}}_{(-)}. \tag{1.F.3}$$

Thus, $\frac{\partial L}{\partial \tau} < 0$. It follows that $M > 0$, and $M^Y = \alpha \cdot M \cdot L^{\alpha - 1} > 0$. Proposition 1 establishes that $-\partial L^s / \partial \tau$ is increasing in A. Thus, M is increasing in A.

Pissarides (2000).—The model has constant returns to scale ($\alpha = 1$) and the wage is flexible. Other than that, the model is identical to the model in Section 1.4.1. The model now has endogenous variables: employment L, labor market tightness τ and the wage w. Equilibrium labor market tightness equalizes quasi-labor supply and aggregate labor demand:

$$L^s(\theta, \tau, w) \quad = \quad L^d(\theta, A, w). \tag{1.F.4}$$

Equilibrium employment is obtained from aggregate labor supply:

$$L \quad = \quad L^s(\theta, \tau, w). \tag{1.F.5}$$

where θ satisfies (1.F.4). When a worker and firm are matched, they bargain over the wage. The workers bargaining power is $\chi \in (0, 1)$. The surplus from each match is shared. The worker keeps a fraction χ of the surplus. The worker's surplus from a match is the utility gain from work ΔU. The firm's surplus is the amount of produced goods by a worker A minus the real wage w. Worker and firm split the total surplus. Thus, the third equilibrium condition is

$$w = A - \frac{1-\chi}{\chi} \cdot \Delta U. \tag{1.F.6}$$

I consider the effect of an increase in A. Implicit differentiation of (1.F.4) yields

$$\frac{d\theta}{dA} = \frac{\theta}{A} - \frac{\theta}{w} \cdot \frac{dw}{dA} = \frac{\theta}{A \cdot w} \cdot (w - \chi \cdot A), \tag{1.F.7}$$

where I have used that $\epsilon^d = +\infty$, $(\partial L^d/\partial A) \cdot (A/L^d) = +\infty$, $(\partial L^d/\partial w) \cdot (w/L^d) = -\infty$, and $dw/dA = \chi$ from implicit differentiation of (1.F.6). From, (1.F.6) we have that $w = \chi A + (1-\chi) \cdot t$. Thus, $d\theta/dA > 0$.

Implicit differentiation of (1.F.5) yields

$$\frac{\partial L}{\partial A} = \underbrace{\frac{\partial L^s}{\partial \theta}}_{(+)} \cdot \underbrace{\frac{d\theta}{dA}}_{(+)} + \chi \cdot \underbrace{\frac{\partial L^s}{\partial w}}_{(+)}. \tag{1.F.8}$$

The sign of $\partial L^s/\partial\theta$ is from Lemma 3. The sign of $\partial L^s/\partial w$ follows from the properties of the optimal search effort $s(\theta, \Delta U)$ in (1.22). Thus, $dL/dA > 0$.

Next, I consider the effect of a tax cut. Implicit differentiation of (1.F.4) yields

$$\frac{d\theta}{d\tau} = -\frac{\theta}{w} \cdot (1-\chi). \tag{1.F.9}$$

where I have used $\epsilon^d = +\infty$, $(\partial L^d/\partial w) \cdot (w/L^d) = -\infty$, and $dw\ d\tau = (1-\chi)$ from implicit differentiation of (1.F.6). Thus, $d\theta/d\tau < 0$. Implicitly differentiating (1.F.5) and plugging in for $d\theta/d\tau$ yields

$$M = -\frac{\partial L}{\partial \tau} = (1-\chi) \cdot \epsilon^s \cdot \frac{L}{w} - \frac{\partial L^s}{\partial \tau}, \tag{1.F.10}$$

From $d\theta/dA > 0$ and Proposition 1, we have that $-\partial L^s/\partial\tau$ is increasing in A. From Proposition 1, we also have that $d\epsilon^s/dA < 0$. Because $dw/dA > 0$, $\partial L/\partial A > 0$ and the fact that firms produce with constant returns to scale, we have that L/w is decreasing in A. Thus, whether M is increasing in A is ambiguous. The multiplier of the flexible wage model coincides with Hall (2005) if workers have full bargaining power $\chi = 1$.

Chapter 2

ARE THE EFFECTS OF FINANCIAL MARKET DISRUPTIONS BIG OR SMALL?

with Regis Barnichon* and Christian Matthes†

2.1 Introduction

What are the effects of financial market disruptions on economic activity? The recent global financial crisis suggests that the effects are large and highly persistent: by 2017, 10 years after the beginning of the crisis, the US, UK and Euro area GDPs remain far —at least 10 percentage points (ppt)— from their pre-crisis trends (Figure 2.1). More systematic narrative studies of financial stress episodes point to similar conclusions. For instance, Romer and Romer (2017a) study a panel of OECD countries and find that GDP is typically 9ppt lower five years after an extreme financial stress episode like the recent crisis.[1]

Although little emphasized so far, the "output loss" implied by these studies stands in sharp contrast with another influential literature on the importance

*Federal Reserve Bank of San Francisco, CEPR. E-mail: r.barnichon@crei.cat

†Federal Reserve Bank of Richmond. E-mail: christian.matthes@rich.frb.org

[1] See also Cerra and Saxena (2008), Jordà et al. (2011), Bordo and Haubrich (2017), Ball (2014), Reinhart and Rogoff (2014), Blanchard et al. (2015), Krishnamurthy et al. (2015).

of financial markets for economic activity: structural VAR studies of the effects of financial shocks —shocks to the effective "risk-bearing capacity" of the intermediary financial sector— find relatively mild and short-lived effects of financial shocks.[2] Notably, the results in Gilchrist and Zakrajšek (2012) imply that output is only 1.3ppt lower 5 years after an adverse financial shock like the one experienced in the recent crisis.

In this paper, we argue that these seemingly conflicting results stem from separate shortcomings of the two leading approaches —narrative accounts and structural VARs—. First, unlike structural VARs, narrative accounts are not designed to identify the causal effect of financial strains on economic activity, only the existence of a correlation. Second, structural VARs do not take into account that financial shocks are likely to have asymmetric effects on economic activity, as has been predicted theoretically (Mendoza, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014). In contrast, narrative accounts implicitly allow for asymmetric effects, because they only focus on adverse financial conditions, i.e., negative "shocks".

To address these limitations, we consider a model designed to (i) identify the causal effects of financial shocks, and (ii) take into account the possible asymmetric effects of financial shocks. Specifically, we estimate a Vector Moving-Average model (VMA) model that can be easily generalized to allow for asymmetric effects of shocks (unlike VARs), and we establish causality by using an identification strategy that builds on but also expands Gilchrist and Zakrajšek (2012). We find that a favorable financial shock —an easing of financial conditions— has little effect on economic activity, but an adverse financial shock has large and persistent effects on economic activity. In a counterfactual simulation based on our parameter estimates, we find that that the 2007-2008 financial shocks persistently lowered output by roughly 7ppt, so two thirds of the "output loss" since 2007 appear to have been caused by the financial crisis and is unlikely to revert.

These results help reconcile the seemingly contradictory findings between narrative accounts and structural time series analyses: structural VARs have found mild and transitory effects of financial shocks on GDP because that literature has

[2] See Helbling et al. (2011), Gilchrist et al. (2009), Gilchrist and Zakrajsek (2011; 2012) and Boivin et al. (2013).

only considered linear models, in which the large and persistent effects of adverse shocks are mixed with the (according to our results) small and transitory effects of favorable shocks, leading to mild *average* effects of financial shocks. In contrast, narrative studies focus solely on crisis episodes, i.e., adverse events, which have large and persistent effects on output.

Our baseline evidence is based on US data, where we identify financial shocks from innovations to Gilchrist and Zakrajšek's (2012, GZ) Excess Bond Premium (EBP), the component of credit spreads purged from the expected default risk of borrowers. We build on and expand GZ's identification strategy by relaxing their causal ordering between the stance of monetary policy and the EBP. To identify changes in the risk bearing capacity of the financial sector that are not due to monetary policy, we use a proxy variable approach —using Romer and Romer's (2004) narrative measure of exogenous monetary policy changes— to separate monetary shocks from financial shocks.

As additional evidence, we also consider the effects of financial shocks from UK and Euro area data, and we obtain very similar conclusions. For the UK, we follow the same identification strategy as in the US, using data on the excess bond premium from Bleaney et al. (2016) and the narrative measure of exogenous monetary policy changes from Cloyne and Hürtgen's (2016). For the Euro area, we follow the approach of Gilchrist and Mojon (2018) and use Monfort and Renne's (2013) *KfW-Bund spread* as an external instrument for the unobserved financial shock.[3] We obtain very similar results to the US case: contractionary credit shocks have large and persistent effects on output.

This paper has two main contributions. First, we highlight the conflicting conclusions reached by the two leading strands of literature on the implications of financial market disruptions. Second, we resolve the apparent conundrum by expanding the more structural time series literature so that it incorporates non-linear effects of shocks, notably the asymmetric effects of financial shocks. Part of the reason for the lack of structural time series studies on the possibly asym-

[3]The argument is that a rise in the KfW-Bund spread signals a rise in the liquidity premium because bonds issued by the KfW, a German government-owned development bank whose debt is guaranteed by the Government, have the same credit quality but are less liquid than the Bund. Monfort and Renne (2013) show that a rise in the KfW-Bund spread transmits to other Euro area bond market yields.

metric nature of the financial shocks is methodological.[4] Standard techniques are often linear, which makes the exploration of nonlinearities difficult. In particular, VARs (or factor-augmented VARs), as used by Gilchrist and Zakrajsek (2011, 2012) and Boivin et al. (2013), cannot allow the impulse response to depend on the sign of the shock. While autoregressive distributed lags models (ADL) or Jordà's (2005) Local Projection method (henceforth LP) can allow for some non-linearities, these methods are limited by efficiency considerations. Moreover, to explore the non-linear effects of shocks, ADL or LP requires a series of previously identified structural shocks or instruments, which are not readily available for financial shocks.

To overcome these technical challenges, we use a method—Functional Approximation of Impulse Responses (FAIR, Barnichon and Matthes, 2016) that combines the strength of the VAR for shock identification with the flexibility of ADL and LP models to allow for non-linearities, in particular asymmetry. The method consists in (i) directly estimating a structural moving average model of the economy, i.e., directly estimating the impulse response functions to structural shocks (unlike the VAR approach, which first estimates a reduced-form VAR and thus requires the existence of a VAR representation), and (ii) approximating the (high-dimensional) impulse response functions with a (small) number of Gaussian basis functions, which offers efficiency gains and allows for the exploration of a rich set of non-linearities (in contrast to the non-parametric ADL and LP approaches). While different families of basis functions are possible, Gaussian basis functions are particularly attractive, because a small number (one or two) of Gaussian functions can already capture a large class of impulse response functions. Thanks to the small number of free parameters allowed by our functional approximation, it is possible to directly estimate the impulse response functions from the data using maximum likelihood or Bayesian methods. The parsimony of the approach, in turn, allows us to estimate more general non-linear models.

The remainder of the chapter is structured as follows. Section 2.2 provides some background and highlights the conflicting conclusions reached by the two leading strands of literature on the effects of financial market disruptions; Section

[4] An exception is Stein (2014) who shows that the correlation between (changes in) EBP and economic activity varies with the sign of the change in EBP. See also López-Salido et al. (2017).

2.3 presents our empirical model, our method to approximate impulse responses using Gaussian basis functions and our strategy to identify financial shocks; Section 2.4 presents our baseline evidence from US data; Section 2.5 presents evidence on the asymmetric effects of financial shocks from UK and Euro area data; Section 2.6 concludes and lays out possible paths for future research.

2.2 Background

In part motivated by the experience of the recent crisis, two separate strands of the literature aim to better understand the effects of financial market disruptions on output. A first "narrative" approach studies the behavior of output around narratively identified financial crisis episodes, focusing on measuring the correlation between financial strain and economic activity. A second approach uses structural Vector AutoRegressions (VARs) to identify the causal effects of shocks originating in financial markets.

As we will see, these two approaches reach strikingly different conclusions: While the narrative approach finds that financial distress is associated with large and persistent drops in output, the structural VAR literature finds relatively mild and short-lived effects of financial distress on output.

Narrative accounts of financial distress episodes

Narrative studies of financial crises go back to Cerra and Saxena (2005) and Reinhart and Rogoff (2009), who estimate the average path of output following financial crisis episodes. While this approach did not initially take into account the severity of the crisis —only attributing a dummy value of one in case of a crisis—, Romer and Romer (2017a, RR) recently refined the methodology by using narrative accounts from the OECD Economic Outlook on country conditions to capture the intensity of financial strains on a 0 (no financial distress) to 15 scale (extreme distress). Their series measures financial distress in 24 OECD countries at a semi-annual frequency for the period 1967-2012.

To estimate the impulse responses of output to an impulse to financial distress, RR use Jordà (2005)'s local projection method. The particular specification they estimate is

$$Y_{j,t+h} = \alpha_j^h + \gamma_t^h + \beta^h F_{j,t} + \sum_{l=1}^{4} \phi_l^h F_{t,t-l} + \sum_{l=1}^{4} \theta_l Y_{j,t-l}, \text{ for } h = 0, 1, ..., 10 \quad (2.1)$$

where the j subscripts index countries, the t subscripts index time, and the h superscripts denote the horizon (in half-years after time t) being considered. $Y_{j,t+h}$ is log real GDP for country j at time $t+h$. $F_{j,t}$ is RR financial distress index for country j at time t. RR use four lags of log real GDP and financial distress as control variables. α_j^h are country fixed effects capturing that the normal behaviour of output may differ across countries. γ_t^h are time fixed effects, included to control for economic developments facing all countries in a given year.

While RR's main evidence uses data from 24 OECD countries, we focus on US data.[5] This allows us to put the results in the context of a wider literature by studying the behaviour of the Excess Bond Premium (EBP) during financial stress episodes. The EBP, proposed by Gilchrist and Zakrajšek (2012) and displayed in Figure 2.2, is the component of US corporate credit spreads purged from expected default risk, liquidity risk, and prepayment risk, and is meant to capture the effective risk-bearing capacity of the financial sector. Compared to the RR index, the EBP is an objective quantitative measure of financial strains that allows us to link the RR results to rest of the literature.[6]

Figure 2.3 Panel (a) plots the IRs of output and the EBP to an innovation to RR financial distress index. The size of the innovation is set so that it raises the EBP by 1ppt at its peak, which corresponds to a moderate financial crisis in the RR scale (an RR financial distress level of close to +7): While the EBP is back to its initial level 2 years after the shock, real GDP is still 5ppt lower 5 years after the shock, and the impulse response shows little sign of mean reversion. In other words, a *transitory* increase in financial distress is associated with a *large* and *persistent* drop in output.

[5]In Appendix 2.B, we show that the results using US data only are very similar to RR's original results using a panel of 24 OECD countries.

[6]More generally, we note that the EBP impulse response can serve to benchmark the magnitude of the financial strains implied by RR's narrative index and thus allows researchers to use the RR distress index to discipline quantitative models with financial frictions.

Structural VARs

The second approach in the literature uses structural Vector AutoRegressions (VARs) to try to identify the causal effects of shocks originating in financial markets. Specifically, the approach builds on Gilchrist and Zakrajšek's (2011, 2012, GZ) EBP measure to identify exogenous innovations to the risk-bearing capacity of the financial sector. GZ use the EBP in a quarterly-frequency VAR along with seven other macroeconomic and financial variables.[7] To identify financial shocks, they use a recursive ordering, i.e., they postulate that macroeconomic variables react with a lag to changes in the EBP, and that the EBP reacts with a lag to changes in monetary policy. Figure 2.3 Panel (b) replicates the results of GZ and plots the impulse responses to a financial shock that raises the EBP by 1ppt. For clarity of exposition, we only show impulse responses for real GDP and the excess bond premium. An exogenous increase in the EBP of 1ppt leads to a 2ppt drop in real GDP one year after the shock, followed by a recovery so that the effect is no longer significantly different from zero after 2 years. In fact, 5 years after the shock, output is only 0.6ppt lower.[8]

Taking stock

Figure 2.3 Panel (c) simultaneously reports the impulse responses obtained with the two different methods —narrative accounts and VARs—. While the impulse response of the EBP is very similar across methods, the behavior of output is very different: compared to the VAR estimates, the drop in output estimated from the RR narrative approach is (i) about 4 times larger (ii) much more persistent.

To put these findings in the context of the recent financial crisis, we note that

[7] The variables in the VAR are: (i) log-difference of real personal consumption expenditures; (ii) log-difference of real business fixed investment; (iii) log-difference of real GDP; (iv) log-difference of the GDP price deflator; (v) quarterly average of the EBP; (vi) quarterly (value-weighted) excess stock market return from CRSP; (vii) the ten-year (nominal) Treasury yield; (viii) the effective (nominal) federal funds rate. GZ estimate the VAR using two lags on all variables.

[8] Other VAR studies report similarly mild and transitory effects of financial shocks on US output, e.g., Boivin et al. (2013) or Gilchrist et al. (2014). Similar results hold for the major Euro area countries (Germany, France, Italy and Spain) with Gilchrist and Mojon (2018) reporting mild and transitory effects of financial shocks on output. In fact, Gilchrist and Mojon (2018) find that economic activity is back to its unconditional mean 5 years after a financial shock.

the two approaches lead to very different conclusions about the role of the 2007-2008 crisis in the persistent "output loss" displayed in Figure 2.1. The RR financial distress index reaches 14 —an *extreme crisis*— in the US in 2008. Thus, the RR estimates imply that the crisis should be followed by a roughly $2 * 4.5 = 9$ppt persistent drop in output, thereby attributing 90 percent of the "output loss" from Figure 2.1 to the financial crisis. The sum of shocks to the EBP identified from the GZ VAR in 2007-2008 is roughly 2ppt. Thus, GZ VAR estimates imply that the 2007-2008 financial shocks —a 2ppt exogenous increase in the EBP— can *only* explain a $0.6 * 2.0 = 1.3$ppt drop in output five years after the shock, so only 13 percent of the 10ppt "ouput loss".

2.3 Estimating the Effects of Adverse Financial Shocks

To better understand the discrepancy between the results from VARs and narrative accounts, we note that the two approaches suffer from two separate shortcomings: (i) causality —unlike structural VARs, narrative accounts are not designed to identify the causal effect of financial strains on economic activity, only the existence of a correlation—, (ii) asymmetry —while a number of papers have argued that financial shocks are likely to have asymmetric effects (Mendoza, 2010; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014), VARs impose symmetric effects of shocks. In contrast, narrative accounts implicitly allow for asymmetric effects, because they only focus on adverse financial conditions, i.e., negative "shocks".[9]

To address these two issues, we estimate a model designed to (i) identify the causal effects of financial shocks, and (ii) take into account the possible asymmetric effects of financial shocks. Specifically, we propose and estimate a Vector Moving-Average model (VMA) model that can be easily generalized to allow for asymmetric effects of shocks (unlike VARs, see Barnichon and Matthes (2016)), and we establish causality by using an identification strategy that builds on but

[9]Another limitation of the VAR approach is that the size of the shock affects economic activity in a linear fashion, that is there is no size dependence in the effects of financial shocks. Interestingly, RR explored the possibility of such non-linearities in the impulse responses to their financial distress index but found little evidence of any size-dependence. We also explored the possibility of size dependence in our model, but similarly found little evidence.

also expand GZ.

2.3.1 A Structural Vector Moving-Average Model (VMA)

Our empirical model is a nonlinear VMA, in which the behavior of a vector of macroeconomic variables is dictated by its response to past and present structural shocks.

Specifically, denoting $\boldsymbol{y}_t$ a vector of stationary macroeconomic variables, the economy is described by

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \boldsymbol{\Psi}_k(\boldsymbol{\varepsilon_{t-k}})\boldsymbol{\varepsilon_{t-k}}, \tag{2.1}$$

where $\boldsymbol{\varepsilon_t}$ is a vector of structural shocks with $E(\boldsymbol{\varepsilon_t}) = 0$, $E(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t'}) = \boldsymbol{I}$, K is the number of lags, which can be finite or infinite, and z_t is a stationary variable that can be a function of past values of $\boldsymbol{y_t}$ or of exogenous variables. $\boldsymbol{\Psi}_k$ is the matrix of lag coefficients, i.e., the impulse response functions to shocks.

Note that (2.1) is a nonlinear VMA, because the coefficients of $\boldsymbol{\Psi}_k$ can depend on the values of the structural innovations $\boldsymbol{\varepsilon_{t-k}}$, so that the impulse response functions to a given structural shock depend on the value of the shock at the time of shock, and a positive shock may trigger a different impulse response than a negative shock.

Importantly, our empirical model is *not* a structural Vector AutoRegression (VAR). While the use of a VAR is a common way to estimate a moving-average model, it relies on the existence of a VAR representation. However, in a nonlinear world where $\boldsymbol{\Psi}_k$ depends on the sign of the shocks $\boldsymbol{\varepsilon}$ as in (2.1), the existence of a VAR is compromised, because inverting (2.1) is generally not possible. Thus, in this paper, we work with an empirical method that side-steps the VAR and instead directly estimates the VMA model (2.1).

2.3.2 Functional Approximations of Impulse Responses (FAIR)

Estimating a moving-average model is difficult, because the number of free parameters $\{\boldsymbol{\Psi}_k\}_{k=0}^{K}$ in (2.1) is very large or possibly infinite. To address this issue, we use Functional Approximations of Impulse Responses (Barnichon and Matthes, 2016), which consists in representing the impulse response functions as expansions in basis functions.

To illustrate the workings of FAIR, consider a linear version of (1), i.e.

$$\boldsymbol{y}_t = \sum_{k=0}^{\infty} \boldsymbol{\Psi}_k \boldsymbol{\varepsilon_{t-k}}. \tag{2.2}$$

Denote by $\psi(k)$ an element of matrix $\boldsymbol{\Psi}_k$, so that $\psi(k)$ is the value of the impulse response function ψ at horizon k. A functional approximation of ψ consists in decomposing ψ into a sum of basis functions, and in this work we will use Gaussian basis functions to write

$$\psi(h) = \sum_{n=1}^{N} a_n e^{-(\frac{h-b_n}{c_n})^2}, \quad \forall h \geq 0 \tag{2.3}$$

with a_n, b_n, and c_n parameters to be estimated.[10]

Gaussian basis functions can be particularly attractive in our context. For instance, we can approximate an oscillating impulse response function, say the impulse response of GDP growth following an adverse financial shock with only two Gaussian functions. As illustrated in Figure 2.4, the first Gaussian captures the first-round effect of the shock—an initial decline in, say, output growth—, while the second Gaussian captures the second-round effect—a later rebound in output growth. The parsimony of the functional approximation has two important advantages. First, it will allow us to directly estimate the impulse responses from the moving-average representation. Second, it will allow us to add more degrees of freedom and introduce possible asymmetric effects of shocks.

To allow for asymmetries, we let $\boldsymbol{\Psi}_k$ depend on the signs of the structural shocks, i.e., we let $\boldsymbol{\Psi}_k$ take two possible values: $\boldsymbol{\Psi}_k^+$ or $\boldsymbol{\Psi}_k^-$. Specifically, a model

[10]For flexibility reasons, we treat the contemporaneous impact coefficient $\psi(0)$ as a free parameter (see Barnichon and Matthes, 2016).

that allows for asymmetric effects of shocks would be

$$\boldsymbol{y}_t = \sum_{k=0}^{K} \left[\boldsymbol{\Psi}_k^+ (\boldsymbol{\varepsilon_{t-k}} \odot \mathbf{1}_{\boldsymbol{\varepsilon_{t-k}>0}}) + \boldsymbol{\Psi}_k^- (\boldsymbol{\varepsilon_{t-k}} \odot \mathbf{1}_{\boldsymbol{\varepsilon_{t-k}\leq 0}}) \right] \tag{2.4}$$

with $\boldsymbol{\Psi}_k^+$ and $\boldsymbol{\Psi}_k^-$ the lag matrices of coefficients for, respectively, positive and negative shocks and $\odot$ denoting element-wise multiplication. In our case of interest, denoting ψ^+, an impulse response function to a *positive* financial shock and similarly for ψ^-, a FAIR model of the impulse response function ψ^+ would write

$$\psi^+(k) = \sum_{n=1}^{N} a_n^+ e^{-\left(\frac{k-b_n^+}{c_n^+}\right)^2}, \ \forall k > 0 \tag{2.5}$$

with a_n^+, b_n^+, c_n^+ some constants to be estimated. A similar expression would hold for $\psi^-(k)$.

We leave the details of the estimation for the appendix, but in a nutshell the estimation boils down to the estimation of a truncated moving-average model (with a FAIR parametrization). The model can be estimated using maximum likelihood or Bayesian methods, and we recursively construct the likelihood by using the prediction error decomposition and assuming that the structural innovations are Gaussian with mean zero and variance one.

2.3.3 Identification

To identify financial shocks from the EBP, we build on GZ and include in our vector $\boldsymbol{y}_t$ macroeconomic variables (output, inflation), an EBP measure and a measure of the monetary stance (e.g., the fed funds rate).

As GZ, we impose a recursive ordering between economic variables and financial variables, so that we order the variables in $\boldsymbol{y}$ such that the EBP and the stance of monetary policy are ordered after the macro variables, and we impose that the right upper-block of $\boldsymbol{\Psi}_0$ is filled with zeros. To make this recursive ordering plausible, we will rely whenever possible on data at a monthly frequency.

Different from GZ or previous approaches in the literature, we do not impose a recursive ordering between the EBP and monetary policy but allow for contemporaneous feedback between the two. Absent any other information, financial shocks and monetary shocks cannot be separately identified. To identify changes in the EBP—or the risk-bearing capacity of the financial sector—that are not due to changes in monetary policy, we add external information on the contemporaneous effect of monetary policy on the EBP by using a proxy variable for the latent monetary policy shock, for instance the Romer and Romer's (2004) monetary shock series in the case of the US. To be more specific, denote a proxy for the monetary policy shock by m_t and the actual monetary policy shock by ε_t^m, we add the following equation to our VMA model (2.1):

$$m_t = \mu^m + \alpha^m \varepsilon_t^m + u_t^m \tag{2.6}$$

where $u_t^m \sim_{iid} N(0, \sigma^2_{u^m})$ captures measurement error in the proxy variable. The parameters of this equation are estimated jointly with all other parameters of the model in our Metropolis-Hastings algorithm. With this equation, we give our model information about which element of $\varepsilon_\mathbf{t}$ is the monetary policy shock and thus also which element is the financial shock. Although used in a different context, this strategy is similar to Caldara and Herbst (2016) identification of monetary shocks in a VAR.

2.4 The Effects of Financial Shocks, US Evidence

In this section, we estimate the effects of financial shocks using US data. We use the FAIR methodology as our baseline, but we also check the robustness of our results using Jordà's (2005) local projection method as an (imperfect) alternative to FAIR.

2.4.1 Evidence from FAIR

We consider a VMA model with four endogenous variables: (i) the log-difference of industrial production (IP); (ii) the log-difference of the CPI price index; (iii) the excess bond premium; (iv) the effective (nominal) federal funds rate:

$$\boldsymbol{y_t} = [\Delta IP_t, \Delta CPI_t, EBP_t, FFR_t]$$

We use a FAIR(2) model—two Gaussian functions per impulse response—as a likelihood-ratio test favors a FAIR(2) over a FAIR(1) or a FAIR(3) (Table 2.1). A FAIR(2) is particularly relevant here because it allows us to capture the mean-reverting pattern of output.

The data are monthly and cover 1973m1–2016m12.[11] When the federal funds rate are at the zero lower bound, we capture the stance of monetary policy with the Wu and Xia (2016) shadow rate.[12] As instrument for monetary shocks, we use the Romer and Romer monetary policy instrument extended to 2007 by Wieland and Yang (2016). Following standard practice in the literature (Stock and Watson, 2012; Gertler and Karadi, 2015; Caldara and Kamps, 2017), we infer the contemporaneous effect of monetary policy on the EBP from the subsample for which the instrument is available.

Allowing for asymmetric effects of credit shocks leads to a large improvement in the goodness of fit of the model. Table 2.1 summarizes the log likelihood of alternative FAIR models, and we can see that allowing for asymmetric effects substantially increases the log likelihood (comparing columns (1) and (2)). Since the FAIR models are nested, we can compare them with likelihood-ratio tests, and we can reject the symmetric FAIR model in favor of the asymmetric FAIR model.

Figure 2.5 presents the estimated impulse responses to credit supply shocks. The thick lines are posterior mode estimates, and the shaded areas cover 90% of the posterior probability. We obtain the impulse responses of IP and CPI from the cumulative impulse responses of ΔIP and ΔCPI. The left panel shows the impulse responses following an adverse financial shock (an increase in the EBP),

[11] As a robustness check, we estimated our model over 1973-2007, i.e., excluding the global financial crisis and the period over which the fed funds rate was at the zero lower bound. Our key results remain unchanged, and the impulse responses are very similar. The only quantitative difference (not shown) is that the decline in output following an adverse financial shock is somewhat smaller being about 0.2ppt lower in the linear model or in the asymmetric FAIR model.

[12] The shadow rate is the hypothetical level of a federal funds rate not constrained by the zero lower bound, given the level of asset purchases and forward guidance. Wu and Xia (2016) construct an estimate of the shadow rate from the observed Treasury yield curve, i.e., by finding the level (positive or negative) of the policy rate that would generate the observed yield curve.

and the right panel shows the impulse responses following a favorable financial shock (a decrease in the EBP). When comparing impulse responses to positive and negative shocks, it is important to keep in mind that the impulse responses to favorable shocks (a decrease in the EBP) were multiplied by -1 to ease comparison across impulse responses. With this convention, when there is no asymmetry, the impulse responses are identical in the left panel (responses to an adverse shock) and the right panel (responses to a favorable shock).

Financial shocks have strongly asymmetric effects. An adverse financial shock causes a large decline in output, while a favorable shock generates little movements in output. In terms of magnitude, an increase of 1ppt in the EBP translates into a 4ppt persistent decline in IP. Moreover, while the GZ VAR estimates—discussed in Section 2.2—suggest a rebound in output one year after the financial shock, the FAIR estimates suggest that the rebound is weak following a contractionary shock. As a result, the level of output appears to be persistently affected by a contractionary financial shock which is in line with the evidence from narrative studies discussed in Section 2.2. Interestingly, asymmetry is also present in the response of inflation with only contractionary shocks generating a significant disinflationary episode.[13]

2.4.2 Digging Deeper

To dig deeper into the effects of financial shocks on the economy, we now explore the asymmetric impulse response functions of five additional macroeconomic variables: (i) real GDP; (ii) real personal consumption expenditures (C); (iii) real business fixed investment (I); (iv) the unemployment rate (U); (v) business investment in research and development ($R\&D$).[14]

To study the effects of financial shocks on variables not included in $\boldsymbol{y_t}$, we proceed in two steps. First, we extract the financial shocks, denoted $\{\hat{\varepsilon}_t\}$, that we identified from our baseline specification.[15] Second, we estimate a univari-

[13]Note that the response of the fed funds rate cannot explain the asymmetric responses of output growth and inflation, because monetary policy is more accommodative following a contractionary shock, which should dampen the asymmetry.

[14]We use private domestic investment in research and development.

[15]More specifically, the Bayesian estimation of the vector-FAIR model described by Equation 2.4 and 2.5 delivers a posterior distribution of the financial shocks $\{\hat{\varepsilon}_t\}$.

ate model - a univariate FAIR - capturing the impulse response of the additional variables. Specifically, denoting y_t a variable of interest, we estimate

$$y_t = \sum_{k=0}^{K} \psi(k)\hat{\varepsilon}_{t-k} + u_t, \tag{2.1}$$

where ψ captures the impulse response function to the financial shock and u_t is the residual. Since the errors are likely serially correlated, we allow for serial correlation in u_t by positing that u_t follows an AR(1) process. Then, we use FAIR as in Equation 2.3 to parametrize the impulse response ψ. We estimate the model with y set to, respectively, ΔGDP,[16] ΔC, ΔI, $\Delta R\&D$ or U, and we use a FAIR(2) to have enough flexibility to capture the (potentially) mean-reverting pattern of our variables. We allow for asymmetric effects of financial shocks by estimating two impulse response functions —ψ^+ and ψ^-—, and we estimate a linear FAIR(2) model to use as a linear benchmark.

Figure 2.6 summarizes our results and shows strongly asymmetric impulse responses of our five variables of interest to a financial shock. The effects of a contractionary financial shock are much larger than the effects of an expansionary financial shock, and the effects on real GDP, consumption, investment or R&D spending are all persistent.

The strong and persistent effect of financial market disruptions on R&D spending is interesting and deserves further exploration. While the response of R&D spending could be driven solely by the strong decline in output, the behavior of R&D also provides a natural link from business cycle fluctuations to long-term economic performance. For instance, it has been argued that adverse transitory shocks that lower R&D spending can inhibit economic performance in the long run (see e.g. Comin and Gertler, 2006; Bianchi and Kung, 2014). In this context, a decline in R&D spending could cause a persistent decline in output.

[16] Since GDP is only available at quarterly frequency, we regress the log-difference of real GDP on the quarterly average of the monthly financial shocks.

2.4.3 Taking Stock

We now contrast our FAIR estimates with those of narrative accounts and VARs. Figure 2.7 plots the impulse responses to an innovation to the RR financial distress variable (estimated as in RR, red line); the impulse responses to a GZ financial shock (estimated as in GZ, blue line); and the FAIR estimate of the impulse responses to an adverse financial shock (black lines). All the impulse responses are scaled such that the peak response of the EBP equals +1ppt.

We can see that our FAIR estimates fall in the midrange between the smaller VAR estimates and the larger estimates from narrative studies. The peak effect of an adverse financial shock on real GDP is -4.5ppt (after approximately 2 years), larger than the VAR estimates but smaller than the RR narrative estimates. After 5 years, real GDP is still -3.5ppt lower. The VAR estimates are smaller, likely because the large effect of adverse shocks are mixed with the small effects of favorable shocks. The RR estimates are larger, likely because the RR approach does not isolate exogenous episodes of financial distress and thus overestimate any adverse causal impact of financial distress on output (Romer and Romer 2017a, page 3114).

Interestingly, although the RR exercise is not meant to identify the causal effect of financial shocks, one could use a recursive ordering similar to GZ in order to try to isolate the causal effect of financial distress on GDP, keeping in mind that the approach is severely limited by the semi-annual frequency of the RR dataset. Indeed, if financial distress takes more than six months to affect economic activity —a much stronger assumption than implied by our monthly recursive ordering—, controlling for the contemporaneous value of output in the RR local projections (2.1) will deliver the causal effect of financial distress. Removing some of the endogenous component of financial distress reduces the magnitude of the response of GDP (Figure 2.7) and in fact brings it remarkably in line with our FAIR estimates. The impulse responses of GDP are on top of each other over the first 2.5 years, diverging only slightly at longer horizons. In other words, once we take into account the issues of causality and asymmetry, narrative accounts and structural time series analysis become remarkably consistent.

2.4.4 US GDP since the Financial Crisis

To examine the recent behavior of US GDP in light of our estimates, we conduct a counterfactual experiment in which we turn off the sequence of financial shocks experienced in 2007-2008.[17] Figure 2.8 plots the actual paths of GDP and the EBP along with their counterfactual paths implied by our FAIR estimates.

Without the large adverse financial shocks experienced in 2007 and 2008, the EBP would have displayed a much smaller increase, driven by the endogenous response of the EBP to the other shocks behind the great recession, and the behavior of GDP would have been very different. The recession would have been relatively mild and GDP would have reverted to its pre-crisis trend. As of end 2017, the gap between output and potential output (as estimated from the CBO in 2007) would only be 3ppt (instead of 10ppt), implying that the 2007-2008 financial crisis persistently lowered output by roughly 7ppt. Thus, according to our FAIR estimates, two thirds of the persistent output loss that ensued following the great recession was in fact caused by the large financial market shock that hit the economy. In other words, a substantial fraction of the current "output loss" (as implied by the 2007 CBO estimate of potential output) is unlikely to revert, and provides some support for CBO's repeated downward revisions to its estimate of potential output (Coibion et al., 2017).

2.4.5 Robustness Check: Evidence from Local Projections

To the best of our knowledge, the FAIR approach used in this paper is the only operational way of identifying structural shocks when the Data Generating Process (DGP) is nonlinear with asymmetric impulse responses.

However, since our approach relies on the parametrization of the impulse response functions with Gaussian basis functions, in this section, we examine the robustness of our results to this parametrization. The idea of the robustness check is to not rely on a FAIR but instead to use a nonparametric method—Jordà's (2005)

[17] Specifically, we draw from the posterior distribution of FAIR parameter estimates and identified financial shocks to obtain a posterior distribution of counterfactual paths for output and the EBP. Figure 2.8 plots the corresponding median counterfactual path. Figure 2.14 in Appendix 2.B plots the time series and a histogram of the US financial shocks estimated from FAIR(2). The sum of exogenous impulses to the EBP in 2007-2008 is approximately 2ppt.

Local Projections (LP)—which imposes little structure on the Data-Generating Process (DGP) and is thus more robust to misspecification than a FAIR model (at the cost of efficiency). The drawback of this approach is that it requires a series of previously identified financial shocks.

We thus use a "VAR-LP" procedure that proceeds in two steps: First, we estimate a standard structural VAR to identify financial shocks denoted $\{\widetilde{\varepsilon}_t\}$.. We use the same identification strategy as for FAIR. That is, we estimate a proxy VAR in which Romer and Romer's (2004) narrative measure of exogenous monetary policy changes serves as an external instrument for the latent monetary shock. Second, we estimate the dynamic effects of these shocks using Local Projections, possibly allowing for asymmetric effects. While such a hybrid VAR-LP procedure is flawed (in fact, not internally consistent since the VAR shocks are identified under the assumption that the DGP is linear), we see it as a useful robustness check of our results based on FAIRs. We come back to this point at the end of the section.

To first have a linear benchmark for the effects of financial shocks, we run linear Local Projections, i.e., we estimate $H + 1$ equations

$$y_{t+h} = \alpha_h + \beta_h \widetilde{\varepsilon}_t + \gamma' x_t + u_{t+h}, \qquad h = 0, 1, ..., H \tag{2.2}$$

where y_{t+h} is the variable of interest, x_t contains 12 lags of y_t, and $\widetilde{\varepsilon}_t$ is our VAR-based estimate of the financial shock at time t. The impulse responses are then given by $\beta^0, \beta^1, ..., \beta^H$. We use a horizon of $H = 60$ months (or 5 years). We report Newey and West (1987) standard errors allowing for autocorrelation of order h in the error terms.

To allow for asymmetric effects of financial shocks, we allow for sign dependence in β_h, that is we estimate the $H + 1$ equations

$$y_{t+h} = \alpha_h + \beta_h^+ \widetilde{\varepsilon}_t^+ + \beta_h^- \widetilde{\varepsilon}_t^- + \gamma' x_t + u_{t+h}, \qquad h = 0, 1, ..., H \tag{2.3}$$

where β_h^+ is the response to a positive financial shock $\widetilde{\varepsilon}_t^+$, and β_h^- is the response to a negative financial shock $\widetilde{\varepsilon}_t^-$ at horizon h.

We estimate Equation 2.2 and 2.3 for the log-difference of industrial production and the log-difference of the CPI price index, and Figure 2.9 plots the impulse responses.[18] Overall, the results are very similar to the results obtained with FAIR models: the effects of adverse financial shocks are larger than implied by linear estimates and highly persistent. Favorable financial shocks, on the other hand, have no significant effects on our variables.

To put these estimates in the context of the 2007-2008 financial crisis, we can do a back-of-the-envelope calculation using the 2007-2008 VAR-identified financial shocks. The sum of exogenous impulses to the EBP in 2007-2008 is approximately 2ppt. According to our hybrid VAR-LP estimates, a 2ppt exogenous increase in the EBP implies a $2 * 4 = 8$ppt output loss, which is close to our baseline FAIR estimates.

As a final remark, note that while the hybrid VAR-LP approach is attractive because it relies only on standard linear regression techniques, it is flawed for two reasons. First, to perform the Local Projection exercise laid out above, one needs to know the structural shocks. Here, we take the shocks identified from the structural VAR as given. They are, however, the result of a first stage estimation and therefore the standard errors obtained from Local Projections are incorrect. Second, if the data are generated by a nonlinear process, a linear model to identify the structural shocks is misspecified and we cannot estimate consistently the true structural shocks. To do so, one should explicitly account for the nonlinearities in the data-generating process. These two drawbacks can, however, be overcome with FAIR.[19]

[18]We obtain the level impulse responses from the cumulative impulse responses of the log-difference of industrial production and the log-difference of the CPI price index.

[19]Despite its shortcomings, we think of the hybrid VAR-Local Projection approach as a useful tool. First, it can be used as a quick test for nonlinearities in the impulse response functions to shocks estimated from a linear VAR. Therefore, one might see it as (visual) test for misspecification in terms of omitted nonlinearities. Second, once structural shocks are estimated from any model (for instance from a VAR or FAIRs), Local Projections can be used to examine whether relaxing the dynamic structure (i.e., the parametric restrictions) imposed by the model alters the results substantially.

2.5 The Effects of Financial Shocks, International Evidence

In this section, we provide independent evidence that adverse financial shocks have large and persistent effects by using alternative sources of variations. Specifically, we study the effects of financial shocks in (i) the United Kingdom (UK) and (ii) the Euro area (EA).

2.5.1 United Kingdom

While the EBP measure was originally constructed for the US, Bleaney et al. (2016) recently constructed EBP measures for some European countries. While the sample size is small for most countries (2003Q2-2010Q3 or even shorter), the EBP measure for the UK covers 1996Q1-2010Q2, offering hope that there might be enough variation to estimate our non-linear VMA with reasonable confidence intervals.

Similarly to the US, our specification uses four endogenous variables: (i) GDP growth (ii) CPI inflation, (iii) the UK excess bond premium (see Figure 2.10), and, (iv) the Official Bank Rate (OBR) of the Bank of England to measure the stance of monetary policy.

$$\boldsymbol{y_t} \quad = \quad [\Delta GDP_t, \Delta CPI_t, EBP_t, OBR_t]$$

We use the same identifying assumption as for the US. That is, we assume that macroeconomic variables react with a lag to financial shocks, and, we now use Cloyne and Hürtgen's (2016) narrative measure of exogenous monetary policy changes as a proxy variable for the latent monetary policy shock in order to identify changes in the EBP that are not due to changes in the stance of monetary policy.

We estimate an asymmetric FAIR(2) model and Figure 2.11 plots our results. The output effects of financial shocks are very similar to the ones we obtained for the US: An adverse financial shock leads to a large and persistent reduction in output.[20] A favorable financial shock, on the other hand, has no significant effect on GDP.[21] As with the US, the asymmetry cannot be explained by the response of the interest rate, since the latter is more accommodative following an adverse financial shock.

To get an estimate of the output loss created by the 2007-2008 financial crisis, we can proceed as with the US and simulate a counterfactual path for GDP without financial shocks in 2007-2008. Similarly to the US, we find that absent the series of financial shocks that raised the UK EBP by about 2ppt overall[22], GDP would have been about 8ppt higher today. Thus, as with the US, we find that the 2007-2008 financial market disruptions in the UK can account for a large fraction of the "output loss" relative to the pre-crisis trend in GDP.

2.5.2 Euro Area

Since the EBP measure of Bleaney et al. (2016) is very short for the Euro area, we use an alternative approach to identify the effects of financial shocks in the Euro area. We follow Gilchrist and Mojon (2018) and Monfort and Renne (2013), and use an instrumental variable approach based on shocks to liquidity in the German bund market that are transmitted to euro area credit spreads.

Specifically, we use the KfW-Bund spread as an external instrument for financial shocks.[23] The KfW-Bund spread is the spread between the KfW, a public sector bank whose debt is guaranteed by the German Government, and the bund. Because KfW debt is less liquid than the Bund, a widening of the KfW-Bund spread signals a rise in the liquidity premium that is then transmitted to other bond market yields, notably euro area credit spreads. Thus, the KfW-Bund spread can serve as an instrument for movements in credit spreads, because movements in the KfW-Bund spread (i) are arguably exogenous to private sector credit risk (satisfying the instrument exclusion restriction), and (ii) transmits to/affects other

[20]We obtain the impulse responses of GDP and CPI from the cumulative impulse responses of ΔGDP and ΔCPI.

[21]The effect of financial shocks on UK prices is smaller than in the US, but the asymmetry goes in the same direction, with only contractionary shocks leading to a disinflationary episode.

[22]See Figure 2.15 in Appendix 2.B

[23]The KfW-Bund spread data from 1997 to 2010 are from Schuster and Uhrig-Homburg (2013). We extent this time-series to 2013 using data from Monfort and Renne (2013).

bond yields and credit spreads (satisfying the instrument relevance condition).

Our specification uses for endogenous variables: (i) industrial production growth; (ii) CPI inflation; (iii) the Euro OverNight Index Average (EONIA); the Euro area bank credit spread series constructed by Gilchrist and Mojon (2018) and shown in Figure 2.12.

$$\boldsymbol{y_t} = [\Delta IP_t, \Delta CPI_t, EONIA_t, Spread_t]$$

As with the US and the UK, we estimate an asymmetric FAIR(2), and Figure 2.13 plots the estimated impulse responses to a one-standard deviation bank spread shock. In line with our US and UK results, an adverse financial shock causes a significant and persistent decline in output, but a favorable shock has no sizable effect.

We again simulate a counterfactual path for GDP[24] without financial shocks in 2007-2008 to get an estimate of the output loss created by the 2007-2008 financial crisis. We find that absent the series of financial shocks that raised the bank spread by about 2ppt overall[25], GDP would have been 8ppt higher today. Thus, as with the US and the UK, the 2007-2008 financial shocks can account for a substantial fraction of the "output loss" relative to the pre-crisis trend in GDP.

2.6 Conclusion

Most advanced economies are still suffering from the aftermaths of a global financial crisis that started over 10 years ago: GDP figures remain far from their pre-crisis trend, and estimates of potential output have been subjected to repeated downward revisions since the beginning of the crisis, implying that the financial crisis lead to large and permanent "output losses".[26] While these disappointing performances as well as more systematic narrative studies (Reinhart and Rogoff, 2014; Romer and Romer, 2017a) led many academics and policy makers to suspect (and worry) that financial market disruptions can have permanent large effects

[24]The impulse response of GDP was obtained from a univariate FAIR as for the US. A 0.3ppt exogenous increase in the bank spread leads to a persistent 1.2ppt decline in GDP.

[25]See Figure 2.15 in Appendix 2.B

[26]See e.g., Reinhart and Rogoff (2014) and Ball (2014).

on output, a separate, VAR-based, literature pioneered by Gilchrist and Zakrajšek (2012) points to relatively mild and transitory effects of financial market disruptions on output.

To see through these seemingly conflicting results, we propose and estimate a non-linear model designed to address some important shortcomings of previous approaches, namely (i) we identify the causal effects of financial shocks (unlike narrative studies), and (ii) we take into account the possible asymmetric effects of financial shocks (unlike VAR studies).

We find that adverse financial shocks have large and persistent effects on output, while positive shocks have little effects.

Our findings confirm the worry that some (although not necessarily all) of the "output loss" is likely to be persistent (possibly even permanent). In fact, our findings indicate that about two thirds of the current US "output gap" (the deviation of output from potential as estimated by the CBO pre-crisis) is due to the 2007-2008 adverse financial shocks, providing some support for CBO's repeated downward revisions to its estimate of potential output (Coibion et al., 2017).

An important avenue for future research is to explore the policy implications of the asymmetric, large and persistent effects of adverse financial shocks for the conduct of monetary policy, as highlighted in a speech by Federal Reserve Governor Jeremy Stein (2014).

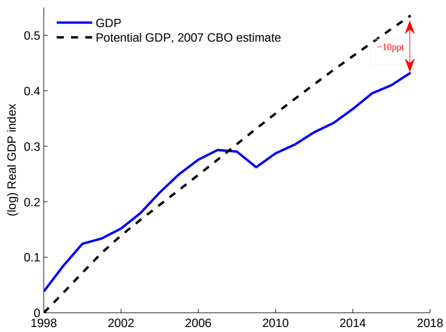
Tables and Figures

Table 2.1: Log likelihood of alternative models

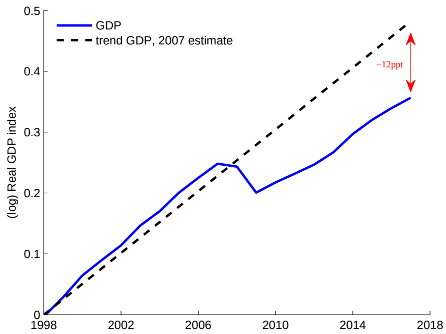
	FAIR(2) Symmetric	**FAIR(1) Asymmetric**	**FAIR(2) Asymmetric**	**FAIR(3) Asymmetric**
	(1)	**(2)**	**(3)**	**(4)**
log likelihood	-2980	-2593	-2467	-2465
LR test		(2) vs (1)	(3) vs (2)	(4) vs (3)
p-value		$<$0.01	$<$0.01	$>$0.1

FAIR model with $\Delta log(IP), \Delta log(CPI), EBP, FFR$ estimated with data from 1973 to 2016. (1) is a symmetric model using a two Gaussian parametrization (FAIR(2)) of the impulse responses. (2) is a model that allows for asymmetric effects of financial shocks using a one Gaussian parametrization (FAIR(1)) of the impulse responses. The LR test is between (2) and (1). (3) is a model that allows for asymmetric effects using a two Gaussian parametrization (FAIR(2)). The LR test is between (3) and (2). (4) is a model that allows for asymmetric effects using a three Gaussian parametrization (FAIR(3)). The LR test is between (4) and (3). (5) is identical to (3) but also allows for state dependent effects of financial shocks.

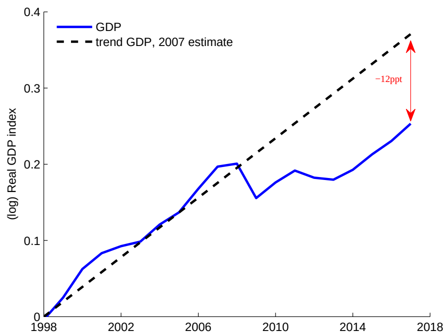
Figure 2.1: Output since the global financial crisis



(a) US



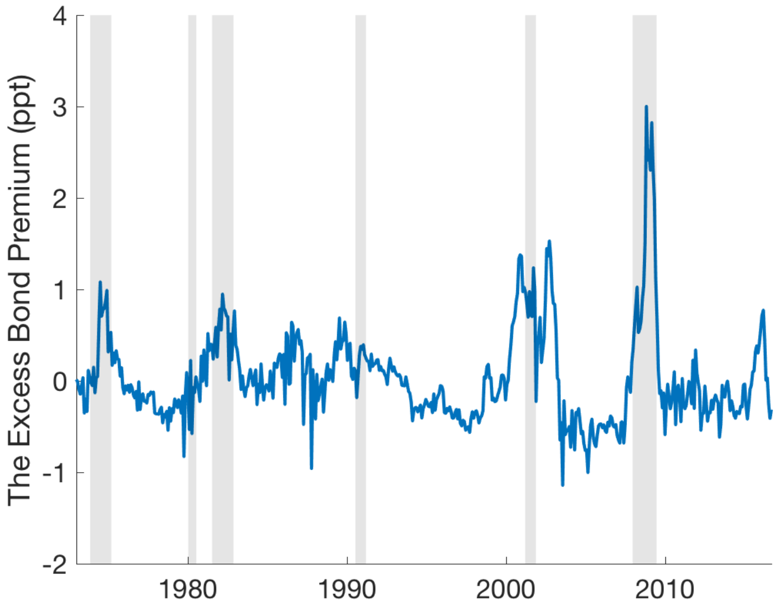
(b) UK



(c) Euro area

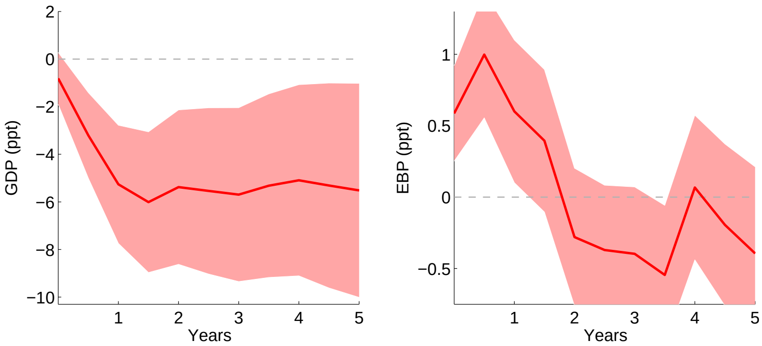
Real GDP since 1998 for US, UK and Euro area. Potential GDP for the US is the CBO estimate as of 2007. Trend GDP for the UK and Euro area is estimated from a linear trend over 1995-2007.

Figure 2.2: The US Excess Bond Premium

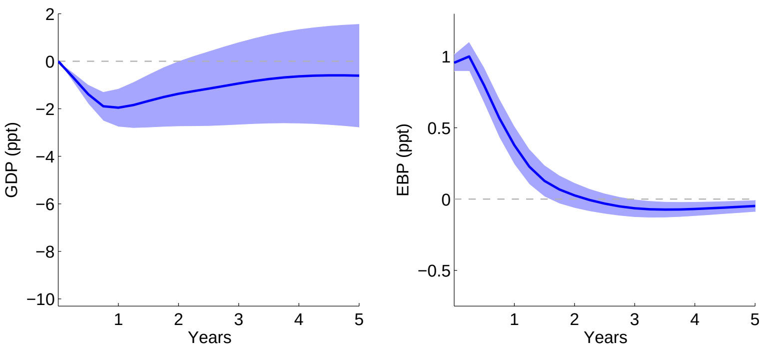


1973-2016. Shaded areas mark NBER recession dates.

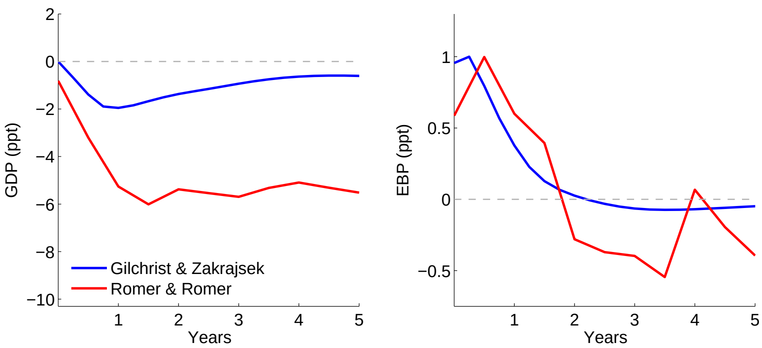
Figure 2.3: Financial strains and economic activity — state of the literature



(a) Romer and Romer (2017a, RR) specification. Impulse response functions of real GDP (GDP) and the excess bond premium (EBP) to an impulse of 7 (*moderate financial crisis*) in RR financial distress index.



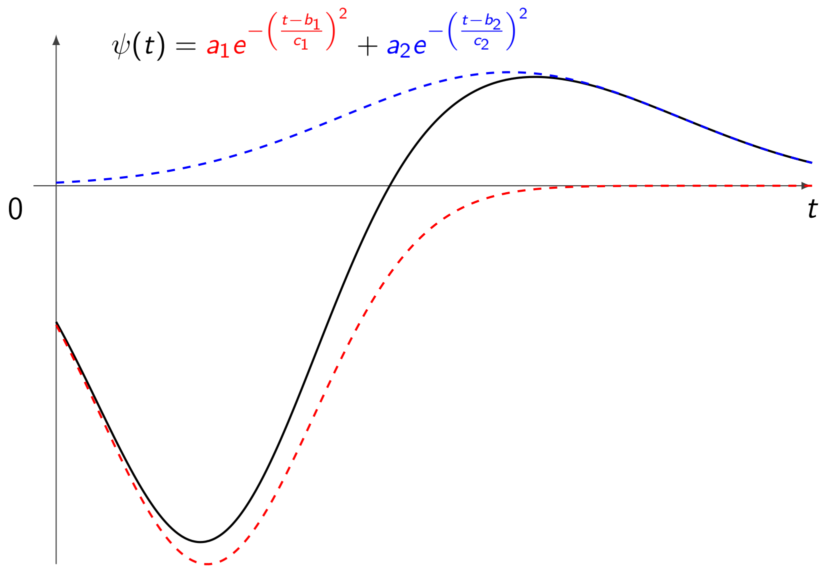
(b) Gilchrist and Zakrajšek (2012, GZ) specification. Impulse response functions of real GDP (GDP) and the excess bond premium (EBP) to a financial shock that raises the EBP by 1 ppt.



(c) Comparison of Romer and Romer (2017a) estimates (red lines) and Gilchrist and Zakrajšek (2012) (blue lines).

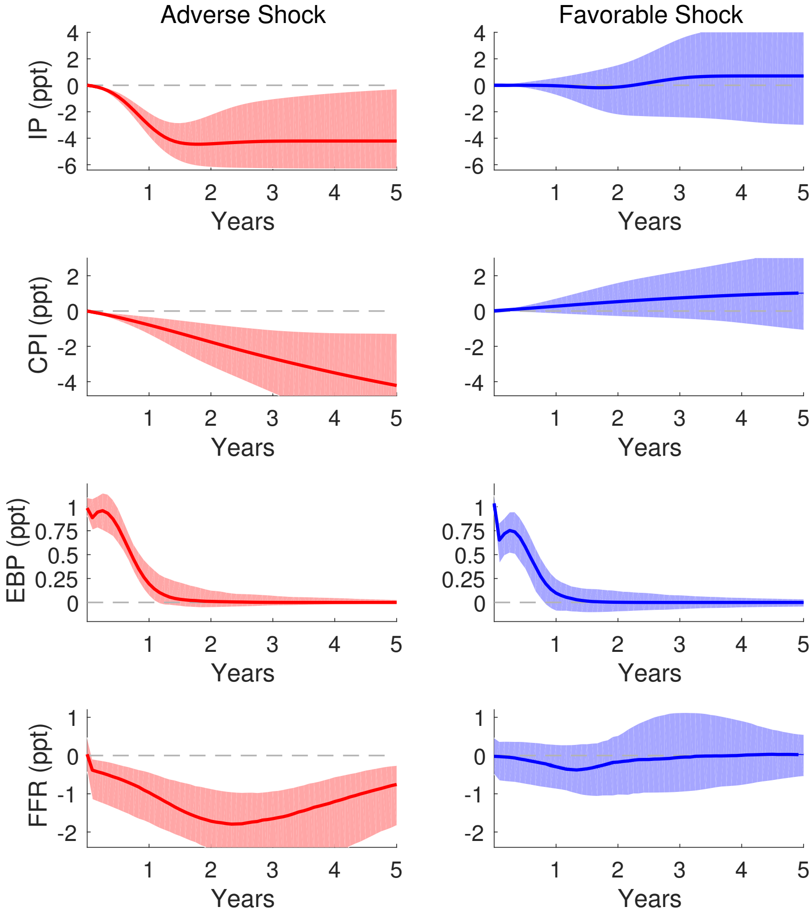
Shaded areas denote the 90 percent confidence bands.

Figure 2.4: A functional approximation of an impulse response (FAIR)



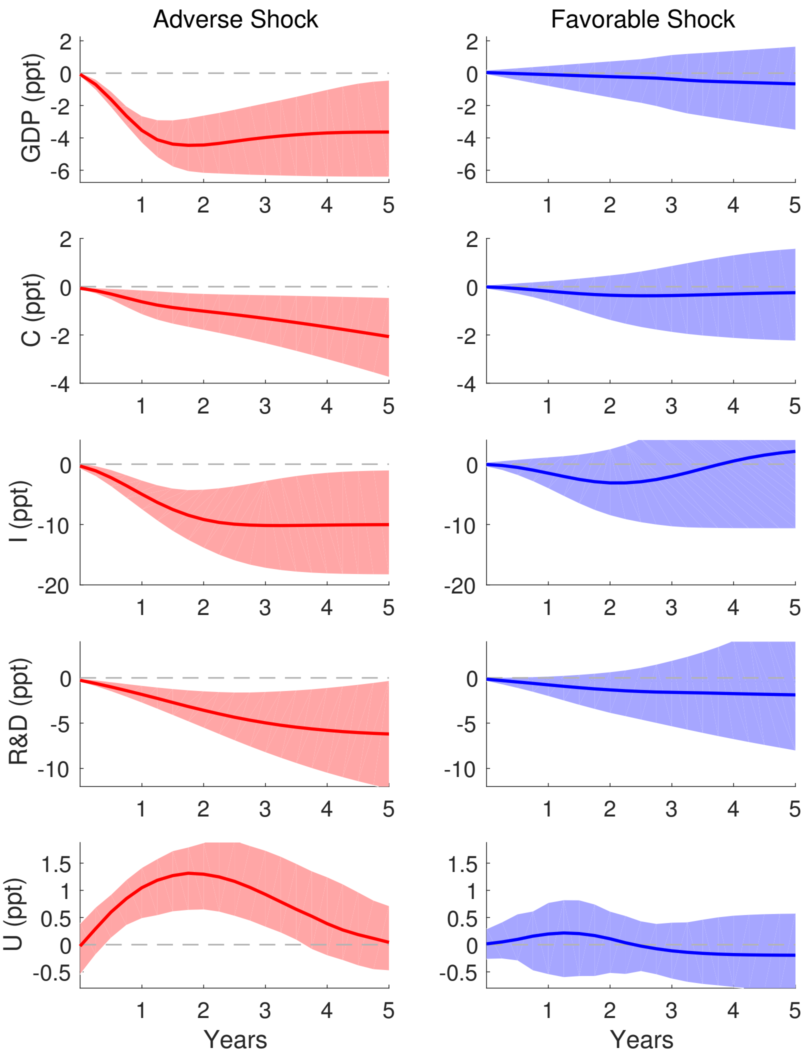
Example of how a FAIR(2) model can capture an oscillating impulse response.

Figure 2.5: The asymmetric effects of financial shocks — US evidence



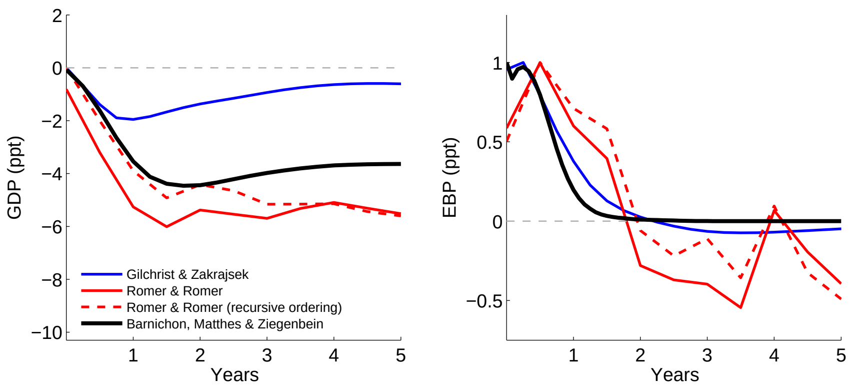
Impulse response functions of Industrial Production (IP), consumer prices (CPI), the excess bond premium (EBP) and the federal funds rate (FFR) to a unit shock to the excess bond premium. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. Estimating using US monthly data for the period 1973m1-2016m12.

Figure 2.6: The asymmetric effects of financial shocks, additional results — US evidence



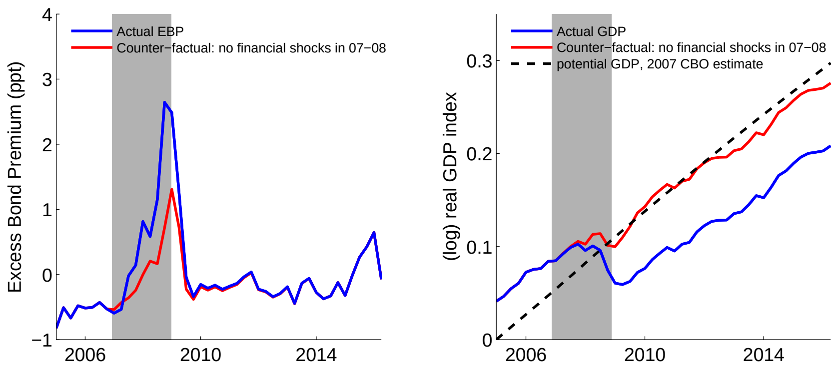
Impulse response functions of real GDP (GDP), personal consumption expenditures (C), business fixed investment (I), business spending in R&D, and the unemployment rate (U) to a unit shock to the EBP. Estimation from a FAIR(2) (plain lines). The shaded areas cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using US data for the period 1973-2016.

Figure 2.7: The effects of financial shocks across methods — US evidence



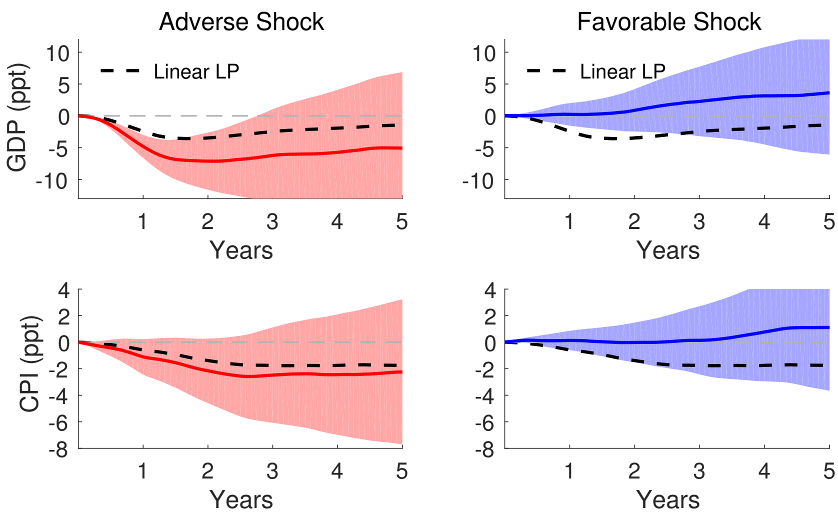
Impulse response functions of real GDP (GDP) and the excess bond premium (EBP) to a financial shock. Red lines: impulse responses to an impulse of 7 (*moderate financial crisis*) in the Romer and Romer (2017a) financial distress variable. Blue lines: impulse responses to a financial shock identified from Gilchrist and Zakrajšek's (2012) Structural VAR. Responses are scaled such that the extremum effect on the EBP is equal to 1 ppt. Black lines: impulse responses to an adverse financial shock (an increase in EBP) identified from an asymmetric FAIR(2). Responses are scaled such that the extremum effect on the EBP is equal to 1 ppt.

Figure 2.8: The effects of the 2008-2009 financial crisis — counterfactual



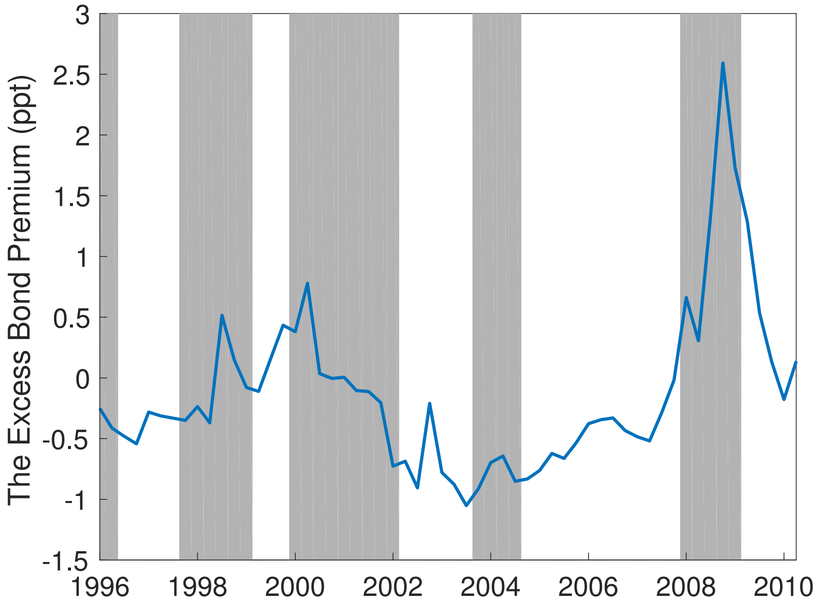
Blue lines: actual real GDP and EBP. Red lines: counterfactual simulated paths of real GDP and EBP assuming no financial shocks in 2008-2009

Figure 2.9: Robustness check — Estimates from hybrid VAR-LP, US evidence



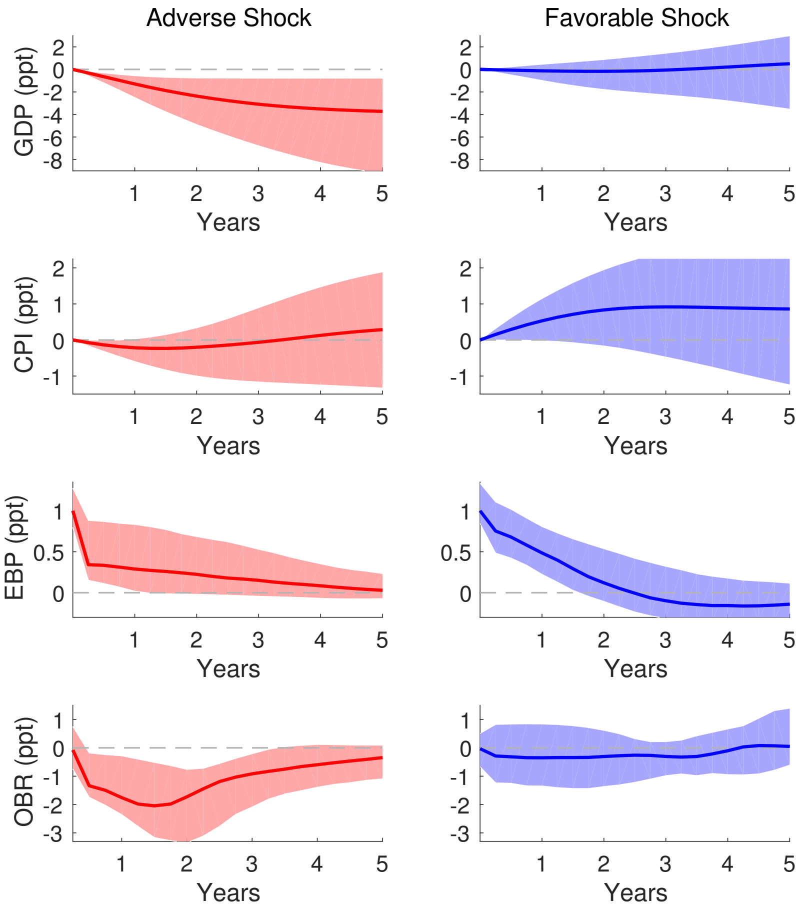
Impulse response functions of industrial production (IP) and consumer prices (CPI) to a unit shock to the EBP. Results from a symmetric model (dashed line) and from a model allowing for asymmetry (plain lines). The shaded areas span 90% confidence bands calculated using Newey-West standard errors. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using US monthly data covering 1973m1-2016m12.

Figure 2.10: The UK Excess Bond Premium



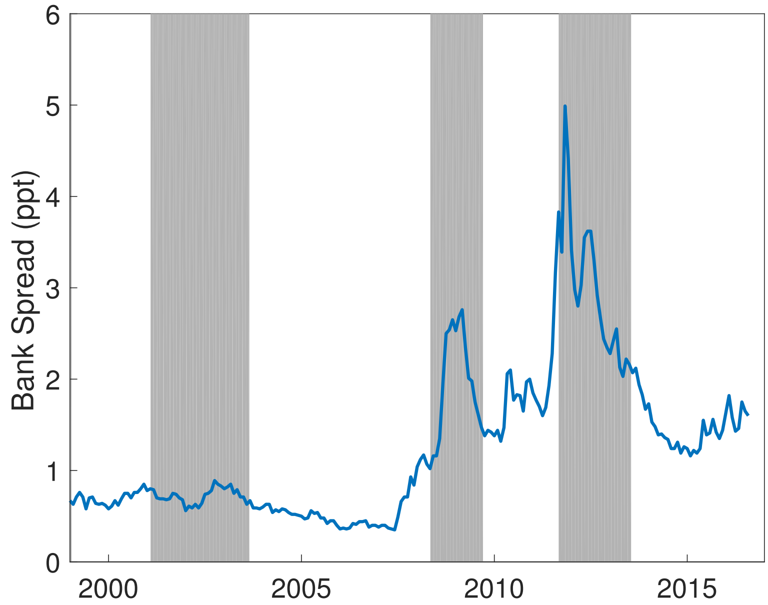
1996-2010. Shaded areas mark OECD recession dates.

Figure 2.11: The asymmetric effects of financial shocks — UK evidence



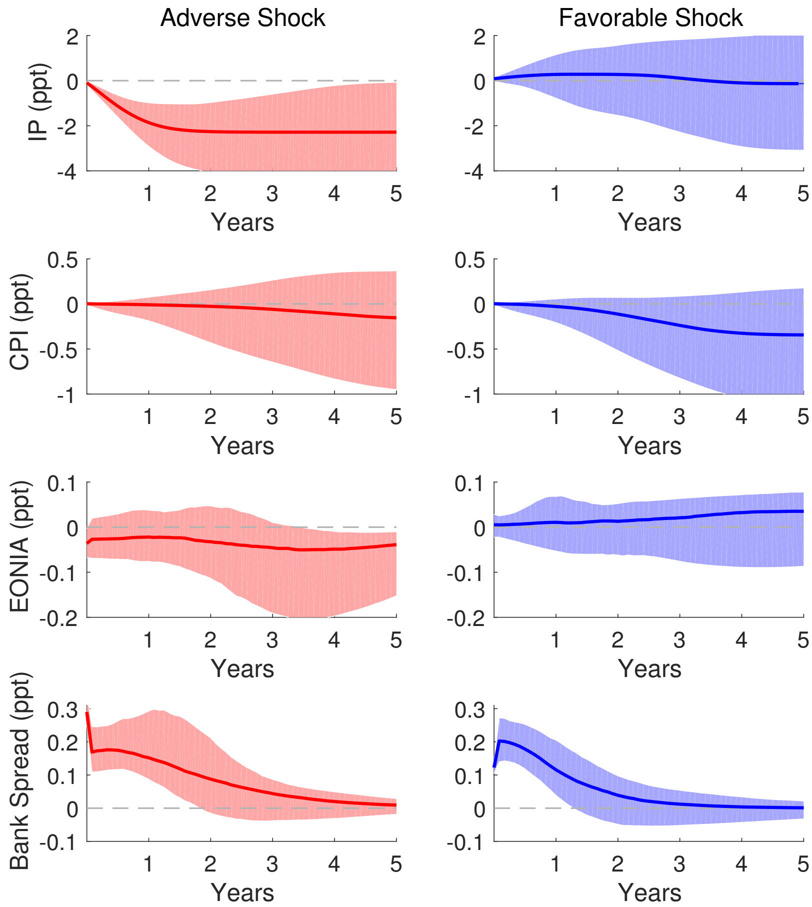
Impulse response functions of real GDP (GDP), consumer prices (CPI), the excess bond premium (EBP) and the official bank rate (OBR) to a unit shock to the excess bond premium. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in EBP) are multiplied by -1 in the right panels. Estimation using UK quarterly data covering 1996q1-2010q2.

Figure 2.12: The Euro area Bank Spread



1999-2016. Shaded areas mark OECD recession dates.

Figure 2.13: The asymmetric effects of financial shocks — Euro area evidence



Impulse response functions of the 10-Year KfW-Bund Spread output, output growth (IP), CPI inflation, and the EONIA to a one-standard deviation shock to the KfW-Bund Spread. Estimation from a FAIR(2) (plain lines). The shaded bands cover 90% of the posterior probability. For ease of comparison between the left and right panels, the responses to a favorable financial shock (a decline in the KfW-Bund Spread) are multiplied by -1 in the right panels. Estimation using Euro area monthly data covering 1999m1-2016m8.

2.A Estimation

We now briefly describe how we use Bayesian methods to estimate a multivariate linear FAIR(N) model with a short-run restriction. The extension to nonlinear models is relatively straightforward bar some technical details.[27]

The key to estimating a moving-average model (2.1) is the construction of the likelihood function $p(\boldsymbol{y}^T|\boldsymbol{\theta})$ of a sample of size T for a moving-average model with parameter vector $\boldsymbol{\theta}$ and where a variable with a superscript denotes the sample of that variable up to the date in the superscript.

We use the prediction error decomposition to break up the density $p(\boldsymbol{y}^T|\boldsymbol{\theta})$ as follows:[28]

$$p(\boldsymbol{y}^T|\boldsymbol{\theta}) = \prod_{t=1}^{T} p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}). \tag{2.A.1}$$

Then, to calculate the one-step-ahead conditional likelihood function $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$, we assume that all innovations $\{\boldsymbol{\varepsilon_t}\}$ are Gaussian with mean zero and variance one, and we note that the density $p(\boldsymbol{y}_t|\boldsymbol{y}^{t-1}, \boldsymbol{\theta})$ can be re-written as $p(\boldsymbol{y}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1}) = p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon_t}|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ since

$$\boldsymbol{y}_t = \boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t + \sum_{k=1}^{K} \boldsymbol{\Psi}_k\boldsymbol{\varepsilon}_{t-k}. \tag{2.A.2}$$

Since the contemporaneous impact matrix is a constant, $p(\boldsymbol{\Psi}_0\boldsymbol{\varepsilon}_t|\boldsymbol{\theta}, \boldsymbol{y}^{t-1})$ is a straightforward function of the density of $\boldsymbol{\varepsilon}_t$.

To recursively construct $\boldsymbol{\varepsilon_t}$ as a function of $\boldsymbol{\theta}$ and $\boldsymbol{y}^t$, we need to uniquely pin down the value of the components of $\boldsymbol{\varepsilon_t}$, that is we need that $\boldsymbol{\Psi}_0$ is invertible. We impose this restriction by only keeping parameter draws for which $\boldsymbol{\Psi}_0$ is invertible. It is also at this stage that we impose the identifying restriction: We order the variables in $\boldsymbol{y}$ such that the EBP is ordered third—after output growth and inflation, but before the fed funds rate—and we add the equation describing our proxy for the monetary policy shock to the system. Finally, to initialize the recursion,

[27] See Barnichon and Matthes (2016).

[28] To derive the conditional densities in decomposition (2.A.1), our parameter vector $\boldsymbol{\theta}$ thus implicitly also includes the K initial values of the shocks: $\{\varepsilon_{-K}...\varepsilon_0\}$. We will keep those fixed throughout the estimation and discuss our initialization below.

we set the first K values of ε to zero.[29,30]

We use flat (improper) priors, and to explore the posterior density, we use a Metropolis-within-Gibbs algorithm (Robert and Casella, 2004) with the blocks given by the different groups of parameters in our model; a, b, and c. Using a flat prior allows us to interpret our results as outcomes of a maximum likelihood estimation. To initialise the Metropolis-Hastings algorithm in an area of the parameter space that has substantial posterior probability, we follow a two-step procedure: first, we estimate a standard VAR using OLS on our data set, calculate the moving-average representation, and we use the impulse response functions implied by the VAR as our starting point.[31] In the nonlinear models, we initialize the parameters capturing asymmetry and state-dependence at zero (i.e., no nonlinearity). This approach is consistent with the starting point (the null) of this paper: shocks have linear effects on the economy, and we are testing this null against the alternative that shocks have nonlinear effects.

2.B Additional Results

Figures 2.14, 2.15, 2.16 plot the time series and a histogram of the US, UK, and Euro area financial shocks, respectively, estimated from FAIR(2). In each case, the distribution is roughly symmetric with respect to positive and negative shocks. The 2007-2008 financial crisis shows up as a series of positive (i.e., adverse) financial shocks in 2007-2008. These exogenous impulse raise the US EBP, the UK EBP and the Euro area bank spread by approximately 2ppt.

Figure 2.17 plots the impulse responses of GDP and the RR financial distress index to an innovation of +7 to the RR index. The blue lines denote estimates obtained using the full set of OECD countries (as in RR), and the red lines denote the estimates using only US data. We can see that tee impulse responses are

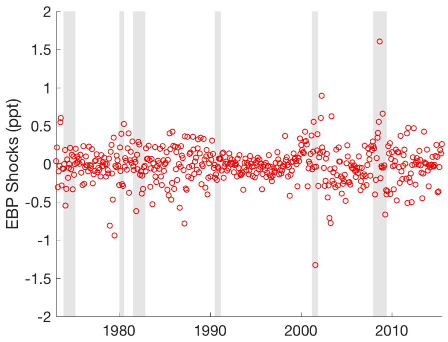
[29] Alternatively, we could use the first K values of the shocks recovered from a structural VAR.

[30] When K, the lag length of the moving average (2.1), is infinite, we truncate the model at some horizon K, large enough to ensure that the lag matrix coefficients $\mathbf{\Psi}_K$ are "close" to zero. Such a K exists since the variables are stationary.

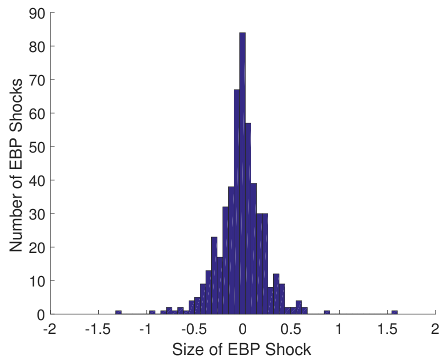
[31] Specifically, we set the parameters of our FAIR model (the a, b, and c coefficients) to minimize the discrepancy (sum of squared residuals) between the impulse responses implied by FAIR and those implied by the estimated VAR.

similar with the same drop in output (about -4.5ppt) 5 years after the impulse.

Figure 2.14: The distribution of US financial shocks

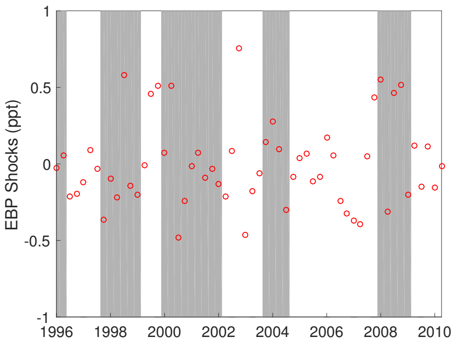


(a) Financial shocks (red dots) and NBER recession dates (grey areas).

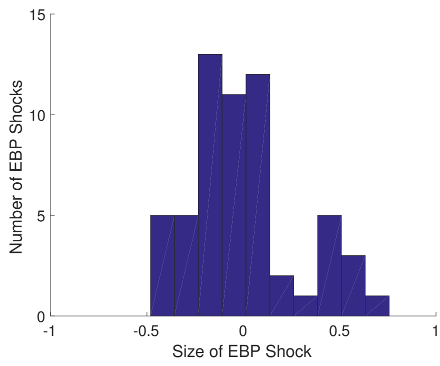


(b) Histogram of financial shocks.

Figure 2.15: The distribution of UK financial shocks

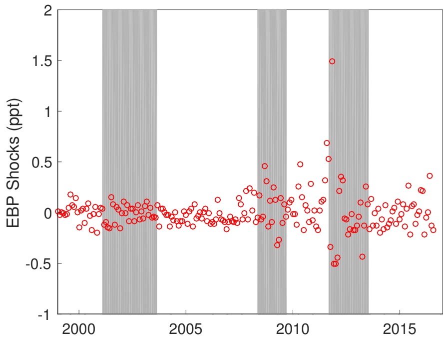


(a) Financial shocks (red dots) and OECD recession dates (grey areas).

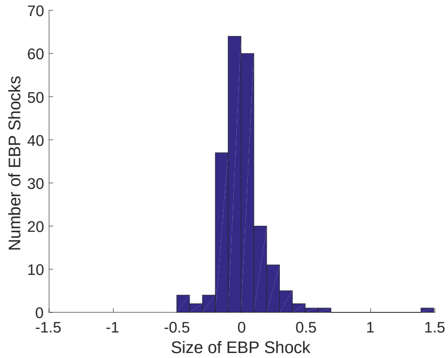


(b) Histogram of financial shocks.

Figure 2.16: The distribution of Euro area financial shocks

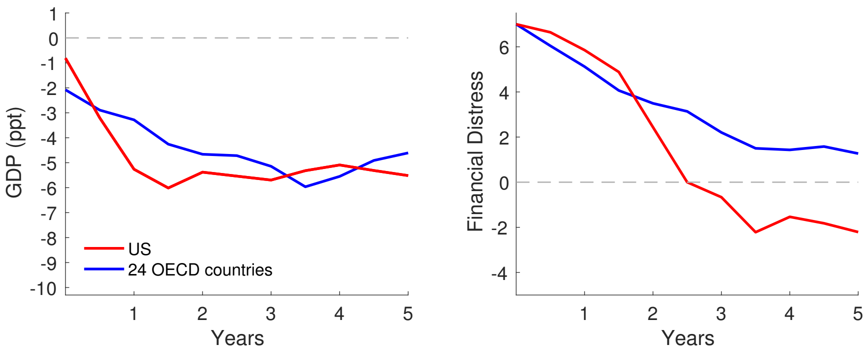


(a) Financial shocks (red dots) and OECD recession dates (grey areas).



(b) Histogram of financial shocks.

Figure 2.17: RR specification — robustness check



Impulse response functions of real GDP (GDP) and the Romer and Romer (2017a) financial distress index to an impulse of 7 (*moderate financial crisis*) to the RR financial distress index. Blue lines: estimates using all data from Romer and Romer (2017a) for 24 OECD countries. Red lines: estimates using data only for the US.

Chapter 3

IS CREDIT EASING VIABLE IN EMERGING AND DEVELOPING ECONOMIES?

with Luis Jácome H.* and Tahsin Saadi Sedik†

3.1 Introduction

Since the onset of the global financial crisis, many central banks in advanced economies have used credit easing[1] to support the financial system, and an empirical literature reaches favourable conclusions regarding its effectiveness.[2] In light of the recent experience, a much-debated question in policy circles is whether credit easing is also a suitable policy for emerging and developing economies.

Credit easing may help to stabilize the financial system, thus avoiding higher output losses. However, using central bank money to "bail out" financial institutions may also call into question the central bank's commitment to price sta-

*Georgetown University. E-mail: lij12@georgetown.edu

†International Monetary Fund. E-mail: tdaadisedik@imf.org

[1]Following Bernanke (2009), we define credit easing as a combination of three sets of policy tools: (1) lending to financial institutions; (2) providing liquidity to key credit markets; (3) purchasing longer-term securities.

[2]Joyce et al. (2012) and Borio and Zabai (2016) summarize the existing literature on the effectiveness of credit easing and other unconventional monetary policies.

bilization, opening the door for sharp increases in inflation and domestic currency depreciation. In bad cases, this can lead to balance-of-payment problems or even a full-fledged currency crisis[3] and the large output losses associated with it.[4] Such worries seem justified considering that banking crises often precede currency crises.[5] In addition, recent evidence shows that, in financially dollarized economies, even small currency depreciations are often contractionary events.[6]

In this paper, we study empirically the macroeconomic effects of credit easing in a large panel of emerging and developing economies. We find that credit easing is followed by rising domestic currency depreciation and inflation, and a reduction in economic growth. While we have some reservations about interpreting our estimates as causal, our findings suggest that credit easing bears the risk of creating new problems and further output losses in emerging and developing economies.

While an extensive literature studies the effects of credit easing in advanced economies,[7] there is little evidence on the effects of credit easing in emerging and developing economies. This is surprising because banking crises are a recurrent phenomenon in emerging and developing economies, and central banks in such countries have repeatedly applied credit easing as defined by Bernanke (2009).

In Section 3.2, we first propose a measure of credit easing. Following Bernanke's (2009) definition, which highlights that the focus of credit easing is on the loans and securities central banks hold, we use data on central banks' claims on the financial system from the IMF's International Financial Statistics (IFS). Using our measure, we highlight that some emerging economies have used credit easing in a similar scale as advanced economies.

Section 3.3 presents our evidence on the effects of credit easing: we find that a large increase in liquidity support equal to 5% of GDP during a systemic bank-

[3]Such dynamics have been predicted theoretically by Velasco (1987) and Chang and Velasco (1998).

[4]Cerra and Saxena (2008) find that output falls by 4ppt in the aftermath of a typical currency crisis, i.e. after a large domestic currency depreciation.

[5]See Kaminsky and Reinhart (1999) and Laeven and Valencia (2013).

[6]If domestic firms and banks borrow in dollar, but equity is denominated in domestic currency, a depreciation increases debt service payments and lowers the capacity to invest (see Serena and Sousa, 2017). In addition, investment may decline further due to an international borrowing constraint: after a depreciation, the collateral value of assets denominated in domestic currency falls and makes it more difficult to borrow from abroad (see Braggion et al., 2009).

[7]See Joyce et al. (2012) for a summary.

ing crisis raises domestic currency depreciation by 30ppt, inflation by 7.5ppt, and lowers economic growth by 3ppt. Our results resemble the dynamics of an unfolding currency crisis and are therefore consistent with the notion that credit easing is an important link connecting banking and currency crises, which has been predicted theoretically.[8] To that end, our findings help to understand why banking crises often precede currency crises. While our results are robust to a series of specification changes, some worries about potential confounding factors remain. Specifically, we can not control for comprehensive bank resolution plans and equity injections/bank recapitalizations due to lack of comprehensive data. Thus, we are reluctant to interpret our estimates as causal.

In Section 3.4, we consider developing economies and emerging economies separately. Emerging economies have, on average, deeper financial systems and are more closely integrated into global financial markets, which leaves them more vulnerable to capital outflows and balance-of-payment problems. Thus, we expect that credit easing has more pronounced effects in emerging economies. Our findings confirm these predictions. However, the results for the sample of developing economies remain economically and statistically significant. Section 3.5 concludes the chapter.

3.2 Measuring Credit Easing

Bernanke (2009) defines credit easing as a combination of three sets of policy tools: (i) lending to financial institutions; (ii) providing liquidity directly to key credit markets; (iii) buying of long-term securities. Thus, the focus of credit easing is on the asset side of central banks' balance sheets. More specifically, it focuses on the loans and securities central banks hold and how these asset holdings affect credit conditions for households and businesses.

To measure credit easing, we start from the International Financial Statistics' (IFS) data on central bank assets. In the IFS, (i)–(iii) are included in two categories, which we sum up: the central bank's claims on deposit money banks (line 12e) and the central bank's claims on other financial institutions (line 12f).

[8] See Velasco (1987) and Chang and Velasco (1998).

To obtain a comparable metrics across countries, we scale annual changes in our measure by countries' nominal GDP.[9]

Figure 3.1 shows the evolution of measured credit easing during major liquidity support events for a selection of emerging and advanced economies. It highlights that emerging market economies have used credit easing in a similar scale as advanced economies have, for instance, during the 2007-2008 global financial crisis.

In emerging and developing economies, central banks extend credit to financial institutions for several purposes, including to help banks withstand deposit withdrawals and to facilitate bank resolution. This is similar to the Fed's Term Auction Facility introduced since August 2007, the European Central Bank's provision of credit in 2011 and 2012 to support banks in the peripheral, and the Bank of England's financial support to Northern Rock and, generally, its rescue plan to financial institutions in 2008.

Macroeconomic and Financial Variables

Our goal is to study the effects of credit easing on economic growth, inflation, and the nominal exchange rate in emerging and developing economies. We first collect quarterly data for a panel of 145 emerging and developing economies, as defined by the IMF's World Economic Outlook (WEO) 2016. We drop 49 countries classified as *least developed nations* by the United Nations due to limited data availability and concerns about data quality, leaving us with 96 countries. For an additional 22 countries, we do not have sufficient data. Thus, we consider an unbalanced panel of 74 emerging and developing countries which contains quarterly data from 1995:Q1, the earliest date for which our credit easing measure is available, to 2012:Q4. In total, the sample consists of 4656 country-quarters. Appendix 3.A. provides additional details on the variables we use, data adjustments, and countries in the panel. We are particularly interested in the ef-

[9] We express credit easing in terms of GDP to take into account the facilities of a country's economy to support its financial system. This results in higher measured credit easing in countries with deeper financial systems. Alternatively, credit easing may be expressed in terms of the size of a country's financial system. Using the size of the financial system to scale credit easing, we find results that are very similar to the ones reported in this paper.

fects of credit easing during systemic banking crises. According to Laeven and Valencia's (2013) financial crisis narrative, our sample encompasses 35 distinct systemic banking crises, and the total number of observations during such crises is 330 quarters.

As a benchmark, we also examine the effects of credit easing in a panel of 13 advanced economies. Again, we start from the list of advanced economies/currency areas as defined by the WEO 2016 and consider all economies for which we have sufficient data. In total, the sample consists of 858 country-quarters, it includes 10 distinct systemic banking crises and the number of observations during such crises is 151 quarters.

In Appendix 3.A., we visualize the co-movement of our credit easing measure with real GDP growth, inflation, the nominal exchange rate, and the systemic banking crises dates. Four observations emerge: (i) large increases in liquidity support occur mostly during systemic banking crises; (ii) credit easing is also employed during minor stress episodes; (iii) credit easing is not used in all banking crises; (iv) credit easing has a high correlation with GDP growth, inflation and the nominal exchange rate.

3.3 Estimating the Effects of Credit Easing

We use Jordà's (2005) local projection method (LP). We prefer the method over a panel Vector AutoRegression (VAR) for a number of reasons. First, the LP approach is more robust to arbitrary forms of model misspecification. Second, the LP approach is more flexible and it is easy to introduce interaction terms or "state-dependence".[10] Third, and most importantly, with identification schemes based on short-run restrictions, we can estimate impulse response functions equation by equation. Such restrictions can be implemented by choosing the appropriate set of control variables.[11] This reduces the parameter space and greatly simplifies the

[10]The computation of state-dependent impulse responses from VARs involves additional and quite restrictive assumptions: for instance, one has to assume when and how the economy transitions from one state to the other.

[11]This point was first made by Ramey and Zubairy (2016).

construction of confidence bands.[12]

We estimate

$$x_{i,t+h} = \beta^h CE_{i,t} + \gamma'^h z_t + \alpha_i^h + \delta_t^h + \epsilon_{i,t+h}, \text{ for } h = 0, 1, ...10 \tag{3.1}$$

where i subscripts index countries, the t subscripts index time, and the h superscripts denote the horizon (in quarters after time t) being considered. $CE_{i,t}$ is the credit easing measure for country i at time t. z_t is a vector of control variables. $x_{i,t+h}$ is the dependent variable of interest for country i at time $t+h$. We consider the effects of credit easing on real GDP growth (Y), CPI inflation (π), credit easing (CE), and nominal exchange rate depreciation (E), i.e. $x_{i,t+h} = \{Y_{i,t+h}, \pi_{i,t+h}, CE_{i,t+h}, E_{i,t+h}\}$. α_i^h are country fixed effects capturing that the normal behaviour of x may differ across countries. δ_t^h are time fixed effects, included to control for economic developments facing all countries in a given year.

We add a number of control variables to identify the effects of credit easing. First, we use four lags of our variables of interest $Y_{i,t}$, $\pi_{i,t}$,CE$_{i,t}$ and $E_{i,t}$. Second, add lags of the short-term interest rate (r)[13] to control for conventional monetary policy. Third, we include Laeven and Valencia's (2013) financial crisis indicator (B) to further isolate the effects of a systemic banking crisis.

We follow a vast literature studying the effects of monetary policy in small open economies and assume that macroeconomic variables react with a lag to monetary policy[14], which includes credit easing, while the nominal exchange rate reacts contemporaneously. Thus, we control for contemporaneous $Y_{i,t}$,$\pi_{i,t}$ and $B_{i,t}$. There is no obvious ordering between $r_{i,t}$ and $CE_{i,t}$. In our baseline specification, we also control for contemporaneous $r_{i,t}$ because it is more conservative. We later show that our results are robust to alternative timing restrictions.

[12]With VARs, one has to rely on bootstrapping or the delta method. With LP, we estimate impulse responses equation by equation using ordinary least squares (OLS). Hence, we can use standard software packages to compute heteroskedasticity and autocorrelation robust (HAC) standard errors to construct confidence bands.

[13]Where possible, we use the central bank policy rate. In economies that do not have an official policy rate, we use short-term deposit rates. We explore alternative measures like discount rates and money market rates and find that our results are not sensitive to such modifications.

[14]See, for instance, Cushman and Zha (1997), Kim and Roubini (2000), and Cologni and Manera.

To construct confidence bands, we use the Driscoll and Kraay (1998) method to adjust standard errors for the possibility of correlation in the residuals across dates t and impulse response horizons h. This is akin to estimating the parameters equation by equation and then averaging the moment conditions across horizons h when calculating Newey-West (1987) standard errors. Following Jordà (2005), we set the maximum autocorrelation lag to $h + 1$.

Estimating the Effects of Credit Easing during Systemic Crises

We are particularly interested in the effects of credit easing during systemic banking crises. Intuitively, its effects might differ depending on the level of stress in the banking system: during minor stress episodes, liquidity support might be helpful as long as it does not interfere with the central bank's price stabilization objective. During systemic banking crises, on the other hand, agents may worry that the central bank abandons its price stabilization goal to "bail out" troubled financial institutions. To focus on the effects of credit easing during systemic banking crises, we introduce an interaction term and estimate

$$\begin{aligned} x_{i,t+h} &= I_{i,t}\left[\beta^{h,B} CE_{i,t} + \gamma'^{h,B} z_t\right] + (1 - I_{i,t})\left[\beta^{h,N} CE_{i,t} + \gamma'^{h,N} z_t\right] \\ &+ \alpha_i^h + \delta_t^h + \epsilon_{i,t+h}, \text{ for } h = 0, 1, ...10 \end{aligned} \tag{3.2}$$

where the indicator $I_{i,t}$ is Laeven and Valencia's (2013) crisis dummy, i.e. $I_{i,t} = B_{i,t}$. The superscript B indicates that the coefficients correspond to the *systemic banking crisis regime*, and N indicates the *no banking crisis regime*.

3.4 Evidence on the Effects of Credit Easing

We first compare the effects of credit easing in advanced economies with those in emerging and developing economies. We then zoom in on the effects during systemic banking crises. Finally, we conduct a series of robustness checks.

3.4.1 The Average Effects of Credit Easing

We estimate Equation 3.1 separately for the panel of advanced economies, and the panel of emerging and developing economies. Figure 3.2 shows the impulse responses to an increase in credit easing equal to 1 percent of GDP (which is also close to the standard deviation of our credit easing measure). The dashed black lines are point estimates and the shaded areas are 90 percent confidence bands.

In the left column, we see that credit easing has the expected positive albeit moderate effect on inflation in advanced economies. Our estimates imply that a large increase in credit easing equal to 5 percent of GDP (as it occurred, for instance, in the 2007-2008 global financial crisis, see Figure 3.1) raises inflation by 0.5 percentage points (ppt). The effects on domestic currency depreciation are small and no longer statistically significantly different from zero after the first quarter. The effects on output are neither economically nor statistically significant.

In the right column, we see that credit easing has relatively large effects in emerging and developing economies: nominal exchange rate depreciation increases by 2.7ppt, inflation by 0.7ppt, and output growth falls by -0.25ppt. Thus, our estimates imply that an increase in credit easing equal to 5 percent of GDP raises nominal exchange rate depreciation by 13.5ppt, inflation by 3.5ppt, and lowers economic growth by -1.25ppt.

3.4.2 The Effects of Credit Easing during Systemic Crises

We zoom in on the effects of credit easing during systemic banking crises and estimate Equation 3.2. Figure 3 shows the results for the panel of emerging and developing economies. To allow for a quick comparison, the left column and the dashed lines are again the results from the symmetric specification from the previous section. The middle column depicts the impulse responses to an increase in credit easing equal to 1 percent of GDP implemented during a systemic banking crisis. The right column displays the effects of credit easing when it is implemented during normal times. Shaded areas denote 90 percent confidence bands.

We find that credit easing has particularly large effects during a systemic banking crisis: domestic currency depreciation increases by 6ppt, inflation by 1.5ppt, and output falls by -0.6ppt. Therefore, a large increases in credit easing equal to 5 percent of GDP raises domestic currency depreciation by 30ppt, inflation by 7.5ppt, and lowers economic growth by -3ppt. These effects resemble the dynamics of a currency crisis.[15] Thus, our results are consistent with the notion that credit easing is a potential link between banking crises and balance-of-payment crises, which has been predicted theoretically (Velasco, 1987; Chang and Velasco, 1998).

We also estimate Equation 3.2 for the panel of advanced economies and Figure 3.4 shows the results. The effects of credit easing during a systemic banking crisis are very close to our results from the symmetric specification.

3.4.3 Understanding the Effects of Credit Easing

Related Literature.—Our results for advanced economies are in line with previous evidence on the effects of credit easing: it raises inflation, although the effect is short-lived..[16] There is no consensus about the effects on output. However, our results are in line with a large literature documenting small or insignificant effects on GDP (see, for instance, Schenkelberg and Watzka, 2013; Chen et al., 2012; and Pesaran and Smith, 2016).

Confounding Factors.—We have some reservations about interpreting the estimates as causal. The biggest concern is that credit easing is likely correlated with other policy measures. Fiscal policy may coordinate with credit easing. Thus, in our sensitivity analysis, we check that our results are robust to controlling for fiscal policy (see Section 3.4.3). However, we can not control for comprehensive bank resolution plans or equity injections/bank recapitalisations because comprehensive data do not exist. Taking, for instance, the effect on output, and assuming the effect of equity injections on output is positive, a negative correlation between equity injections and credit easing would imply that we are underestimating the beneficial effects of credit easing. Another worry is that the control variables do not isolate sufficiently the effects of a banking crisis. Therefore, in our sensitivity analysis, we check that our results are robust to controlling for credit conditions.

[15]For instance, Cerra and Saxena (2008) find that output falls by 4ppt in the aftermath of a typical currency crisis, i.e. after a large domestic currency depreciation.

[16]See Gagnon et al. (2011), Krishnamurthy and Vissing-Jorgensen (2011), and Joyce et al. (2012).

Why are the results so different for the two panels?—An important difference might be the trust in the domestic currency and the central bank to maintain price stability. Many advanced economies issue reserve currencies and central banks have an established reputation which helps them to credibly commit to price stabilization. Then, an increase in liquidity support does not lead to a large currency depreciation or high inflation. Emerging and developing economies do not issue reserve currencies and central banks in many countries did not yet establish a strong reputation. Indeed, many countries have a recent history of high inflation and balance-of-payment problems. In these economies, an increase in liquidity support may call into question the central bank's role as a guarantor of price stability, giving way to rising inflation expectations and currency depreciation.

There might be other reasons related to confounding factors. For instance, it is possible that banking crises are due to solvency issues in emerging and developing economies, and due to liquidity shortages in advanced economies. Disentangling solvency and liquidity crises is difficult because they are highly correlated and liquidity crises may cause solvency crises. However, narrative evidence from Laeven and Valencia (2013) suggests that most banking crises are associated with insolvency *and* illiquidity and there are no systematic differences between crises, in this respect, in advanced versus emerging and developing economies.[17] In addition, it is possible that credit easing in advanced economies is backed by comprehensive bank resolution plans and equity injections/bank recapitalizations while it is not in emerging and developing economies. In particular, it is conceivable that emerging and developing countries that can not stem such measures are the most likely to use central bank money to rescue the financial system. While, as noted before, we can not control for these measures due to lack of comprehensive data, the narrative account of Laeven and Valencia (2013) again suggests that there are no systematic differences between advanced versus emerging and developing economies in this regard.

Why is the effect of credit easing on growth negative in emerging and developing economies?—In addition to the costs usually associated with rising inflation[18],

[17]See Table 1 in Laeven and Valencia (2013).

[18]For instance, higher inflation is associated with higher uncertainty and hence lower levels of investment; it devalues savings and real personal income, thus reducing consumption; it distorts relative prices and leads to high menu costs.

large currency depreciations can cause sudden capital outflows and balance-of-payment crises, which are associated with large output losses.[19] However, even small currency depreciations are often contractionary events. If domestic firms and banks borrow in dollar, but equity is denominated in domestic currency, a depreciation increases debt service payments and lowers the capacity to invest (see Serena and Sousa, 2017). In addition, investment may decline further due to an international borrowing constraint: after a depreciation, the collateral value of assets denominated in domestic currency falls and makes it more difficult to borrow from abroad (see Braggion et al., 2009).

3.4.4 Sensitivity Analysis

We now study the sensitivity of our results to changes in the specification.

Alternative Crisis Chronology.—Banking crisis chronologies differ at times because it is often hard to draw the line between crisis and no crisis. We study whether our results are robust to using an alternative source by re-estimating Equation 3.1 and Equation 3.2 using the Reinhart and Rogoff (2009) chronology instead. Figure 3.5 shows that the estimates are very similar to our baseline results.

Timing Restrictions.—We consider two extreme alternatives. First, we repeat our analysis imposing that all variables can react contemporaneously to credit easing, i.e. we do not control for contemporaneous values of any variable (Figure 3.6). [20] Second, we impose that no variable reacts contemporaneously to credit easing, that is we control for contemporaneous values of all variables (3.7). We find that our results are not sensitive to alternative timing restrictions.

Additional Controls.—We explore whether our results are robust to expanding the set of controls and add: (i) private sector credit growth to more precisely isolate the effects of financial distress; (ii) primary deficits scaled by nominal GDP to control for the stance of fiscal policy, in particular because credit easing and fiscal policy might be coordinated; (iii) international reserves scaled by nominal GDP to control for countries' external financial strength; (iv) the Dincer and Eichengreen

[19] Cerra and Saxena (2008) find that a typical balance-of-payment crisis lowers output by approximately 4 percent, on average.

[20] In terms shock identification, this is equivalent to estimating a VAR ordering CE first, i.e. $X = [CE, Y, \pi, B, r, E]$, and using a Cholesky decomposition.

(2014) central bank credibility index to control for the degree of legal central bank independence. For simplicity, we repeat our analysis using both lagged and contemporaneous values of (i)–(iv) as controls. The results are depicted in Figure 3.8 and show that our baselines results are robust to using additional controls.

3.5 Further Explorations

We consider two extensions. First, we split our sample into a subsample of emerging market economies and a subsample of developing economies. Second, we study whether increases and reductions in liquidity support have asymmetric effects.

3.5.1 Emerging Markets versus Developing Economies

Emerging market economies have, on average, deeper financial systems than developing countries and are more closely integrated into global financial marketss, which leaves them more vulnerable to large capital outflows and balance-of-payment problems. Thus, credit easing likely has more pronounced effects in emerging economies. To look at this, we split our sample into (i) emerging economies and (ii) developing countries, using again the IMF's WEO 2016 country classifications, and re-estimate Equation 3.1 and 3.2 for each group separately. Figure 3.9 and Figure 3.10 show the results for emerging market economies and developing countries, respectively. Our findings confirm that the effects are somewhat larger in emerging market economies.

3.5.2 Increases and Reductions in Liquidity Support

The figures in Appendix 3.A. show that periods of credit easing— or, increases in liquidity support— are often followed by quick policy reversals. Our findings suggest that credit easing may be costly in emerging and developing economies. Thus, it is important to understand whether expansionary and contractionary policies have similar effects, and, more specifically, whether the costly side effects from credit easing can be contained by reducing liquidity support. To look at this, we estimate

$$x_{i,t+h} = \beta^{h,+} CE_{i,t} \times I_{CE_{i,t}>0} + \beta^{h,-} CE_{i,t} \times I_{CE_{i,t}\leq 0} \quad (3.1)$$

$$+ \gamma'^h z_t + \alpha_i^h + \delta_t^h + \epsilon_{i,t+h}, \text{ for } h = 0, 1, ...10 \quad (3.2)$$

where $I_{CE_{i,t}>0}$ takes value 1 if $CE_{i,t} > 0$ and 0 otherwise. The set of controls z_t now also includes four lags of the interaction terms.

Figure 3.11 reports the results. As a benchmark, the left column and dashed lines repeat the estimates from the symmetric model. The middle and right column show the effects of credit easing and a reduction in liquidity support, respectively. For ease of comparison, responses to a reduction (right column) are multiplied by -1. We find that credit easing has larger effects than the symmetric model implies, while reductions in liquidity support have smaller effects. The finding suggests that the costly side effects of credit easing can not be contained through a policy reversal.

3.6 Conclusion

Many advanced economies have used credit easing in the aftermath of the 2007-2008 global financial crisis. An important policy question is whether credit easing is also a suitable tool to stabilize financial systems in emerging and developing economies.

In this paper, we present a measure of credit easing and use it to study the effects of credit easing in a large panel of emerging and developing economies. We find that credit easing is followed by rising domestic currency depreciation and inflation, and a reduction in economic growth.

While we have some reservations about interpreting our estimates as causal, they suggest that credit easing has substantial adverse side effects in emerging and developing economies. In particular, our findings are consistent with the notion that credit easing is an important link connecting banking and currency crises, which has been predicted theoretically.[21] Thus, our findings help to understand why banking crises often precede currency crises

[21] See Velasco (1987) and Chang and Velasco (1998).

Tables and Figures

Table 3.1: Countries in the panel of emerging and developing economies

Albania	Cote d'Ivoire	Kyrgyz Republic	Poland*
Algeria	Dominica	Latvia	Romania*
Argentina*	Dominican Republic	Libya	Russian Federation*
Armenia	Egypt	Lithuania	Serbia, Republic
Azerbaijan, Rep.	Fiji	Macedonia, FYR	Seychelles
Barbados	Gabon	Malaysia*	South Africa
Belize	Georgia	Mauritius	Sri Lanka
Bolivia	Ghana	Mexico*	Swaziland
Botswana	Grenada	Moldova	Syrian Arab Republic
Brazil*	Guatemala	Mongolia	Tajikistan
Brunei Darussalam	Guyana	Morocco	Thailand*
Cabo Verde	Honduras	Namibia	Trinidad and Tobago
Cameroon	Hungary*	Nicaragua	Turkey*
Chile*	Indonesia*	Nigeria	Ukraine*
China, P.R.*	Iran, I.R. of	Pakistan*	Uruguay
Colombia*	Jamaica	Papua New Guinea	Venezuela, Rep.*
Comoros	Jordan	Paraguay	Vietnam
Congo, Republic	Kenya	Peru*	
Costa Rica	Kuwait	Philippines*	

* Defined as emerging market economies in the IMF *World Economic Outlook 2016*.

Table 3.2: Countries in the panel of advanced economies

Australia	Iceland	New Zealand	United States
Canada	Israel	Norway	
Denmark	Japan	Sweden	
Euro Area	Korea	Switzerland	

Table 3.3: Variable description

Variable	**Description**	**Source**
Nominal exchange rate (E)	Units of domestic currency per US dollar.	IFS, line rf
Credit easing (CE)	Central bank claims on deposit money banks plus claims on other financial institutions divided by nominal GDP.	IFS, line 12e + 12f
Real GDP (Y)	Gross domestic product at constant prices.	WDI, WEO, IFS
Nominal GDP	Gross domestic product at current prices.	WDI, WEO, IFS
CPI Inflation (π)	Annual rate of change in the consumer price index.	IFS, line 64
Short-term interest rate (r)	Short-term deposit rate.	IRFS, line 601
Policy rate (r)	Central banks' key policy rate.	IFS, line 601
Private credit	Bank claims on the private sector divided by nominal GDP .	IFS, line 22d
International reserves	Total reserves minus gold divided by nominal GDP.	IFS, line 11d
Public debt	General government debt divided by nominal GDP.	WEO, series GGXWDGCD
Government deficit	Central government net lending divided by nominal GDP.	WEO, series GGXCNL
Terms of Trade	Terms of trade in goods and services.	WEO, series TT
Banking crisis dates 1 (B)	Indicator variables that takes value 1 during a systemic banking crisis and 0 otherwise.	Laeven and Valencia (2013)
Banking crisis dates 2 (B)	Indicator variables that takes value 1 during a systemic banking crisis and 0 otherwise.	Reinhart and Rogoff (2009)
Central bank independence	Central bank independence index.	Dincer and Eichengreen (2014)

IFS: International Monetary Fund *International Financial Statistics*
WEO: International Monetary Fund *World Economic Outlook*
WDI: World Bank Development Indicators.

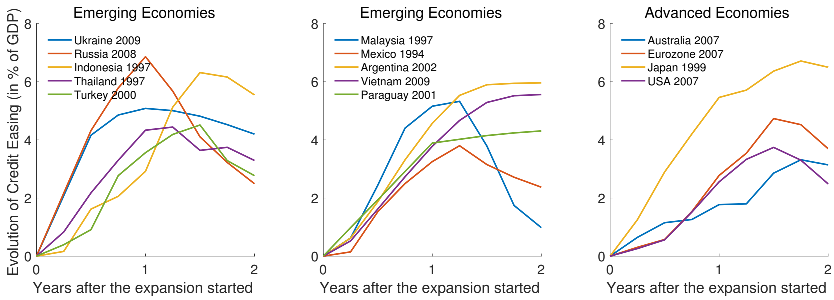
Data Adjustments

GDP data—In some instances, data on GDP (real and nominal) are not available at quarterly frequency. In those cases, we use annual data and use the proportional Denton method in Eviews12 to interpolate annual into quarterly frequency. To make sure our results are unaffected by the choice of the conversion method, we check the robustness of our results in two ways. First, we repeat our analysis, leaving out all countries that do not report quarterly GDP data. Second, we repeat our analysis using two alternative conversion methods: Litterman frequency conversion and cubic splines. Our results remain unchanged. Leaving out countries that do not report quarterly GDP data leads to slightly larger confidence bands due to the smaller amount of observations.

Terms of trade and public debt data—In most cases, data on terms of trade and general government debt are only available at annual frequency. We use the proportional Denton method in Eviews12 to interpolate annual into quarterly frequency. While we use both series only for one of our robustness checks and both can be considered slow moving, we again make sure that our choice of frequency conversion does not affect our results in a significant way. We perform the same steps as for the GDP data and find that our results remain unchanged.

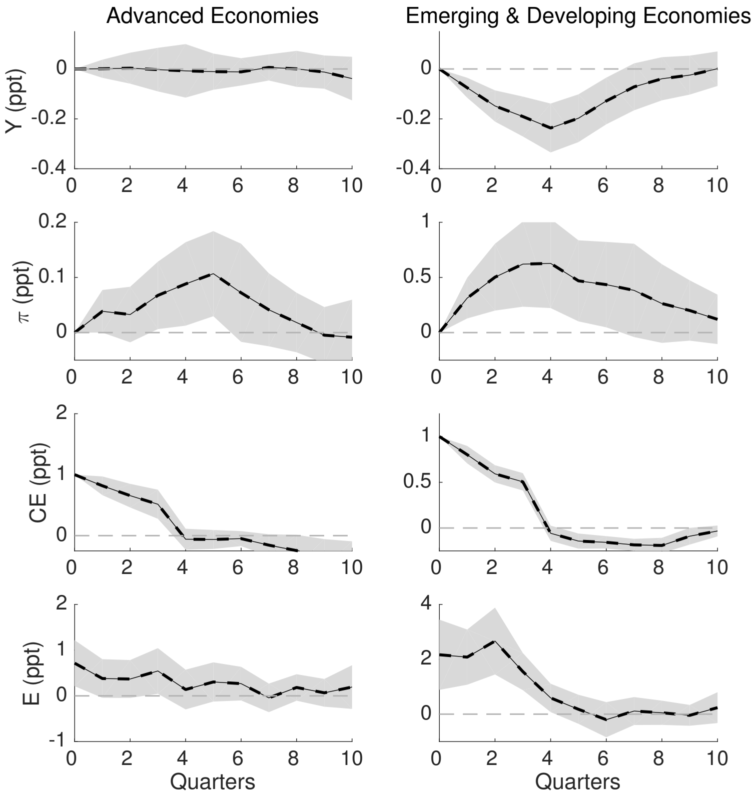
Banking crises—Laeven and Valencia (2013) report start and end dates of banking crises. We code our indicator variable such that it takes value 1 from start date through end date and 0 otherwise.

Figure 3.1: Credit easing events in advanced, emerging & developing economies



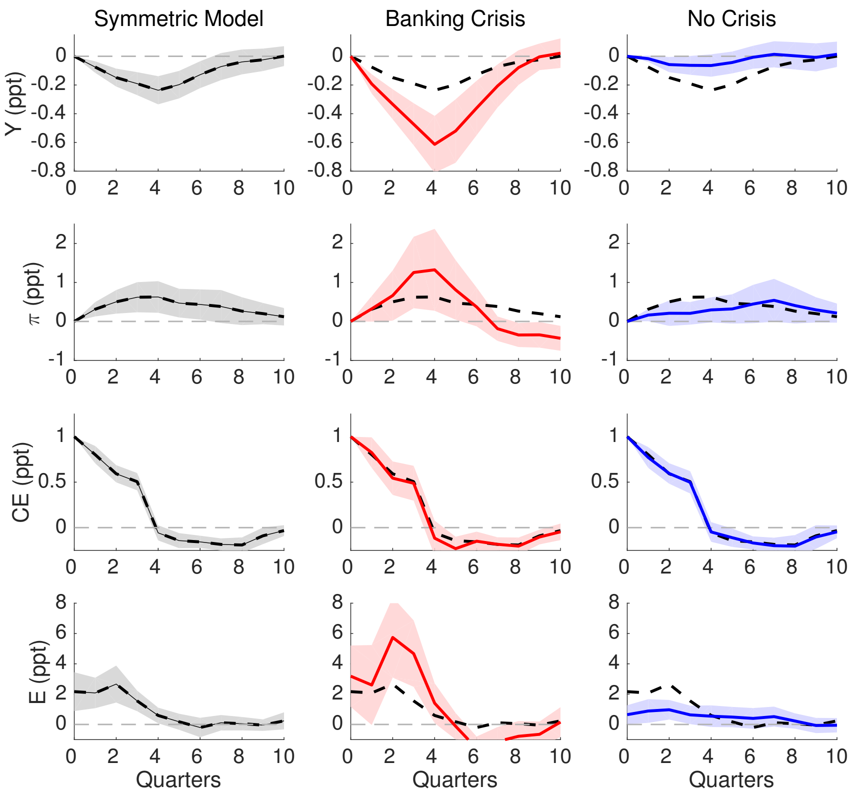
Selected liquidity support expansions in advanced, emerging, and developing economies. Credit easing is measured by central bank claims on banks and other financial institutions and scaled by nominal GDP. Data are from the IMF's International Financial Statistics (IFS) and World Economic Outlook (WEO).

Figure 3.2: The effects of credit easing in AEs vs. EMEs & DCs



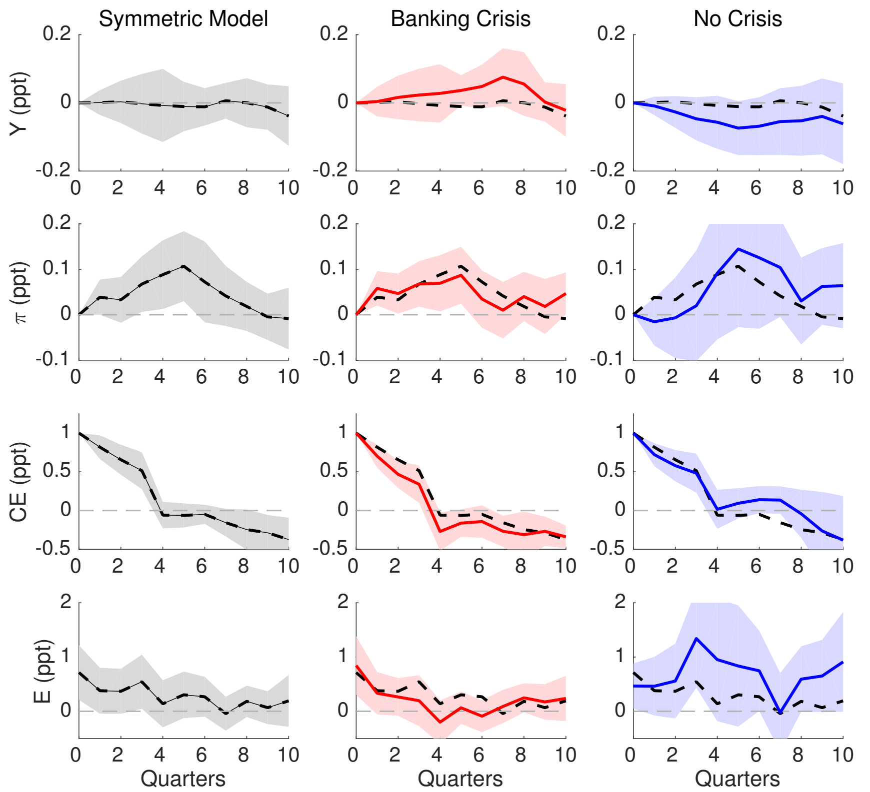
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the local projections in Equation 3.1 using a panel of 13 advanced economies (left column) and a panel of 74 emerging and developing economies (right column). Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.3: The effects of credit easing during systemic crises — EMEs & DCs



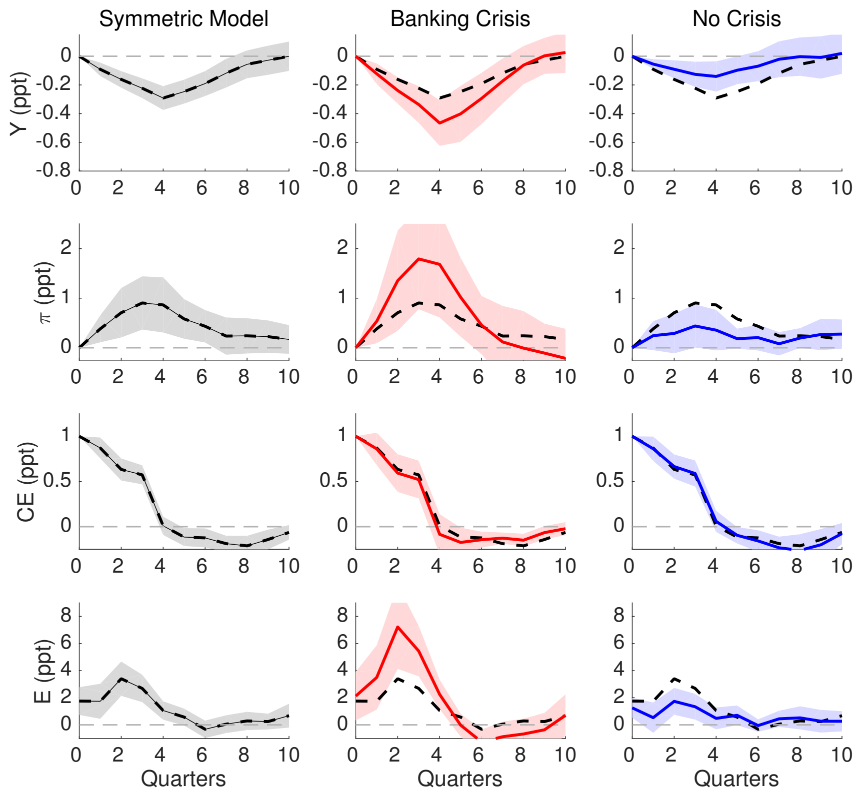
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.4: The effects of credit easing during systemic crises — AEs



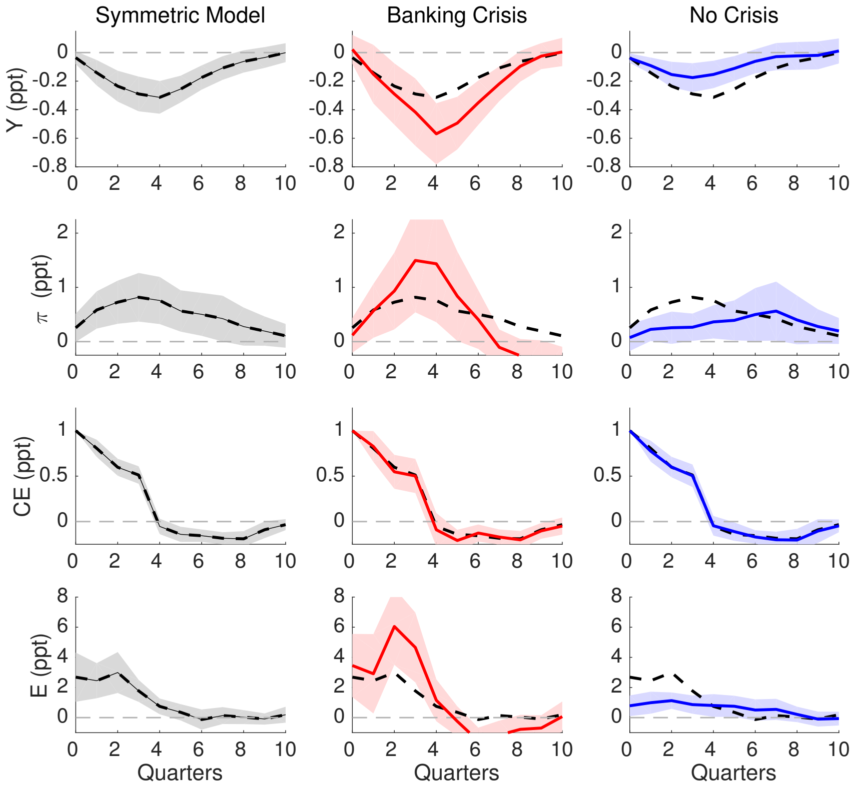
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 13 advanced economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.5: Robustness check — alternative crisis chronology



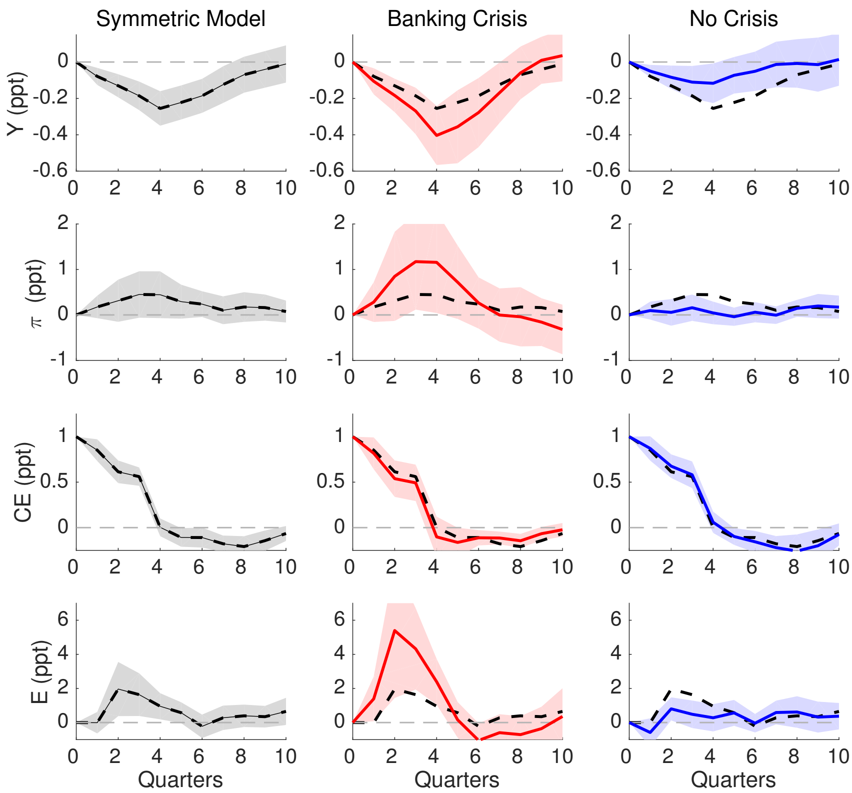
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.6: Robustness check — alternative specification I



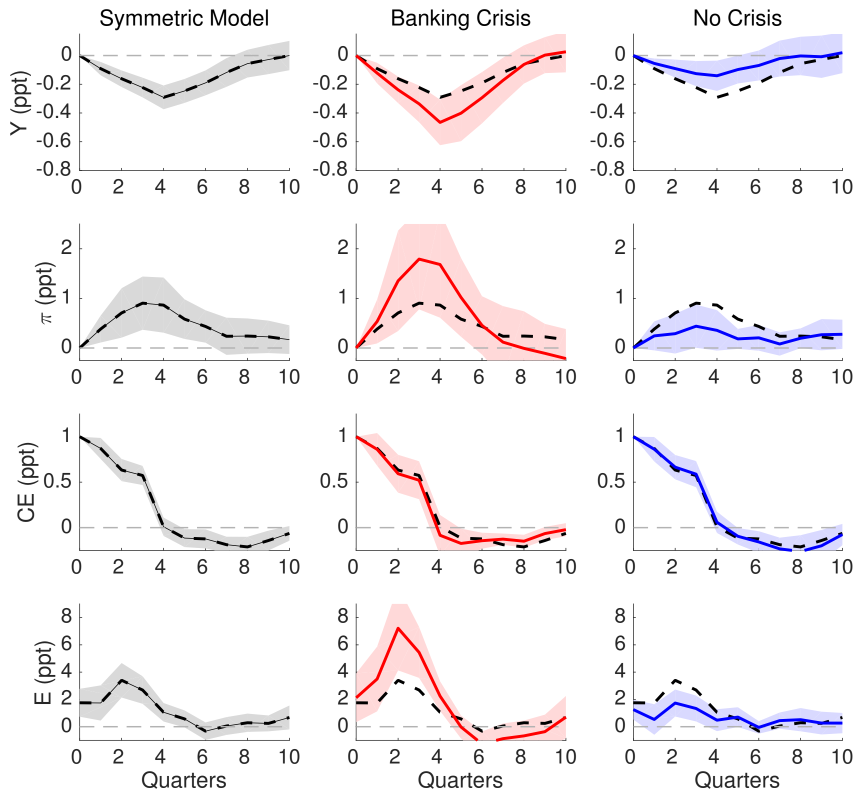
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.7: Robustness check — alternative specification II



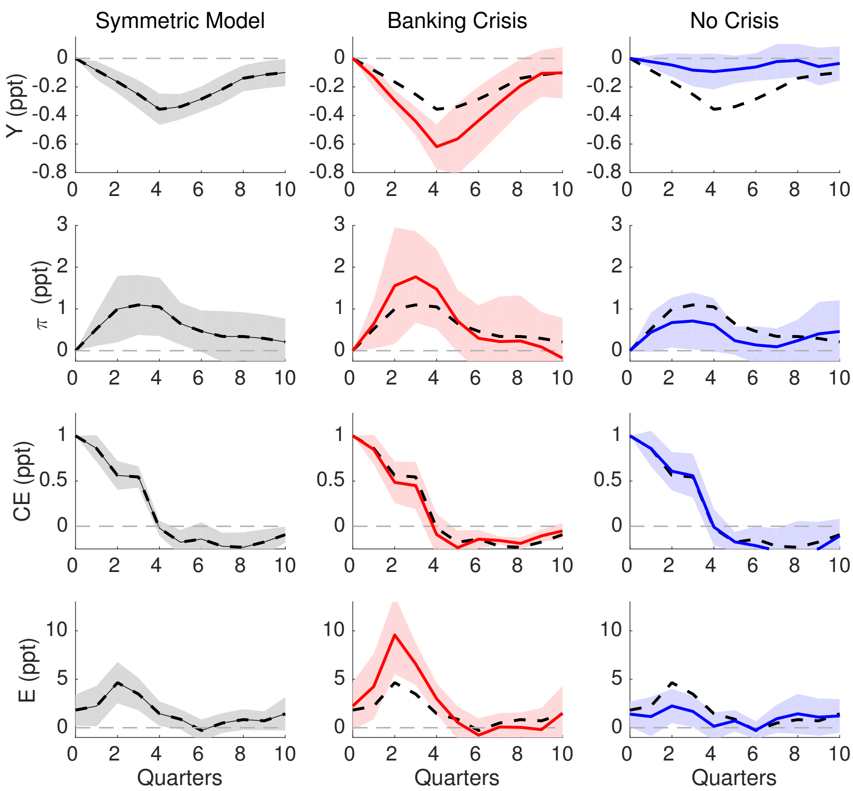
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.8: Robustness check — additional controls



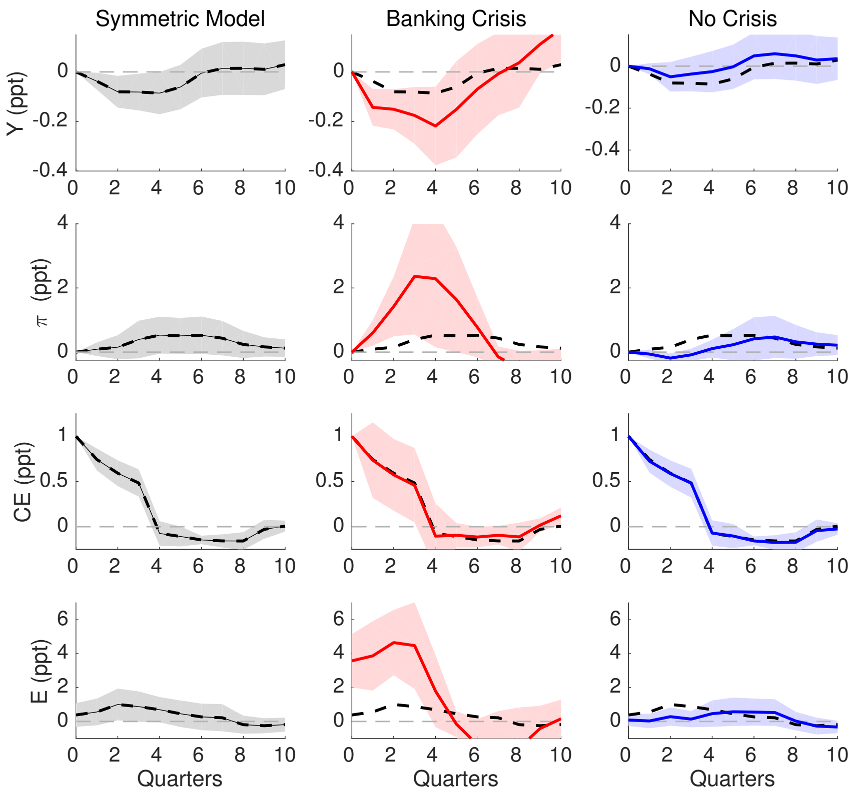
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.9: The effects of credit easing in emerging economies



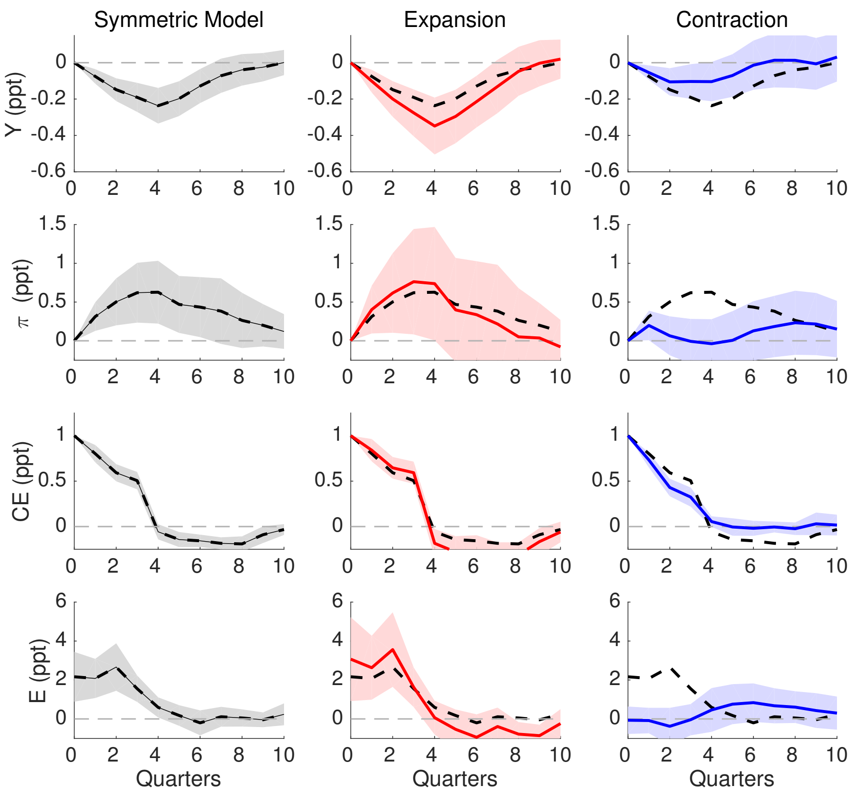
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 20 emerging economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

Figure 3.10: The effects of credit easing in developing economies



Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the state-dependent local projections in Equation 3.2 (middle and right column; plain lines) using a panel of 54 developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

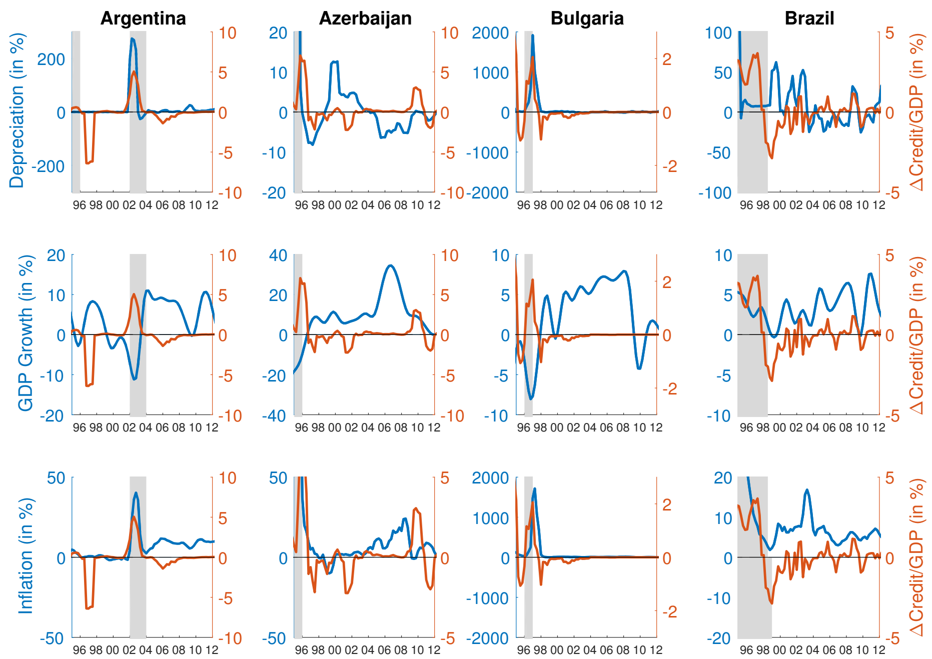
Figure 3.11: The sign-dependent effects of credit easing



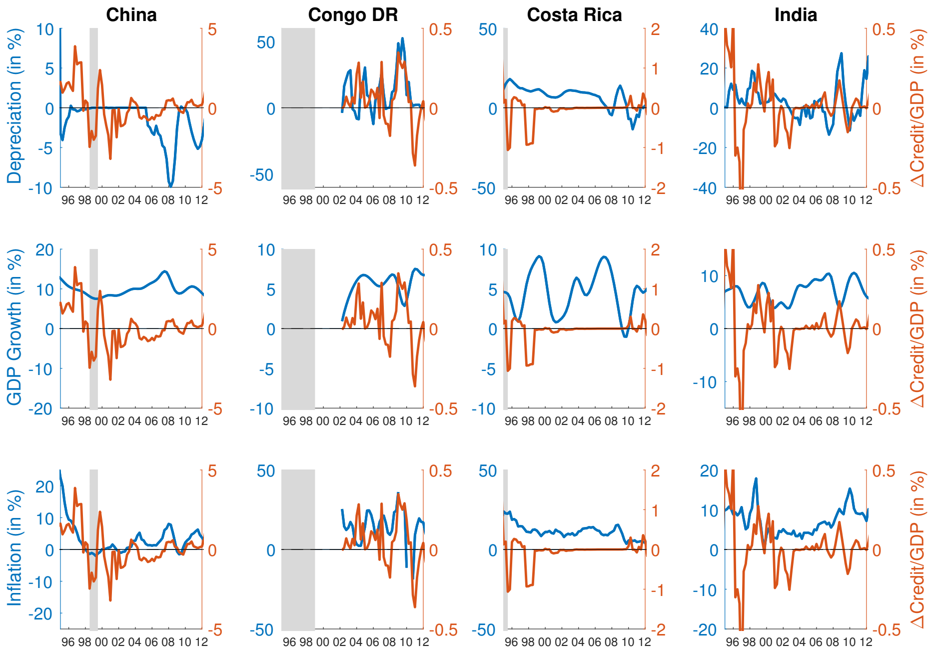
Impulse responses of real GDP growth, CPI inflation, and nominal exchange rate depreciation to an increase in credit easing equal to 1 percent of GDP. Estimates from the symmetric local projections in Equation 3.1 (left column; dashed lines) or the sign-dependent local projection model in Equation XXX (middle and right column; plain lines) using a panel of 74 emerging and developing economies. Shaded areas are 90% confidence bands calculated using Newey-West standard errors. Estimation using quarterly data from 1995 to 2012.

3.A Credit Easing and Macroeconomic Aggregates

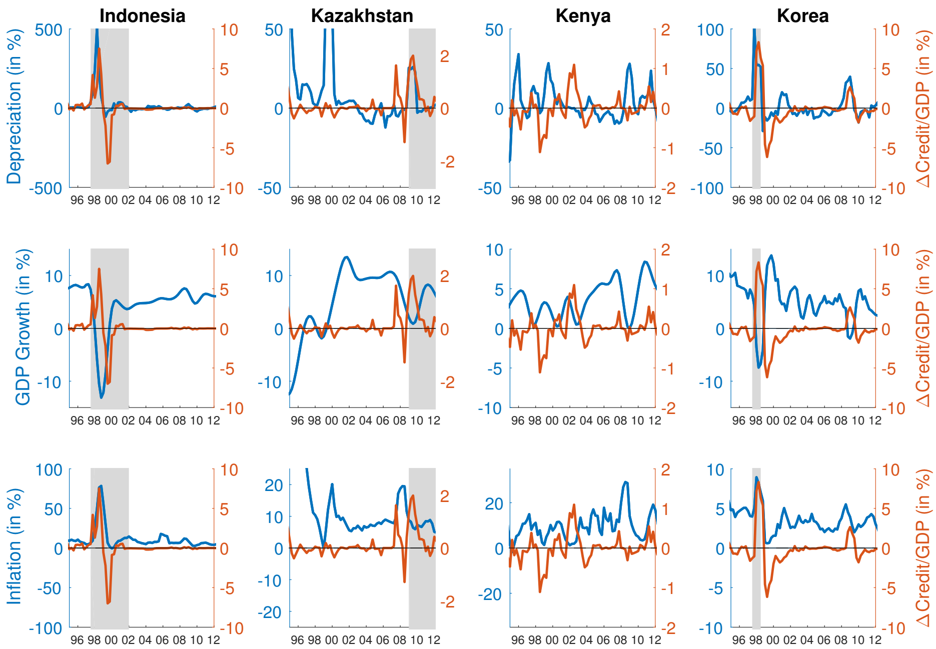
Figure 3.12: Credit easing and key macroeconomic variables



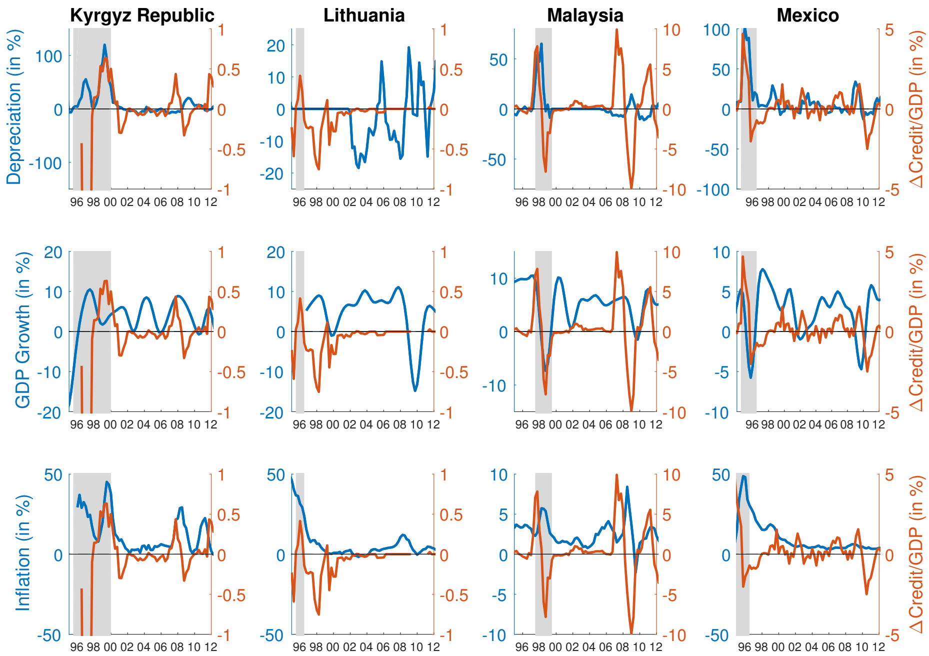
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



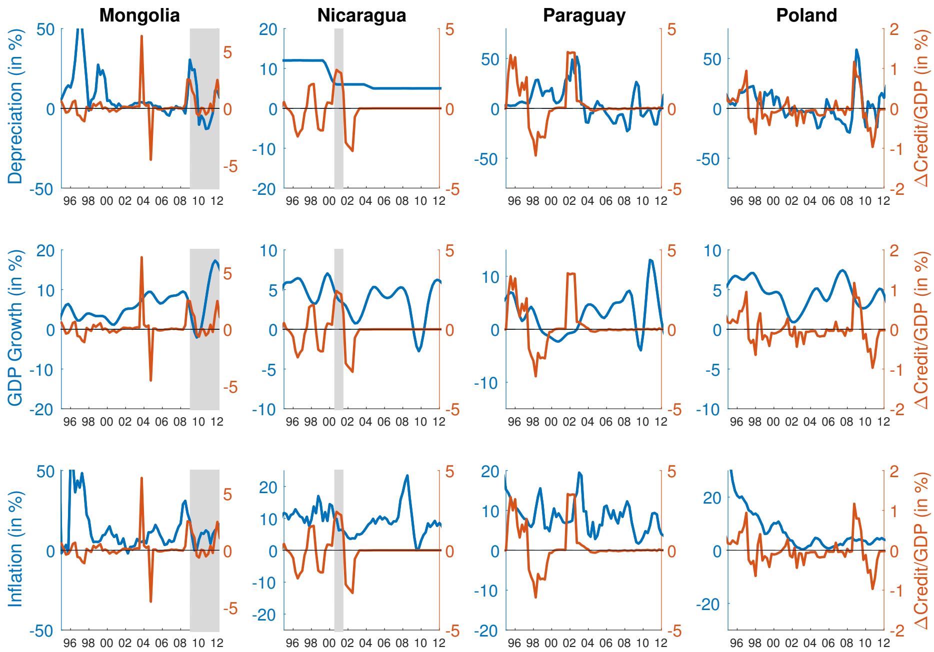
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



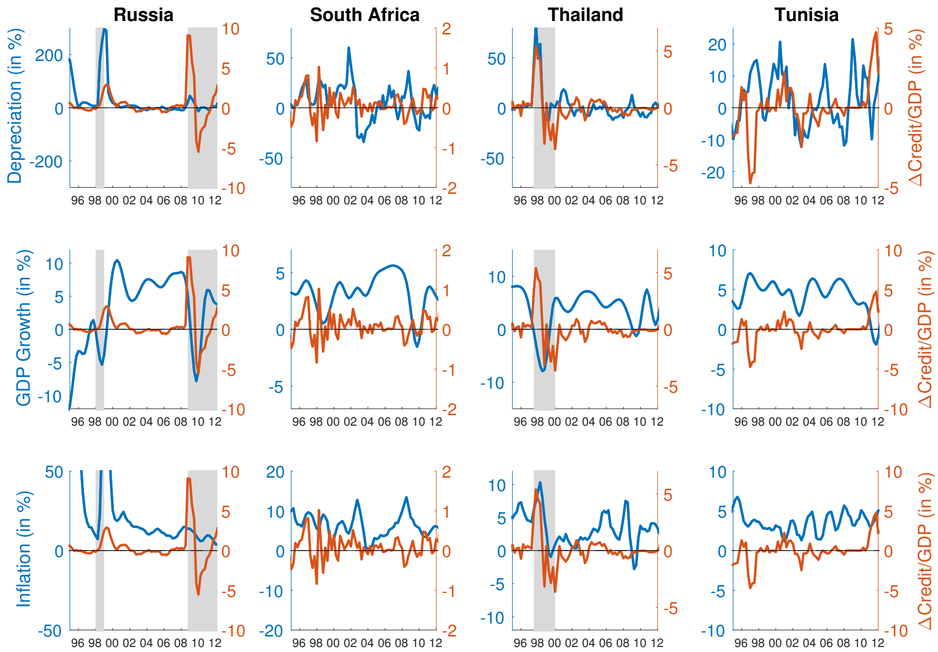
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



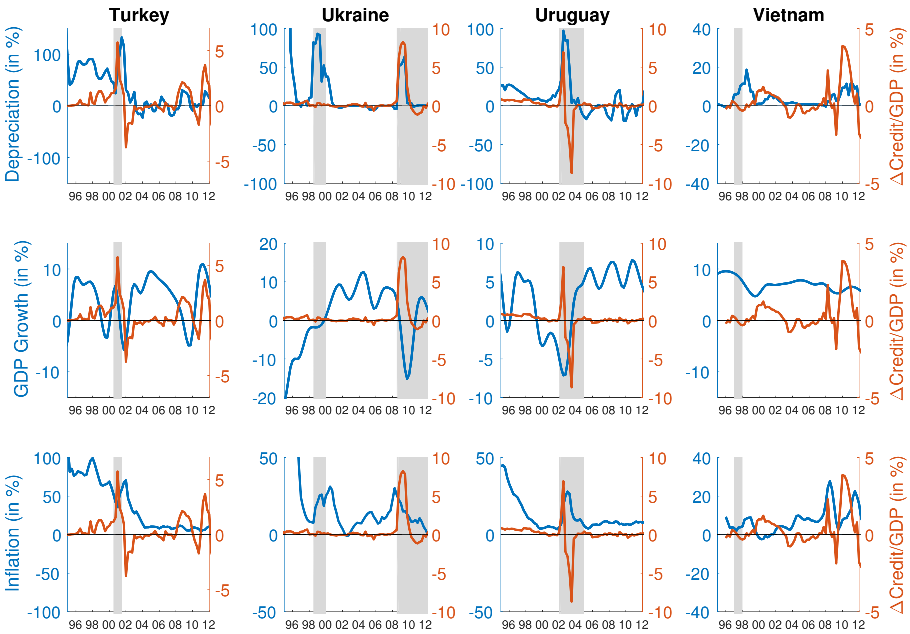
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



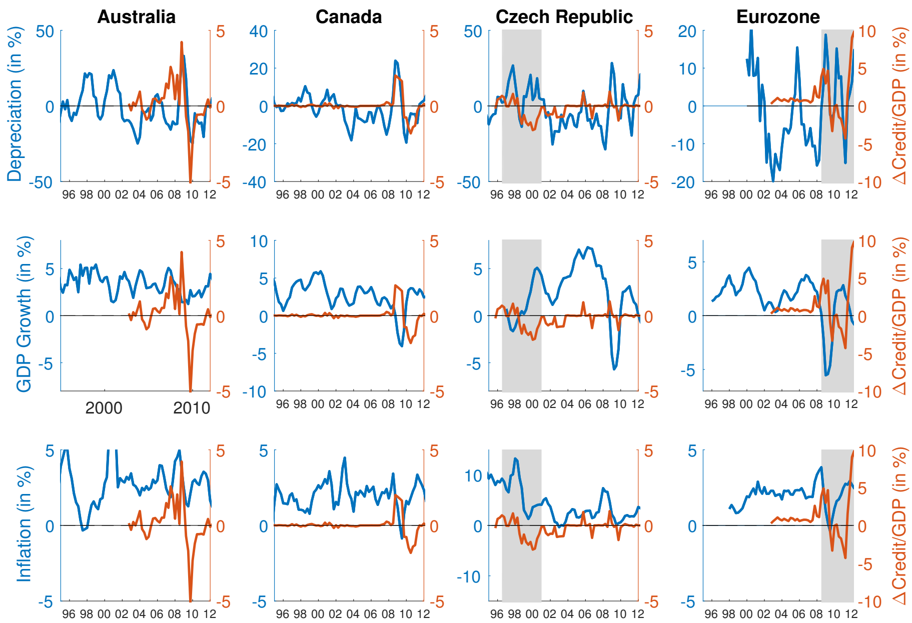
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



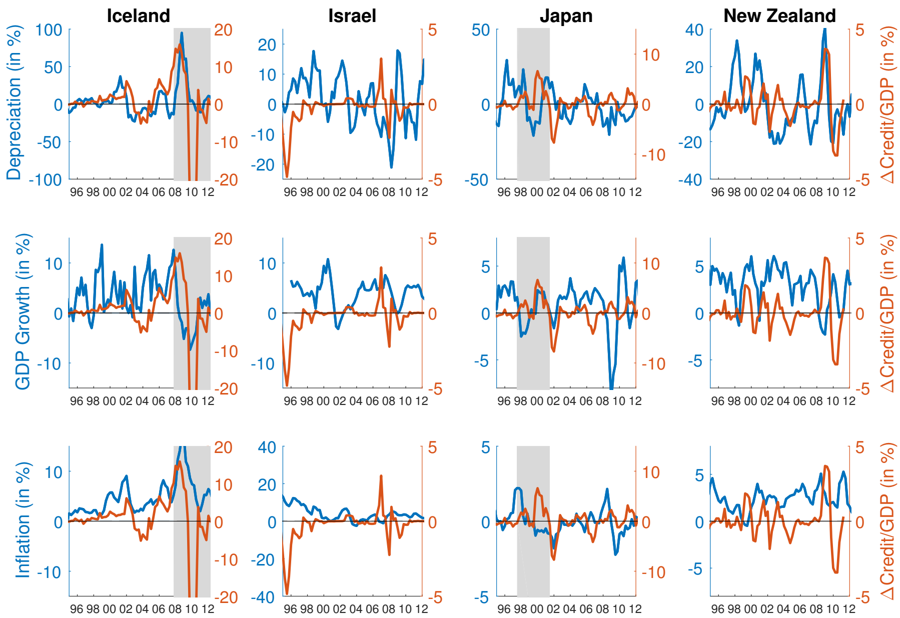
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



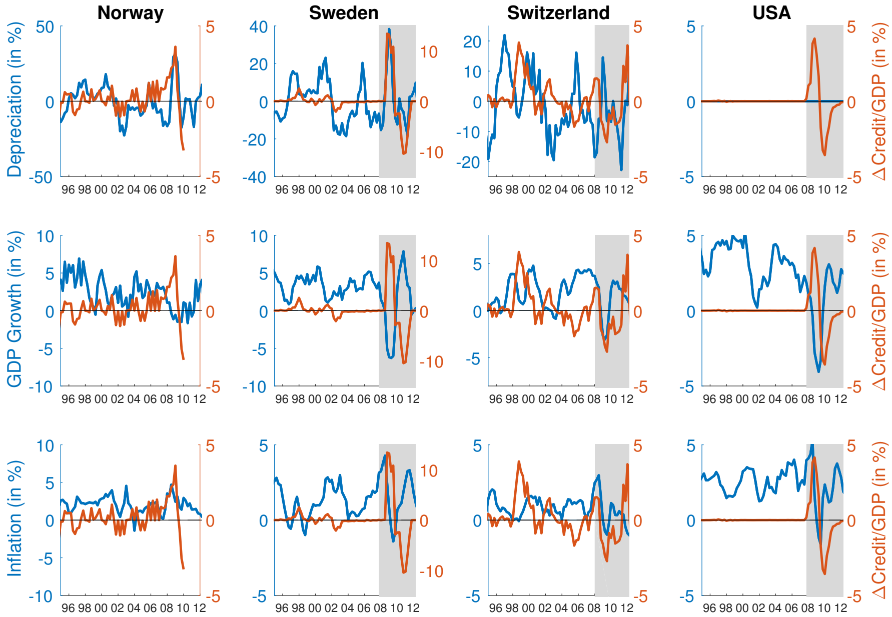
Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).



Comovements of domestic currency depreciation, real GDP growth and CPI inflation with central bank liquidity support (right axis, scaled by nominal GDP). Shaded areas are systemic banking crises as identified by Laeven and Valencia (2013).

Bibliography

Anderson, T. W. and Rubin, H. (1949). Estimation of the parameters of a single equation in a complete system of stochastic equations. *The Annals of Mathematical Statistics*, 20(1):46–63.

Auerbach, A. J. and Gorodnichenko, Y. (2012a). Fiscal multipliers in recession and expansion. In *Fiscal Policy after the Financial Crisis*, pages 63–98. University of Chicago press.

Auerbach, A. J. and Gorodnichenko, Y. (2012b). Measuring the output responses to fiscal policy. *American Economic Journal: Economic Policy*, 4(2):1–27.

Ball, L. M. (2014). Long-term damage from the Great Recession in OECD countries. NBER Working Paper No. 20185, National Bureau of Economic Research, Inc.

Barnichon, R. and Matthes, C. (2016). Gaussian Mixture Approximations of Impulse Responses and The Non-Linear Effects of Monetary Shocks. CEPR Discussion Paper No. DP11374.

Barnichon, R. and Matthes, C. (2017). Understanding the size of the government spending multiplier: It's in the sign. CEPR Discussion Paper No. DP11373.

Barnichon, R., Matthes, C., and Ziegenbein, A. (2016). Assessing the Non-Linear Effects of Credit Market Shocks. CEPR Discussion Paper No. DP11410.

Barro, R. J. and Redlick, C. J. (2011). Macroeconomic effects from government purchases and taxes. *The Quarterly Journal of Economics*, 126(1):51–102.

Baxter, M. and King, R. G. (1993). Fiscal policy in general equilibrium. *The American Economic Review*, pages 315–334.

Bernanke, B. S. (2009). The crisis and the policy response: a speech at the Stamp Lecture, London School of Economics, London, England, January 13, 2009. Speech 442, Board of Governors of the Federal Reserve System (U.S.).

Bianchi, F. and Kung, H. (2014). Growth, Slowdowns, and Recoveries. CEPR Discussion Paper No. DP10291.

Blanchard, O., Cerutti, E., and Summers, L. (2015). Inflation and activity–Two explorations and their monetary policy implications. NBER Working Paper No. 21726, National Bureau of Economic Research, Inc.

Blanchard, O. and Galí, J. (2010). Labor markets and monetary policy: A new keynesian model with unemployment. *American Economic Journal: Macroeconomics*, 2(2):1–30.

Blanchard, O. and Katz, L. (1997). What we know and do now know about the natural rate of unemployment. *Journal of Economic Perspectives*, 11(1):51–72.

Blanchard, O. and Perotti, R. (2002). An empirical characterization of the dynamic effects of changes in government spending and taxes on output. *The Quarterly Journal of Economics*, 117(4):1329–1368.

Bleaney, M., Mizen, P., and Veleanu, V. (2016). Bond spreads and economic activity in eight european economies. *The Economic Journal*, 126(598):2257–2291.

Boivin, J., Giannoni, M. P., and Stevanović, D. (2013). Dynamic effects of credit shocks in a data-rich environment. Cahier de recherche 1324, CIRPEE.

Bordo, M. D. and Haubrich, J. G. (2017). Deep recessions, fast recoveries, and financial crises: Evidence from the american record. *Economic Inquiry*, 55(1):527–541.

Borio, C. and Zabai, A. (2016). Unconventional monetary policy: a re-appraisal. BIS Working Papers No 570, Bank for International Settlements.

Braggion, F., Christiano, L. J., and Roldos, J. (2009). Optimal monetary policy in a sudden stop. *Journal of Monetary Economics*, 56(4):582 – 595.

Brückner, M. and Pappa, E. (2012). Fiscal expansions, unemployment, and labor force participation: Theory and evidence. *International Economic Review*, 53(4):1205–1228.

Brunnermeier, M. K. and Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421.

Burnside, C., Eichenbaum, M., and Fisher, J. D. (2004). Fiscal shocks and their consequences. *Journal of Economic Theory*, 115(1):89–117.

Caldara, D. and Herbst, E. (2016). Monetary Policy, Real Activity, and Credit Spreads : Evidence from Bayesian Proxy SVARs. Finance and Economics Discussion Series No. 2016-049, Board of Governors of the Federal Reserve System (U.S.).

Caldara, D. and Kamps, C. (2017). The analytics of SVARs: a unified framework to measure fiscal multipliers. *The Review of Economic Studies*, 84(3):1015–1040.

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

Card, D. and Hyslop, D. (1997). Does inflation "grease the wheels of the labor market"? In *Reducing inflation: Motivation and strategy*, pages 71–122. University of Chicago Press.

Cerra, V. and Saxena, S. C. (2005). Did Output Recover from the Asian Crisis? *IMF Staff Papers*, 52(1):1–23.

Cerra, V. and Saxena, S. C. (2008). Growth dynamics: the myth of economic recovery. *American Economic Review*, 98(1):439–57.

Chang, R. and Velasco, A. (1998). Financial crises in emerging markets: a canonical model. FRB Atlanta Working Paper 98-10, Federal Reserve Bank of Atlanta.

Chen, H., Curdia, V., and Ferrero, A. (2012). The macroeconomic effects of large-scale asset purchase programmes. *The Economic Journal*, 1222(564):F289–F315.

Chen, Y. and Rogoff, K. (2003). Commodity Currencies and Empirical Exchange Rate Puzzles. DNB Staff Reports No. 76, Netherlands Central Bank.

Cloyne, J. (2013). Discretionary tax changes and the macroeconomy: new narrative evidence from the United Kingdom. *The American Economic Review*, 103(4):1507–1528.

Cloyne, J. and Hürtgen, P. (2016). The Macroeconomic Effects of Monetary Policy: A New Measure for the United Kingdom. *American Economic Journal: Macroeconomics*, 8(4):75–102.

Coibion, O., Gorodnichenko, Y., and Ulate, M. (2017). The Cyclical Sensitivity in Estimates of Potential Output. NBER Working Paper No. 23580, National Bureau of Economic Research, Inc.

Cologni, A. and Manera, M. (2008). Oil prices, inflation and interest rates in a structural cointegrated VAR model for the G-7 countries. *Energy Economics*, 30(3):856–888.

Comin, D. and Gertler, M. (2006). Medium-term business cycles. *American Economic Review*, 96(3):523–551.

Crépon, B., Duflo, E., Gurgand, M., Rathelot, R., and Zamora, P. (2013). Do labor market policies have displacement effects? evidence from a clustered randomized experiment. *The Quarterly Journal of Economics*, 128(2):531–580.

Cushman, D. O. and Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary Economics*, 39(3):433–448.

Dincer, N. N. and Eichengreen, B. (2014). Central Bank Transparency and Independence: Updates and New Measures. *International Journal of Central Banking*, 10(1):189–259.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *The Review of Economics and Statistics*, 80(4):549–560.

Favero, C. and Giavazzi, F. (2012). Measuring tax multipliers: The narrative method in fiscal VARs. *American Economic Journal: Economic Policy*, 4(2):69–94.

Fazzari, S. M., Morley, J., and Panovska, I. (2015). State-dependent effects of fiscal policy. *Studies in Nonlinear Dynamics & Econometrics*, 19(3):285–315.

Fisher, J. D. and Peters, R. (2010). Using stock returns to identify government spending shocks. *The Economic Journal*, 120(544):414–436.

Gagnon, J., Raskin, M., Remache, J., and Sack, B. (2011). The Financial Market Effects of the Federal Reserve's Large-Scale Asset Purchases. *International Journal of Central Banking*, 7(1):3–43.

Gautier, P. A., Rosholm, M., Svarer, M., and van der Klaauw, B. (2012). Estimating equilibrium effects of job search assistance. IZA Discussion Paper No. 6748.

Gentry, W. M. and Hubbard, R. G. (2004). The effects of progressive income taxation on job turnover. *Journal of Public Economics*, 88(11):2301–2322.

Gertler, M. and Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, 7(1):44–76.

Gilchrist, S. and Mojon, B. (2018). Credit risk in the euro area. *The Economic Journal*, 128(608):118–158.

Gilchrist, S., Sim, J. W., and Zakrajek, E. (2014). Uncertainty, Financial Frictions, and Investment Dynamics. NBER Working Paper No. 20038, National Bureau of Economic Research, Inc.

Gilchrist, S., Yankov, V., and Zakrajšek, E. (2009). Credit market shocks and economic fluctuations: Evidence from corporate bond and stock markets. *Journal of monetary Economics*, 56(4):471–493.

Gilchrist, S. and Zakrajšek, E. (2011). Monetary policy and credit supply shocks. *IMF Economic Review*, 59(2):195–232.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, 102(4):1692–1720.

Giorno, C., Richardson, P., Roseveare, D., and Van den Noord, P. (1995). Estimating potential output, output gaps and structural budget balances. OECD Economic Studies No. 24.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping autoregressions with conditional heteroskedasticity of unknown form. *Journal of Econometrics*, 123(1):89–120.

Hall, R. E. (2005). Employment fluctuations with equilibrium wage stickiness. *The American Economic Review*, 95(1):50–65.

Hamilton, J. D. (1994). *Time series analysis*, volume 2. Princeton university press Princeton.

He, Z. and Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, 103(2):732–70.

Helbling, T., Huidrom, R., Kose, M. A., and Otrok, C. (2011). Do credit shocks matter? a global perspective. *European Economic Review*, 55(3):340–353.

Jacome H., L. I., Saadi Sedik, T., and Townsend, S. (2012). Can emerging market central banks bail out banks? A cautionary tale from Latin America. *Emerging Markets Review*, 13(4):424–448.

Jordà, Ò. (2005). Estimation and Inference of Impulse Responses Local Projections. *The American Economic Review*, 95(1):161–182.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2011). Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review*, 59(2):340–378.

Jordà, Ò., Schularick, M., and Taylor, A. M. (2015). Betting the house. *Journal of International Economics*, 96:S2–S18.

Jordà, Ò. and Taylor, A. M. (2016). The time for austerity: estimating the average treatment effect of fiscal policy. *The Economic Journal*, 126(590):219–255.

Joyce, M., Miles, D., Scott, A., and Vayanos, D. (2012). Quantitative Easing and Unconventional Monetary Policy? An Introduction. *Economic Journal*, 122(564):271–288.

Kadiyala, K. R. and Karlsson, S. (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics*, pages 99–132.

Kaminsky, G. L. and Reinhart, C. M. (1999). The twin crises: The causes of banking and balance-of-payments problems. *American Economic Review*, 89(3):473–500.

Keane, M. P. (2011). Labor supply and taxes: A survey. *Journal of Economic Literature*, 49(4):961–1075.

Kim, S. and Roubini, N. (2000). Exchange rate anomalies in the industrial countries: A solution with a structural VAR approach. *Journal of Monetary Economics*, 45(3):561–586.

Krishnamurthy, A., Muir, T., and Yale, S. (2015). Credit spreads and the severity of financial crises. Unpublished Manuscript.

Krishnamurthy, A. and Vissing-Jorgensen, A. (2011). The Effects of Quantitative Easing on Interest Rates: Channels and Implications for Policy. NBER Working Paper No. 17555, National Bureau of Economic Research, Inc.

Laeven, L. and Valencia, F. (2013). Systemic Banking Crises Database. *IMF Economic Review*, 61(2):225–270.

Landais, C., Michaillat, P., and Saez, E. (2016a). A macroeconomic approach to optimal unemployment insurance: Applications. *American Economic Journal: Economic Policy*, forthcoming.

Landais, C., Michaillat, P., and Saez, E. (2016b). A macroeconomic approach to optimal unemployment insurance: Theory. *American Economic Journal: Economic Policy*, forthcoming.

Leeper, E. M. (2010). Monetary science, fiscal alchemy. NBER Working Paper No. 16510, National Bureau of Economic Research, Inc.

Leeper, E. M., Walker, T. B., and Yang, S.-C. S. (2011). Foresight and information flows. NBER Working Paper No. 16951, National Bureau of Economic Research, Inc.

López-Salido, D., Stein, J. C., and Zakrajšek, E. (2017). Credit-market sentiment and the business cycle. *Quarterly Journal of Economics*, 132(3):1373–1426.

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *American Economic Review*, 100(5):1941–66.

Mendoza, E. G., Razin, A., and Tesar, L. L. (1994). Effective tax rates in macroeconomics: Cross-country estimates of tax rates on factor incomes and consumption. *Journal of Monetary Economics*, 34(3):297–323.

Mertens, K. and Ravn, M. O. (2011). Understanding the aggregate effects of anticipated and unanticipated tax policy shocks. *Review of Economic Dynamics*, 14(1):27–54.

Mertens, K. and Ravn, M. O. (2012). Empirical evidence on the aggregate effects of anticipated and unanticipated US tax policy shocks. *American Economic Journal: Economic Policy*, 4(2):145–181.

Mertens, K. and Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the United States. *The American Economic Review*, 103(4):1212–1247.

Mertens, K. and Ravn, M. O. (2014). A reconciliation of SVAR and narrative estimates of tax multipliers. *Journal of Monetary Economics*, 68:S1–S19.

Michaillat, P. (2014). A theory of countercyclical government multiplier. *American Economic Journal: Macroeconomics*, 6(1):190–217.

Miranda-Agrippino, S. and Ricco, G. (2017). The transmission of monetary policy shocks. Staff Working Paper No. 657, Bank of England.

Monfort, A. and Renne, J.-P. (2013). Decomposing euro-area sovereign spreads: credit and liquidity risks. *Review of Finance*, 18(6):2103–2151.

Newey, W. K. and West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708.

Olea, J. L. M. and Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31(3):358–369.

Owyang, M. T., Ramey, V. A., and Zubairy, S. (2013). Are government spending multipliers greater during periods of slack? Evidence from twentieth-century historical data. *The American Economic Review*, 103(3):129–134.

Perotti, R. (1999). Fiscal policy in good times and bad. *The Quarterly Journal of Economics*, 114(4):1399–1436.

Perotti, R. (2012). The effects of tax shocks on output: not so large, but not small either. *American Economic Journal: Economic Policy*, 4(2):214–237.

Pesaran, M. H. and Smith, R. P. (2016). Counterfactual analysis in macroeconometrics: An empirical investigation into the effects of quantitative easing. *Research in Economics*, 70(2):262–280.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT press.

Ramey, V. A. (2011). Identifying government spending shocks: it's all in the timing. *The Quarterly Journal of Economics*, 126(1):1–50.

Ramey, V. A. (2016). Macroeconomic Shocks and Their Propagation. NBER Working Paper No. 21978, National Bureau of Economic Research, Inc.

Ramey, V. A. and Zubairy, S. (2016). Government spending multipliers in good times and in bad: evidence from US historical data. *Journal of Political Economy*, forthcoming.

Reinhart, C. M. and Rogoff, K. S. (2009). *This Time Is Different: Eight Centuries of Financial Folly*. Princeton University Press, Princeton, New Jersey.

Reinhart, C. M. and Rogoff, K. S. (2014). Recovery from financial crises: Evidence from 100 episodes. *American Economic Review*, 104(5):50–55.

Robert, C. P. and Casella, G. (2004). *Monte Carlo Statistical Methods*. Springer.

Romer, C. D. and Romer, D. H. (2004). A new measure of monetary shocks: Derivation and implications. *American Economic Review*, 94(4):1055–1084.

Romer, C. D. and Romer, D. H. (2010). The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks. *The American Economic Review*, 100:763–801.

Romer, C. D. and Romer, D. H. (2017a). New evidence on the aftermath of financial crises in advanced countries. *American Economic Review*, 107(10):3072–3118.

Romer, C. D. and Romer, D. H. (2017b). New evidence on the aftermath of financial crises in advanced countries. *American Economic Review*, 107(10):3072–3118.

Rotemberg, J. J. (1982). Sticky prices in the united states. *Journal of Political Economy*, 90(6):1187–1211.

Sahay, R., Cespedes, L., and Cashin, P. (2002). Keynes, cocoa, and copper; in search of commodity currencies. IMF Working Paper No 02/223, International Monetary Fund.

Schenkelberg, H. and Watzka, S. (2013). Real effects of quantitative easing at the zero lower bound: Structural var-based evidence from japan. *Journal of International Money and Finance*, 33:327 – 357.

Schuster, P. and Uhrig-Homburg, M. (2013). The term structure of bond market liquidity conditional on the economic environment: An analysis of government guaranteed bonds. Working Peper Series in Economics 45, Karlsruhe Institute of Technology, Department of Economics and Engineering.

Serena, J. M. and Sousa, R. (2017). Does exchange rate depreciation have contractionary effects on firm-level investment? BIS Working Papers No 624, Bank for International Settlements.

Shimer, R. (2010). *Labor Markets and Business Cycles*. Princeton University Press.

Staiger, D. and Stock, J. H. (1997). Instrumental Variables Regression with Weak Instruments. *Econometrica*, 65(3):557–586.

Stein, J. (2014). Incorporating Financial Stability Considerations into a Monetary Policy Framework: a speech at the International Research Forum on Monetary Policy, Washington, DC, March 21, 2014. Speech 796, Board of Governors of the Federal Reserve System (U.S.).

Stock, J. H. and Watson, M. W. (2012). Disentangling the channels of the 2007-2009 recession. NBER Working Paper No. 18094, National Bureau of Economic Research, Inc.

Stock, J. H. and Watson, M. W. (2017). Identification and estimation of dynamic causal effects in macroeconomics. Manuscript based on 2017 Sargan Lecture, Royal Econometric Society.

Stone, M. R., Yehoue, E. B., and Ishi, K. (2009). Unconventional Central Bank Measures for Emerging Economies. IMF Working Paper No 09/226, International Monetary Fund.

Tenreyro, S. and Thwaites, G. (2016). Pushing on a string: US monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74.

Toohey, D. (2017). The effectiveness of work-search requirements over the business cycle: evidence for job rationing. https://sites.google.com/site/desmondtoohey/ searchreqs170130.pdf.

Velasco, A. (1987). Financial crises and balance of payments crises : A simple model of the southern cone experience. *Journal of Development Economics*, 27(1-2):263–283.

West, K. D. and Newey, W. K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708.

Wieland, J. F. and Yang, M.-J. (2016). Financial Dampening. NBER Working Paper No. 22141, National Bureau of Economic Research, Inc.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.