

lpirfs: An R package to estimate impulse response functions by local projections

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Abstract Impulse response analysis is a cornerstone in applied (macro-)econometrics. Estimating impulse response functions by local projections (LP) has become an appealing alternative to the traditional SVAR approach, since LP impose less restrictions on the data generating process. Despite its growing popularity and applications, no R package yet existed which uses this method. In this paper, I introduce **lpirfs**, a fast and flexible R package that provides a broad framework to compute and visualize impulse response functions by LP for a variety of data sets.

Introduction

Since the seminal paper of Sims (1980), analysing economic time series by Vector Autor Regressive (VAR) models has become a main pillar in empirical macroeconomic analysis. VARs have been traditionally used to recover structural shocks in order to estimate their propagating effects on economic variables. This approach, however, has been criticized for several drawbacks such as the imposed dynamics on the (economic) system, the curse of dimensionality and the more difficult application to nonlinearities (Auerbach and Gorodnichenko, 2013).

Estimating impulse response functions by local projections (LP) have become an appealing alternative which is reflected in the approx. 900 citations of the pioneering paper by Òscar Jordà (2005). Instead of extrapolating the parameters into increasingly distant horizons from a given model, LP estimate the parameters sequentially at each point of interest. In general, LP offer three advantages over the traditional SVAR approach. First, LPs are easier to estimate as they solely rely on simple linear regressions. Second, the point or joint-wise inference is easily conducted, and third, impulse responses that are estimated by LP are more robust when a (linear) VAR is misspecified (Òscar Jordà, 2005). Although the latter argument has been questioned by Kilian and Kim (2011), a recent study shows equal and even better performance of LP when the lag lengths for each forecast horizon are adequately fixed (Brugnolini, 2018). One limitation of the LP approach is that the estimated LP coefficients can suffer from high variance, making the interpretation sometimes more difficult.

Since their introduction in 2005, LP have been broadly applied to, e.g., investigate the macroeconomic effects of oil price shocks (Hamilton, 2011), state-dependent government spending multipliers (Owyang et al., 2013; Auerbach and Gorodnichenko, 2012, 2013), the effects of monetary policy on financial markets and economic aggregates (Tenreyro and Thwaites, 2016; Swanson, 2017; Òscar Jordà et al., 2019), as well as the link between credit growth, monetary policy, house prices, and financial stability (Òscar Jordà et al., 2015; Favara and Imbs, 2015; Òscar Jordà and Taylor, 2016). Apart from the different research questions, these studies further differ regarding the data structures as they use panel and non-panel data.

Despite the increasing popularity and applications of LP, no R-package yet existed to estimate impulse responses by LP. The only exception is the code for the smooth local projection approach by Barnichon and Brownlees (2018), which allows reducing the variance of the LP parameters with a linear B-spline basis function. The code is partly available on GitHub and has been applied by Garín et al. (2016). The **vars** package by Pfaff (2008) only allows estimating impulse response functions that are based on the traditional SVAR approach.

As a remedy, this paper introduces **lpirfs**, a fast and flexible R package allowing to estimate and visualize impulse responses by LP for a variety of data sets. The first part of this paper outlines the theory of LP and the differences to the traditional SVAR approach. The second part shows how to apply the package and, among others, replicates empirical results from the economic literature.

The SVAR approach vs. local projections

A structural VAR (SVAR) with n variables can be written as

$$\begin{bmatrix} \beta_{11}^0 & \dots & \beta_{1n}^0 \\ \vdots & \ddots & \vdots \\ \beta_{n1}^0 & \dots & \beta_{nn}^0 \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_t = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} + \begin{bmatrix} \beta_{11}^1 & \dots & \beta_{1n}^1 \\ \vdots & \ddots & \vdots \\ \beta_{n1}^1 & \dots & \beta_{nn}^1 \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{t-1} + \dots + \begin{bmatrix} \beta_{11}^p & \dots & \beta_{1n}^p \\ \vdots & \ddots & \vdots \\ \beta_{n1}^p & \dots & \beta_{nn}^p \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}_{t-p} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}_t, \quad (1)$$

which more concisely becomes

$$\mathbf{B}_0 \mathbf{Y}_t = \boldsymbol{\alpha}_t + \mathbf{B}(\mathbf{L}) \mathbf{Y}_t + \boldsymbol{\varepsilon}_t. \quad (2)$$

The residuals $\boldsymbol{\varepsilon}_t$ are assumed to be white noise with zero mean.¹ This representation is appealing from an economic perspective as the structural shocks are contemporaneously uncorrelated and the variables have a contemporaneous impact on each other. The contemporaneous impact is measured by the square matrix \mathbf{B}_0 . However, estimating this SVAR without further assumptions is not possible because of the simultaneous identification problem. Merely assuming that the structural shocks are orthogonal does not fully identify the system.

The SVAR in reduced form (henceforth VAR) equals:

$$\mathbf{Y}_t = \tilde{\boldsymbol{\alpha}} + \tilde{\mathbf{B}}(\mathbf{L}) \mathbf{Y}_t + \mathbf{u}_t, \quad (3)$$

where

$$\tilde{\boldsymbol{\alpha}} = \mathbf{B}_0^{-1} \boldsymbol{\alpha}, \quad \tilde{\mathbf{B}}(\mathbf{L}) = \mathbf{B}_0^{-1} \mathbf{B}(\mathbf{L})$$

and

$$E[\mathbf{u}_t, \mathbf{u}_\tau'] = \begin{cases} \begin{bmatrix} \sigma_1^2 & \dots & \sigma_{1,n}^2 \\ \vdots & \ddots & \vdots \\ \sigma_{n,1} & \dots & \sigma_n^2 \end{bmatrix}, & \text{for } t = \tau \\ 0, & \text{else.} \end{cases}$$

The coefficient matrix $\tilde{\mathbf{B}}(\mathbf{L})$ is a nonlinear function of the contemporaneous parameter matrix \mathbf{B}_0 and the structural parameter matrix $\mathbf{B}(\mathbf{L})$. In contrast to the SVAR, the VAR residuals \mathbf{u}_t are contemporaneously correlated which impedes an unbiased economic interpretation. The reduced VAR residuals are assumed to be linked to the SVAR shocks by

$$\mathbf{u}_t = \mathbf{B}_0^{-1} \boldsymbol{\varepsilon}_t, \quad E[\mathbf{u}_t \mathbf{u}_t'] = \boldsymbol{\Sigma}_u = \mathbf{B}_0^{-1} \mathbf{B}_0^{-1'}.$$

Given that the covariance matrix of $\boldsymbol{\varepsilon}_t$ equals the identity matrix, one still has to impose $n(n-1)/2$ restrictions to estimate the structural form. The most general approach is to separate the residuals into orthogonal shocks by calculating a Choleski decomposition of the covariance matrix $\boldsymbol{\Sigma}_u$. The first variable in such a system responds to its own exogenous shock, the second variable to the first variable plus an exogenous shock to the second variable, and so on. Results thus depend on ordering (Keating, 1992). The Wold representation states that any covariance-stationary time series can be rewritten as a sum of present and past innovations. This theorem enables mapping the estimated VAR (p) coefficients recursively to the VMA(∞) coefficients (Brugnolini, 2018). Impulse response functions are estimated iteratively by rewriting the VAR(p) into its companion form, i.e., a VAR(1):

$$\hat{I}\hat{R}(0) = \mathbf{B}_0^{-1} \quad (4)$$

$$\hat{I}\hat{R}(1) = \boldsymbol{\Phi}^1 \mathbf{B}_0^{-1} \quad (5)$$

$$\hat{I}\hat{R}(2) = \boldsymbol{\Phi}^2 \mathbf{B}_0^{-1} \quad (6)$$

$$\vdots \quad (7)$$

where the matrix $\boldsymbol{\Phi}$ contains the coefficients of the VAR(1).

In his pioneering paper, Òscar Jordà (2005) proposes an alternative approach to estimate impulse

¹The assumption of *i.i.d.* innovations is common in applied work but can be relaxed (Kilian and Kim, 2011).

responses. His first step consists of OLS regressions for each forecast horizon:

$$\mathbf{y}_{t+h} = \boldsymbol{\alpha}^h + \mathbf{B}_1^h \mathbf{y}_{t-1} + \dots + \mathbf{B}_p^h \mathbf{y}_{t-p} + \mathbf{u}_{t+h}^h, \quad h = 0, 1, \dots, H-1, \quad (8)$$

where $\boldsymbol{\alpha}^h$ is a vector of constants, \mathbf{B}_i^h are parameter matrices for lag p and forecast horizon h . The vector \mathbf{u}_{t+h}^h are autocorrelated and/or heteroscedastic disturbances. The collection of all regressions of (8) are called local projections. The slope matrix \mathbf{B}_1^h can be interpreted as the response of \mathbf{y}_{t+h} to a reduced form shock in t (Kilian and Kim, 2011). Structural impulse responses are then estimated by:

$$\hat{IR}(t, h, \mathbf{d}_i) = \hat{\mathbf{B}}_1^h \mathbf{d}_i, \quad (9)$$

where $\mathbf{d}_i = \mathbf{B}_0^{-1}$. As in the SVAR approach, the shock matrix \mathbf{d}_i has to be identified from a linear VAR. The LP approach thus does not overcome the problem of identification. Given the serial correlation of \mathbf{u}_{t+h}^h , Óscar Jordà (2005) proposes to estimate robust standard errors by the approach of Newey and West (1987). **lpirfs** follows this suggestion and estimates standard errors with this methodology. The truncation parameter increases with the number of horizons h as suggested by Óscar Jordà (2005) and applied in Ramey and Zubairy (2018).

A great advantage of LP is their easy extension to nonlinear frameworks. The most simple approach to separate data into two regimes is a binary (dummy) approach. The drawback, however, is that it lowers the degrees of freedom. As a remedy, Auerbach and Gorodnichenko (2012) propose to compute state probabilities with a logistic function that allows using all observations for the estimations. **lpirfs** includes both approaches. The logistic function equals:

$$F(z_t) = \frac{e^{(-\gamma z_t)}}{(1 + e^{(-\gamma z_t)})}, \quad (10a)$$

$$var(z_t) = 1, E(z_t) = 0, \quad (10b)$$

where z_t is normalized so that $\gamma (> 0)$ is scale invariant. The value of γ has to be provided by the user. For example, if z_t corresponds to changes in the inflation rate at time t , an increase of z_t would lead to a decrease of $F(z_t)$. Values close to zero of $F(z_t)$ would thus indicate periods of high inflation rates. To obtain a normalized variable z_t , one can apply the filter by Hodrick and Prescott (1997) to a time series such as GDP (Auerbach and Gorodnichenko, 2013). The HP-filter is implemented in **lpirfs** as well and written with **Rcpp** to improve efficiency. To separate the data into two regimes, the endogenous variables are multiplied with the values of the transition function:

$$\begin{aligned} \text{Regime 1 } (R_1) : \mathbf{y}_{t-l} \cdot (1 - F(z_{t-1})), \quad l = 1, \dots, p, \\ \text{Regime 2 } (R_2) : \mathbf{y}_{t-l} \cdot F(z_{t-1}), \quad l = 1, \dots, p. \end{aligned} \quad (11)$$

Auerbach and Gorodnichenko (2012) use values of the transition function at $t-1$ which is the default in **lpirfs**. This option, however, can be suppressed. In case of a dummy approach, the values of $F(z_t)$ correspond to a binary variable (0/1), which has to be provided by the user. Structural nonlinear impulse responses are estimated by:

$$\begin{aligned} \hat{IR}^{R_1}(t, h, \mathbf{d}_i) &= \hat{\mathbf{B}}_{1,R_1}^h \mathbf{d}_i, \quad h = 0, \dots, H-1, \\ \hat{IR}^{R_2}(t, h, \mathbf{d}_i) &= \hat{\mathbf{B}}_{1,R_2}^h \mathbf{d}_i, \quad h = 0, \dots, H-1, \end{aligned} \quad (12)$$

where $\hat{\mathbf{B}}_{1,R_1}^0 = I$ and $\hat{\mathbf{B}}_{1,R_2}^0 = I$. The coefficient matrices $\hat{\mathbf{B}}_{1,R_1}^h$ and $\hat{\mathbf{B}}_{1,R_2}^h$ are obtained from the following local projections:

$$\begin{aligned} \mathbf{y}_{t+h} = \boldsymbol{\alpha}^h + \mathbf{B}_{1,R_1}^h (\mathbf{y}_{t-1} \cdot (1 - F(z_{t-1}))) + \dots + \mathbf{B}_{p,R_1}^h (\mathbf{y}_{t-p} \cdot (1 - F(z_{t-1}))) + \\ \mathbf{B}_{1,R_2}^h (\mathbf{y}_{t-1} \cdot F(z_{t-1})) + \dots + \mathbf{B}_{p,R_2}^h (\mathbf{y}_{t-p} \cdot F(z_{t-1})) + \mathbf{u}_{t+h}^h, \end{aligned} \quad (13)$$

with $h = 0, \dots, H-1$. This nonlinear approach has been used by, e.g., Ahmed and Cassou (2016) to investigate the impact of consumer confidence on durable goods during periods of economic expansions and recessions.

Estimating impulse responses with identified shock or by IV method

Beside the easy extension to nonlinear frameworks, another advantage of local projections is their flexible application to situations where an exogenous shock can be identified outside of a SVAR.

For example, [Ramey and Zubairy \(2018\)](#) construct a military news shock to investigate whether US government spending multipliers are higher during periods of economic slack or when interest rates are near the zero lower bound. Once an exogenous shock has been identified, impulse responses can be directly estimated by univariate OLS regressions:

$$y_{t+h} = \alpha^h + \beta_h \text{shock}_t + \phi x_t + u_{t+h}^h, \quad h = 0, 1, \dots, H-1, \quad (14)$$

where α^h denotes the regression's constant, x_t is a vector of control variables and shock_t is the identified shock variable. The coefficient β_h corresponds to the response of y at time $t+h$ to the shock variable (*shock*) at time t . The impulse responses are the sequence of all estimated β_h . As above, robust standard errors are estimated by the approach of [Newey and West \(1987\)](#). If the shock variable is endogenous, shock_t can be estimated by two-stage least squares (2SLS) regressions. In case of nonlinearities, the variables can either be multiplied with a dummy variable or with the values of the transition function in (11). **lpirfs** provides all outlined options.

Table 1 compares the inputs of four functions that allow to estimate impulse responses by LP. The first two functions (*lp_lin* and *lp_nl*) should be used when the shock has to be identified within the VAR. The other two functions (*lp_lin_iv* and *lp_nl_iv*) should be used when the shock is exogenous or when it shall be estimated by 2SLS.

Table 1: Comparison of linear and nonlinear LP functions.

Input name	Function names				Input description
	<i>lp_lin()</i>	<i>lp_nl()</i>	<i>lp_lin_iv()</i>	<i>lp_nl_iv()</i>	
endog_data	✓	✓	✓	✓	Data.frame with endogenous variables for VAR model.
shock	-	-	✓	✓	One column data.frame, including the identified shock.
use_2sols	-	-	✓	-	Option to estimate shock with 2SLS approach.
instrum	-	-	✓	-	Data.frame with the instrument(s) for the 2SLS approach.
lags_endog_lin	✓	✓	✓	-	Number of lags for linear model.
lags_endog_nl	-	✓	-	✓	Number of lags for nonlinear model (13).
lags_criterion	✓	✓	✓	✓	Choose lags based on information criterion (<i>AICc</i> , <i>AIC</i> or <i>BIC</i>)
max_lags	✓	✓	✓	✓	Maximum number of lags for information criteria.
trend	✓	✓	✓	✓	Options to include constant, trend and quadratic trend.
shock_type	✓	✓	-	-	Two types of shock: standard deviation or unit shock.
confint	✓	✓	✓	✓	Value for width of confidence bands.
hor	✓	✓	✓	✓	Number of horizons for impulse responses.
switching	-	✓	-	✓	Switching variable z_t . See (10b).
lag_switching	-	✓	-	✓	Option to lag the values of the logistic function $F(z_t)$. See (11).
use_logistic	-	✓	-	✓	Option to use logistic function. See (10a).
use_hp	-	✓	-	✓	Option to use filter by Hodrick and Prescott (1997) for z_t .
lambda	-	✓	-	✓	Value of lambda for HP-filter. See Ravn and Uhlig (2002) .
gamma	-	✓	-	✓	Value of gamma. See (10a).
exog_data	✓	✓	✓	✓	Optional data for exogenous variables.
lags_exog	✓	✓	✓	✓	Number of lags for exogenous variables.
contemp_data	✓	✓	✓	✓	Variables with contemporaneous impact.
num_cores	✓	✓	✓	✓	Option to choose number of cores.

The table compares the options for *lp_lin*, *lp_nl*, *lp_lin_iv*, and *lp_nl_iv*. The symbol ✓ indicates whether the option, denoted by row, is available for the function, denoted by column. The functions estimate linear and nonlinear impulse responses for models where the structural shocks are identified within a VAR (*lp_lin* and *lp_nl*) as well as for models where the structural shock can be identified externally (*lp_lin_iv* and *lp_nl_iv*). The possible lag length criteria are by [Hurvich and Tsai \(1989\)](#), [Akaike \(1974\)](#) and [Schwarz \(1978\)](#).

Extension to estimate impulse responses for panel data

Another advantage of LP is that they can be used for panel data as well. Estimating impulse responses based on panel data has been put forward by, e.g., [Auerbach and Gorodnichenko \(2013\)](#), [Owyang et al. \(2013\)](#) and [Òscar Jordà et al. \(2015\)](#). The general equation for panel data is:

$$y_{i,t+h} = \alpha_{i,h} + \text{shock}_{i,t} \beta_h + x_{i,t} \gamma_h + \varepsilon_{i,t+h}, \quad h = 0, 1, \dots, H-1, \quad (15)$$

where $\alpha_{i,h}$ denotes (cross-section) fixed effect, $x_{i,t}$ is a vector of control variables, and $\text{shock}_{i,t}$ denotes the identified shock variable. Besides using absolute values of y_t , **lpirfs** also allows estimating cumulative impulse responses by using $(y_{i,t+h} - y_{i,t-1})$ as endogenous variable. This is commonly done for panel data (see, e.g., [Òscar Jordà et al. \(2015\)](#)). Similar to the univariate approach, $\text{shock}_{i,t}$ can also be first estimated by an IV approach (see, e.g., [Òscar Jordà et al., 2019](#)). To estimate the parameters, **lpirfs** uses the well established **plm** package by [Croissant and Millo \(2008\)](#), which also allows including, among others, time effects. In addition, **lpirfs** includes the possibility to estimate a variety of clustered and robust standard errors as outlined in [Millo \(2017\)](#). The importance of robust

standard errors in the context of corporate finance and asset pricing has been shown by [Petersen \(2009\)](#).

The function `lp_nl_panel` allows estimating nonlinear impulse responses for panel data. The options for separating the data into two states are identical to the other two nonlinear functions. More precisely, the data can be separated by a simple binary variable (0/1) or by the logistic function in (10). For transparency and further analyses, the panel functions in **lpirfs** return the data sets that are used for each estimation step. The list is named `xy_data_sets`.

R implementation

In this section I apply the functions of **lpirfs** to three different settings. The impulse responses are built and visualized with the functions `plot_lin` and `plot_nl` for linear and nonlinear impulse responses, respectively. Two exercises replicate empirical results by [Òscar Jordà \(2005\)](#) and [Ramey and Zubairy \(2018\)](#). The data sets are included in **lpirfs** as well.

The third example uses the external *Jordà-Schularick-Taylor Macroeconomic Database* which covers 17 advanced economies since 1870 on an annual basis and comprises 25 real and nominal variables. I estimate how an increase in the interest rate affects mortgage lending. This example is based on a STATA code provided on [Òscar Jordà's website](#). Due to copyright issues, the database could not be included in the package. However, I show how the data can be easily downloaded with R.

Traditional approach: replicating results by Jordà (2005)

lpirfs provides two functions to estimate linear (`lp_lin`) and nonlinear (`lp_nl`) impulse responses when the shocks have to be identified first. Based on [Òscar Jordà \(2005\)](#), **lpirfs** uses a recursive scheme to identify the shocks. The following code replicates parts of Figure 5 in [Òscar Jordà \(2005\)](#) on page 176. It shows how the GDP gap, inflation rate and the Federal Funds rate react to the corresponding structural shocks. The results are shown in Figure 1. Note that the first horizon, denoted on the x-axis, equals $h = 0$, i.e., the contemporaneous impact of the shock. This follows the convention by [Òscar Jordà \(2005\)](#). To visualize the impulse responses in one figure, I use the packages **ggpubr** and **gridExtra**. To reduce dependencies, **lpirfs** does not import them automatically.

```
--- Code to replicate Figure 5 in Jordà (2005)

# Load packages
> library(lpirfs)
> library(ggpubr)
> library(gridExtra)

# Load data set
> endog_data <- interest_rules_var_data

# Estimate linear model
> results_lin <- lp_lin(endog_data = endog_data, lags_endog_lin = 4, trend = 0,
                        shock_type = 1, confint = 1.96, hor = 12)

# Create plots
> linear_plots <- plot_lin(results_lin)

# Show impulse responses
> lin_plots_all <- sapply(linear_plots, ggplotGrob)
> marrangeGrob(lin_plots_all, nrow = ncol(endog_data),
               ncol = ncol(endog_data), top = NULL)

--- End example code
```

The example above only estimates impulse responses for the linear case, but [Òscar Jordà \(2005\)](#) also tests for nonlinearities. Although he finds no “business-cycle” asymmetries, he identifies significant asymmetries for several lags of both inflation and the Federal Funds rate. The following code uses a dummy approach to estimate the nonlinear impulse responses of the variables to a shock in the Federal Funds rate. [Òscar Jordà \(2005\)](#) uses a threshold value of 4.75 percent for the inflation rate, applied to its third lag. Figure 2 shows empirical results for the nonlinear example. The results are

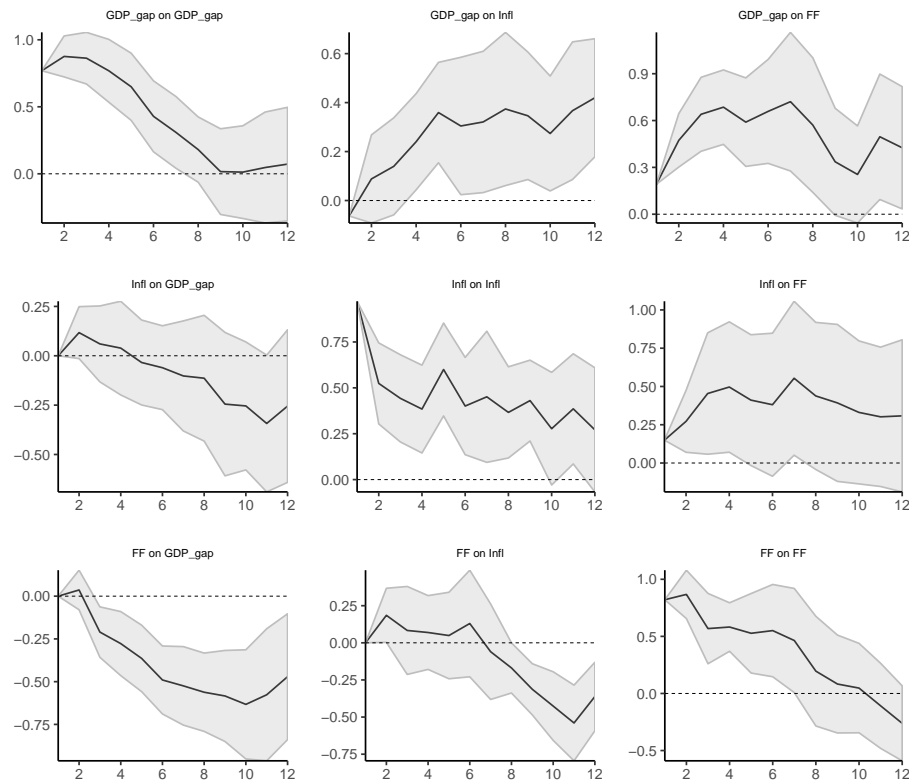


Figure 1: Replication of Figure 5 in Óscar Jordà (2005)

comparable to the findings by Óscar Jordà (2005), namely that the magnitudes of responses of inflation and output to interest rates are more responsive in the low-inflation regime (left panel) than in the high-inflation regime (right panel).

--- Code for nonlinear effects of Federal Funds rate. Based on Jordà (2005)

```
# Create dummy: apply threshold of 4.75 percent to the third lag of the inflation rate
< switching_data <- if_else(dplyr::lag(endog_data$Infl, 3) > 4.75, 1, 0)
```

```
# Estimate nonlinear model
< results_nl <- lp_nl(endog_data,
  <               lags_endog_lin = 4,           lags_endog_nl = 4,
  <               trend          = 1,           shock_type   = 0,
  <               confint        = 1.67,        hor           = 12,
  <               switching      = switching_data, lag_switching = FALSE,
  <               use_logistic   = FALSE)
```

```
# Create nonlinear impulse responses
< nl_plots <- plot_nl(results_nl)
```

```
# Combine and show plots by using 'ggpubr' and 'gridExtra'
< single_plots <- nl_plots$gg_s1[c(3, 6, 9)]
< single_plots[4:6] <- nl_plots$gg_s2[c(3, 6, 9)]
< all_plots <- sapply(single_plots, ggplotGrob)
< marrangeGrob(all_plots, nrow = 3, ncol = 2, top = NULL)
```

--- End example code

Using external shock: replicating results by Ramey and Zubairy (2018)

lpirfs contains two functions to estimate linear (*lp_lin_iv*) and nonlinear (*lp_nl_iv*) impulse responses

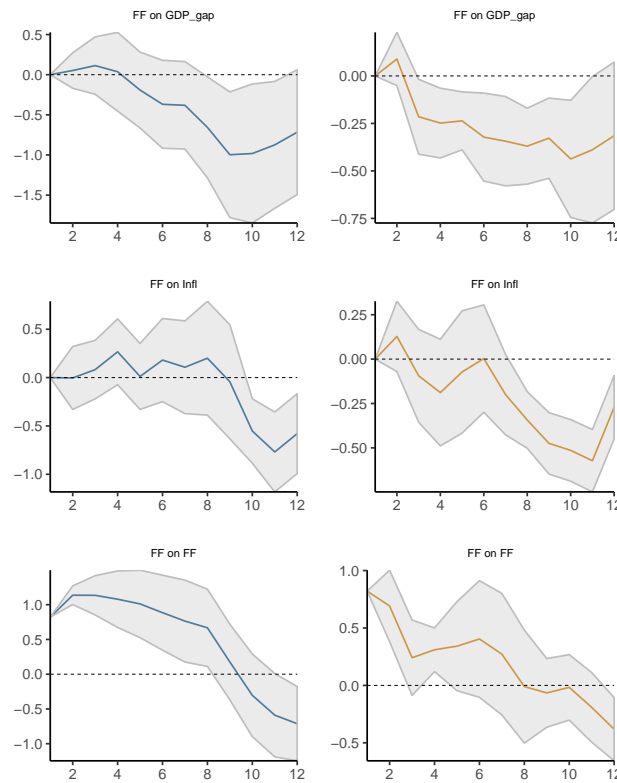


Figure 2: Nonlinear impulse responses based on Òscar Jordà (2005)

The figure depicts nonlinear impulse responses of the GDP gap, inflation rate and the Federal Funds rate to a shock in the Federal Funds rate during periods of low (left panel) and high (right panel) inflation rates. The threshold of 4.75 is applied to the third lag of the inflation rate.

when a shock is identified outside of a VAR. In this section, I replicate empirical results by Ramey and Zubairy (2018). Among others, the authors re-evaluate findings by Auerbach and Gorodnichenko (2012), who argue that government spending multipliers are more pronounced during economic recessions than during economic expansions. Auerbach and Gorodnichenko (2012) apply a smooth transition VAR (STVAR) to estimate state-dependent fiscal multipliers. Ramey and Zubairy (2018), however, show that the estimated fiscal multipliers are much smaller when the impulse responses are estimated by LP. The reason is that the local projection approach does not assume that the system remains in a fixed regime once it has entered it.

The following code replicates parts of Figure 12 on page 35 in the supplementary appendix by Ramey and Zubairy (2018). The results are depicted in Figure 3. It shows how government spending and GDP react to a government spending shock in the linear case as well as during periods of economic expansions and recessions. The linear shock is identified according to Blanchard and Perotti (2002). The absolute values of the figures differ because Ramey and Zubairy (2018) have multiplied the log output response by a conversion factor of 5.6.

```
--- Code to replicate parts of Figure 12 in the supplementary appendix by
--- Ramey and Zubairy (2018)
```

```
# Load data from package
< ag_data      <- ag_data
< sample_start <- 7
< sample_end   <- dim(ag_data)[1]

# Endogenous data
< endog_data <- ag_data[sample_start:sample_end, 3:5]

# Shock variable
< shock      <- ag_data[sample_start:sample_end, 3]
```



```

# Estimate linear model
< results_lin_iv <- lp_lin_iv(endog_data = endog_data, lags_endog_lin = 4,
                             shock      = shock,      trend      = 0,
                             confint    = 1.96,        hor         = 20)

# Make and save linear plots
< iv_lin_plots <- plot_lin(results_lin_iv)

# Nonlinear shock (estimated by Ramey and Zubairy (2018))
< shock <- ag_data[sample_start:sample_end, 7]

# Use moving average growth rate of GDP as exogenous variables
< exog_data <- ag_data[sample_start:sample_end, 6]

# Use moving average growth rate of GDP as switching variable
< switching_variable <- ag_data$GDP_MA[sample_start:sample_end] - 0.8

# Estimate nonlinear model
< results_nl_iv <- lp_nl_iv(endog_data = endog_data, lags_endog_nl = 3,
<                          shock      = shock,      exog_data      = exog_data,
<                          lags_exog   = 4,          trend          = 0,
<                          confint    = 1.96,        hor            = 20,
<                          switching   = switching_variable, use_hp    = FALSE,
<                          gamma      = 3)

# Make and save nonlinear plots
< plots_nl_iv <- plot_nl(results_nl_iv)

# Make list to save all plots
< combine_plots <- list()

# Save linear plots in list
< combine_plots[[1]] <- iv_lin_plots[[1]]
< combine_plots[[2]] <- iv_lin_plots[[3]]

# Save nonlinear plots for expansion period
< combine_plots[[3]] <- plots_nl_iv$gg_s1[[1]]
< combine_plots[[4]] <- plots_nl_iv$gg_s1[[3]]

# Save nonlinear plots for recession period
< combine_plots[[5]] <- plots_nl_iv$gg_s2[[1]]
< combine_plots[[6]] <- plots_nl_iv$gg_s2[[3]]

# Show all plots
< lin_plots_all <- sapply(combine_plots, ggplotGrob)
< marrangeGrob(lin_plots_all, nrow = 2, ncol = 3, top = NULL)

--- End example code

```

Estimating impulse responses for panel data

To estimate impulse response functions for panel data, **lpirfs** relies on the well established *R* package **plm** by Croissant and Millo (2008). Because of this dependency, the panel functions in **lpirfs** work slightly different than the other four functions outlined in Sections 2.2 and 2.2.1. Instead of providing the endogenous and exogenous variables separately, the user has to provide the entire panel data set first and then specify the column names of the endogenous and exogenous variables. The default is to estimate the panel model with fixed effects. However, all options available for the **plm**-package, such as time effects, are also available for **lpirfs**.

The following code estimates impulse responses of the ratio of mortgage lending divided by GDP to a +1% change in the short term interest rate. To do so, it uses the *Jordà-Schularick-Taylor Macrohistory*

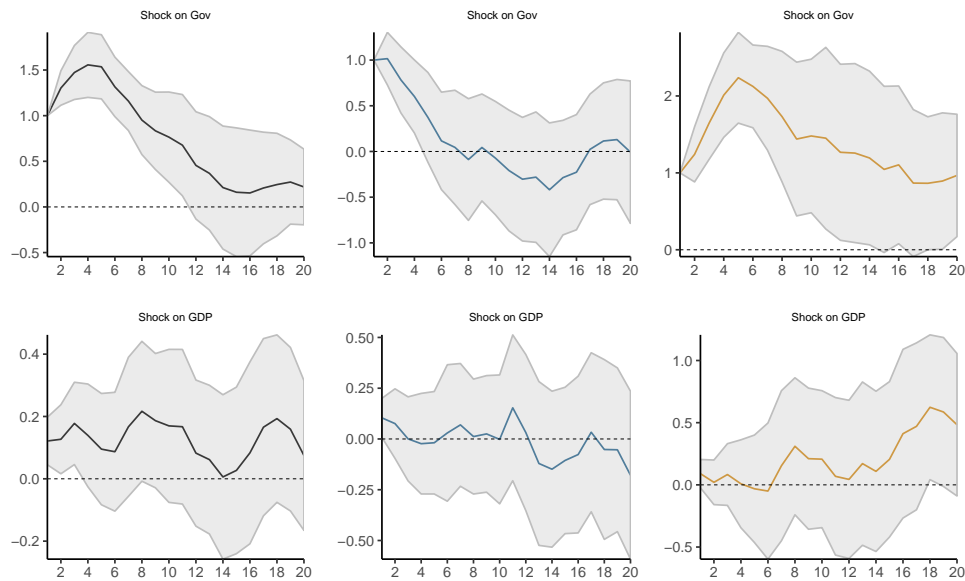


Figure 3: The figure replicates empirical results of Figure 12 from the supplementary appendix by [Ramey and Zubairy \(2018\)](#). The left panel shows the (linear) reaction of government spending (first row) and GDP (second row) to a government spending shock. The middle panel shows the reactions during periods of economic expansion and the right panel during periods of economic slack.

Database. Observations during the two world wars and observations after 2013 are excluded.² The empirical results are shown in Figure 4. It can be seen that an increase in the short term interest rate leads to a decrease in the mortgage lending rate whose effect attenuates after approximately 8 years.

```
#--- Begin code for panel data

# Load libraries to download and read excel file from the website
< library(httr)
< library(readxl)
< library(dplyr)

# Retrieve the external JST Macrohistory Database
< url_jst <- "http://www.macrohistory.net/JST/JSTdatasetR3.xlsx"
< GET(url_jst, write_disk(jst_link <- tempfile(fileext = ".xlsx")))
< jst_data <- read_excel(jst_link, 2L)

# Remove observations after 2013 and swap the first two columns
< jst_data <- jst_data %>%
<   dplyr::filter(year <= 2013) %>%
<   dplyr::select(country, year, everything())

# Prepare variables
< data_set <- jst_data %>%
<   mutate(stir = stir) %>%
<   mutate(mortgdp = 100*(tmort/gdp)) %>%
<   mutate(hpreal = hpnom/cpi) %>%
<   group_by(country) %>%
<   mutate(hpreal = hpreal/hpreal[year==1990][1]) %>%
<   mutate(lhpreal = log(hpreal)) %>%

<   mutate(lhpy = lhpreal - log(rgdppc)) %>%
<   mutate(lhpy = lhpy - lhpy[year == 1990][1]) %>%
<   mutate(lhpreal = 100*lhpreal) %>%
<   mutate(lhpy = 100*lhpy) %>%
```

²**lpirfs** first computes all lags and lags of first differences of the exogenous data. If the user wants to use a sub-sample (see example), the observations will be dropped after the lags have been constructed.

```

<      ungroup()                                %>%

<      mutate(lrgdp = 100*log(rgdppc))          %>%
<      mutate(lcpi = 100*log(cpi))              %>%
<      mutate(lriy = 100*log(iy*rgdppc))        %>%
<      mutate(cay = 100*(ca/gdp))               %>%
<      mutate(tnmort = tloans - tmort)          %>%
<      mutate(nmortgdp = 100*(tnmort/gdp))      %>%
<      dplyr::select(country, year, mortgdp, stir, ltrate,
<                      lhpy, lrgdp, lcpi, lriy, cay, nmortgdp)

# Exclude observations from WWI and WWII
< data_sample <- seq(1870, 2016)[which(!(seq(1870, 2016) %in%
<                                     c(seq(1914, 1918),
<                                     seq(1939, 1947)))]

# Estimate linear panel model
< results_panel <- lp_lin_panel(data_set = data_set, data_sample = data_sample,
<                               endog_data = "mortgdp", cumul_mult = TRUE,
<                               shock = "stir", diff_shock = TRUE,
<                               panel_model = "within", panel_effect = "individual",
<                               robust_cov = "vcovSCC", c_exog_data = "cay",
<                               c_fd_exog_data = colnames(data_set)[c(seq(4,9),11)],
<                               l_fd_exog_data = colnames(data_set)[c(seq(3,9),11)],
<                               lags_fd_exog_data = 2, confint = 1.67,
<                               hor = 10)

# Create and plot irfs
< plot_lin_panel <- plot_lin(results_panel)
< plot(plot_lin_panel[[1]])

#--- End example

```

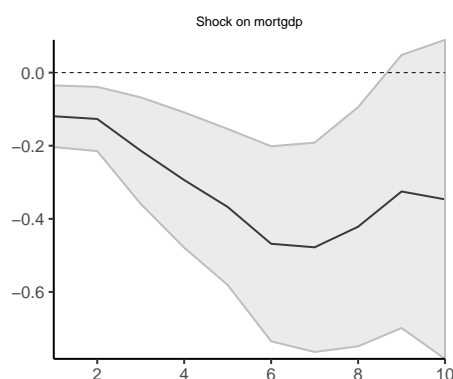


Figure 4: The figure shows the reaction of the ratio of mortgage lending divided by GDP to a +1% change in the short term interest rate.

Nonlinear impulse responses for panel data can be estimated with the function *lp_nl_panel*. The following example uses the Hodrick-Prescott filter to decompose the log-GDP time series for each country to obtain the variable z_t for the logistic function in (10). Figure 5 shows the impulse responses for both regimes. The mortgage lending ratio declines in both regimes, although more pronounced during periods of economic expansions (left panel) than during periods of economic slack (left panel).

--- Begin example

```

# Estimate panel model
< results_panel <- lp_nl_panel(data_set = data_set, data_sample = data_sample,

```

```

<          endog_data      = "mortgdp", cumul_mult  = TRUE,
<          shock           = "stir",   diff_shock   = TRUE,
<          panel_model     = "within", panel_effect  = "individual",
<          robust_cov      = "vcovSCC", switching   = "lrgdp",
<          lag_switching   = TRUE,      use_hp      = TRUE,
<          lambda          = 6.25,      gamma       = 10,
<          c_exog_data     = "cay",
<          c_fd_exog_data  = colnames(data_set)[c(seq(4,9),11)],
<          l_fd_exog_data  = colnames(data_set)[c(seq(3,9),11)],
<          lags_fd_exog_data = 2,
<          confint         = 1.67,
<          hor             = 10)

```

```

# Create and show linear plots
< nl_plots      <- plot_nl(results_panel)
< combine_plots <- list(nl_plots$gg_s1[[1]], nl_plots$gg_s2[[1]])
< marrangeGrob(combine_plots, nrow = 1, ncol = 2, top = NULL)

```

--- End example

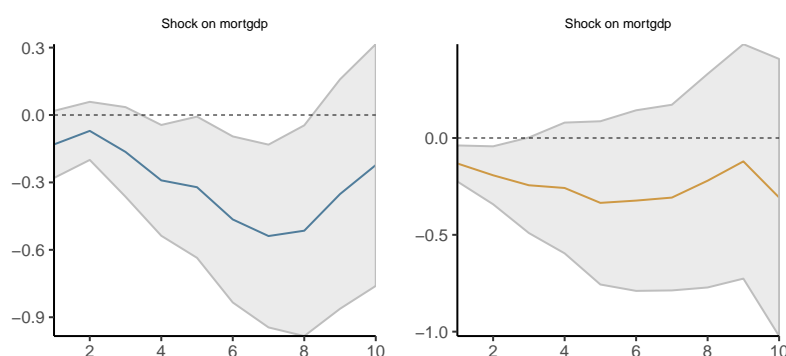


Figure 5: The figure shows the reaction of the ratio of mortgage lending divided by GDP to a +1% change in the short term interest rate during periods of economic expansions (left panel) and economic slack (right panel).

Summary

Since the 1980s, impulse response analysis has become a cornerstone in (macro-)econometrics. The traditional approach of recovering the impulse responses recursively from a (linear) VAR has been criticized due to several drawbacks such as the imposed dynamics on the (economic) system, the curse of dimensionality and the more difficult application to nonlinear frameworks.

Local projections (LP) by [Òscar Jordà \(2005\)](#) offer an appealing alternative to estimate impulse response functions as they, e.g., relax the assumptions on the data generating process. This paper has introduced **lpirfs**, an R-package that provides a broad framework for estimating and visualizing impulse response functions by LP for a variety of data sets. I replicated empirical results from the economic literature to prove the validity of the package and to show its usefulness for future research.

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