# Measuring Fiscal Policy Spillovers using Mixed-Frequency Data

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**Abstract**

(Note: I may change the scope of the paper to focus primarily on the effect of fiscal policy on exchange rates and interest rates, since this seems like the context in which mixed-frequency data would have the most relevance.)

## 1 Background

The aim of this paper is to use a mixed-frequency data set to measure the short-run (or high-frequency) impact of U.S fiscal shocks on some of its trading partners. The primary contribution I make to the existing literature is in the use of both monthly and quarterly data to measure fiscal policy spillovers, thereby exploiting information that is not available in single-frequency datasets.

Since the Great Recession there has been a resurgence of research on the effects of fiscal policy, and while most of the discussion has focused on the domestic-economy effects, it is also important to understand the international dimensions of a change in domestic fiscal policy. Some of the relevant questions include: Do other countries benefit or suffer from an expansion or contraction in U.S. government spending? Is some of the potential benefit of fiscal expansion lost through trade and financial flows? Do spillovers effects manifest primarily through trade flows or through financial flows? Indeed, some of these questions have been addressed — both empirically and theoretically — in my own work (Nicar (2015)) and other recent papers,

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including Auerbach and Gorodnichenko (2013), Auerbach and Gorodnichenko (2016), Cook and Devereux (2011b), Cook and Devereux (2011a), Corsetti et al. (2010), de Castro and Garrote (2015), Faccini et al. (2015), Fujiwara and Ueda (2013). There is also work that reflects issues predating the recession; the “twin-deficits” hypothesis, for example, that relates current account deficits to government budget deficits (Kim and Roubini (2008) and Boileau and Normandin (2012)) or the advent of the euro and the resulting common monetary policy (Beetsma et al. (2006) and Giuliodori and Beetsma (2005)).

As the primary focus of this paper (for now) is empirical, I will briefly outline the conclusions that emerge from prior empirical work. Most of the papers in this area look at the effects of U.S. fiscal shocks on an aggregate of other countries, typically large trading partners of the U.S., with the response variables of interest including the real exchange rate, the trade balance or current account, domestic and foreign real interest rates or interest-rate differentials, and sometimes foreign GDP. Faccini et al. (2015), de Castro and Garrote (2015), Enders et al. (2011), Monacelli and Perotti (2010), Kim and Roubini (2008) and Ravn et al. (2007) all find that increases in U.S. government spending or the primary budget deficit lead to a U.S. real exchange rate depreciation. Enders et al. (2011) and Corsetti and Müller (2006) also find that spending shocks decrease the terms of trade. Kim and Roubini (2008) and Corsetti and Müller (2006) find that increases in the primary deficit have a small but positive effect on the current account or trade balance, while Monacelli and Perotti (2010) and García-Solanes et al. (2011) find a negative effect on the trade balance. Boileau and Normandin (2012), in a multi-country study including the U.S., find that U.S. tax cuts increase the external deficit.

A few papers have focused on the bilateral effects of U.S. fiscal policy shocks. In Nicar (2015), I found that the response to U.S. fiscal shocks was not uniform across countries: while positive U.S. spending shocks had positive effects on foreign GDP, and resulted in a negative response of the short-term interest rate differential across countries (resulting most likely from a rise in the short-term U.S. real interest rate), the short-run response of the trade balance and the real exchange rate varied across countries (eventually resulting, however, in an improvement in the U.S. trade balance and an appreciation of the U.S. real exchange rate). My results were consistent with those of Arin and Koray (2009), who used a different identification methodology and only looked at the effect on Canada. Canzoneri et al. (2003) also found that expansionary U.S. fiscal shocks had positive effects on foreign GDP and led to a real depreciation of the *foreign* currency.

## 2 Methodology

A common element in all of the studies mentioned above is their reliance on data sampled at a single frequency — almost exclusively quarterly.[1] Many of the variables of interest, however, are available at higher frequency (particularly the financial variables, though some trade data is available monthly). The usual approach is to aggregate, through simple averaging or the use of end-of-period values, the monthly or daily variables to match the quarterly availability of GDP, government spending, and tax data. In doing so, it is clear that the researcher is throwing away some of the information contained in the high-frequency variables. Ghysels (2016), in both a numerical simulation and an empirical example, demonstrates that aggregating high-frequency data can indeed lead to quite different impulse responses than those estimated using a mixed-frequency vector autoregression model (VAR).[2] Whether the information that is being discarded is important for understanding the nature and dynamics of fiscal policy spillovers is an empirical question, one which I aim to answer by making use of a mixed-frequency sample in my analysis.

While there are several ways one can incorporate mixed-frequency data in an empirical analysis, I will be following the approach of Ghysels (2016), which extends the univariate mixed-data sampling (MIDAS) approach of Andreou et al. (2010) to a VAR. [Future draft will include more discussion of alternative approaches.]

[1]The exception is Auerbach and Gorodnichenko (2016), which makes use of daily data.

[2]The empirical example estimates the effect of shocks to monthly U.S. industrial production, inflation, and unemployment on quarterly real GDP. Compared to a VAR where all data are at quarterly frequency, he finds that shocks to industrial production and inflation have a smaller immediate effect on GDP which also dies out more quickly. For unemployment shocks, however, the low- and mixed-frequency VARs largely agree.

## 2.1 The empirical model

For reasons of both tractability and data availability, I am using in my analysis quarterly and monthly data for the U.S, Canada, France, Germany, Japan, and the U.K. The time period covered is the post-Bretton Woods period from 1975 to 2015 and the response variables I am interested in are the real exchange rate, the trade balance, real interest rates, and real GDP.

The $K$ endogenous variables in the VAR are comprised of $K_L$ low-frequency (quarterly) variables and $K_H$ high-frequency (monthly) variables, so that $K_L + K_H = K$. Using Ghysels (2016)'s notation,

- the low-frequency period is denoted $\tau_L$,
- within $\tau_L$, there are $k_H = 1, \ldots, m$ high-frequency periods
- observations on the low-frequency variables at time $\tau_L$ are denoted $x_L(\tau_L)$
- observations on the high-frequency variables within $\tau_L$ are denoted $x_H(\tau_L, k_H)$

Accordingly, the expression for a MIDAS-VAR with $P$ lags is:

$$x(\tau_L) = A_0 + \sum_{j=1}^{P} A_j \, x(\tau_L - j) + \varepsilon(\tau_L), \tag{1}$$

where

$$x(\tau_L) = \begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix}.$$

The difference in frequencies is accommodated by treating each high-frequency variable measured at each within-$\tau_L$ period as a separate endogenous variable; if the low-frequency variable is observed after all of the high-frequency variables, the observations on the high-frequency variables are stacked before the observations on the low-frequency variables.

For purposes of illustration, assume $K_L = K_H = 1$, with quarterly and monthly data and the quarterly variable is observed in the last month of the quarter. With one (quarterly) lag, $P = 1$ and $m = 3$ and the system of equations in the VAR looks like:

$$\begin{bmatrix} x_H(\tau_L, 1) \\ x_H(\tau_L, 2) \\ x_H(\tau_L, 3) \\ x_L(\tau_L) \end{bmatrix} = \begin{bmatrix} a_0^1 \\ a_0^2 \\ a_0^3 \\ a_0^4 \end{bmatrix} + \begin{bmatrix} a_1^{11} & a_1^{12} & a_1^{13} & a_1^{14} \\ a_1^{21} & a_1^{22} & a_1^{23} & a_1^{24} \\ a_1^{31} & a_1^{32} & a_1^{33} & a_1^{34} \\ a_1^{41} & a_1^{42} & a_1^{43} & a_1^{44} \end{bmatrix} \begin{bmatrix} x_H(\tau_L - 1, 1) \\ x_H(\tau_L - 1, 2) \\ x_H(\tau_L - 1, 3) \\ x_L(\tau_L - 1) \end{bmatrix} + \begin{bmatrix} \varepsilon(\tau_L)^1 \\ \varepsilon(\tau_L)^2 \\ \varepsilon(\tau_L)^3 \\ \varepsilon(\tau_L)^4 \end{bmatrix}.$$

The last equation in this system (which represents the low-frequency variable) is the same as the ADL MIDAS regression model discussed in Andreou, Ghysels, and Kourtellos (2010):

$$x_L(\tau_L) = a_0^{m+1} + a_1^{m+1,m+1} x_L(\tau_L - 1) + \sum_{k=1}^{m} a_1^{m+1,k} x_H(\tau_L - 1, k) + \varepsilon(\tau_L)^{m+1}. \tag{2}$$

A MIDAS-VAR model extends this by adding the initial three equations to the system: these represent the high-frequency variable at each month, and allow one to estimate the high-frequency effect of shocks to the low-frequency variable. Conveniently for the type of question I am analyzing here, this is precisely what I would like to do.

## 2.2 Estimation

VAR models in general, and MIDAS-VAR models in particular suffer from a a large number of parameters which can create problems for estimation. In univariate MIDAS models this issue is often dealt with using distributed lag polynomials (essentially a set of non-linear restrictions on the relationship between regression parameters), and Ghysels (2016) discusses an estimation strategy using this approach for MIDAS-VARS. As Foroni et al. (2015) show, however, for small differences in sampling frequency (e.g., quarterly and monthly) an unrestricted approach can outperform the MIDAS polynomial approach in forecast accuracy (not really relevant for my purposes) and is simpler to estimate (which is relevant for this study). The estimation approach is Bayesian, and described in more detail below.

The general expression for a mixed frequency VAR with $P$ low-frequency lags is:

$$\begin{bmatrix} x_H(\tau_L, 1) \\ \vdots \\ x_H(\tau_L, m) \\ x_L(\tau_L) \end{bmatrix} = A_0 + \sum_{j=1}^{P} \begin{bmatrix} A_j^{1,1} & \cdots & A_j^{1,m} & A_j^{1,m+1} \\ \vdots & \ddots & \vdots & \vdots \\ A_j^{m,1} & \cdots & A_j^{m,m} & A_j^{m,m+1} \\ A_j^{m+1,1} & \cdots & A_j^{m+1,m} & A_j^{m+1,m+1} \end{bmatrix} \begin{bmatrix} x_H(\tau_L - j, 1) \\ \vdots \\ x_H(\tau_L - j, m) \\ x_L(\tau_L - j) \end{bmatrix} + \varepsilon(\tau_L)$$

Each $A_j^{a,b}$ is (possibly) a sub-matrix:

- For $a \leq m$ and $b \leq m$, $A_j^{a,b}$ is $(K_H \times K_H)$
- For $a \leq m$ and $b = m + 1$, $A_j^{a,b}$ is $(K_H \times K_L)$
- For $a = m + 1$ and $b \leq m + 1$, $A_j^{a,b}$ is $(K_L \times K_H)$
- For $a = m + 1$ and $b = m + 1$, $A_j^{a,b}$ is $(K_L \times K_L)$

I use an Independent Normal-Wishart prior for the parameters, with the hyperparameters specified as follows. I refer to the first $mK_H$ equations as the "high-frequency" block and the remaining $K_L$ equations as the "low-frequency" block.

**High-Frequency Block**:

Assume the high-frequency variables follow an AR(1) process. The hyperparameter $\lambda$ governs the overall tightness of the prior distributions around specification for the high frequency process. [Prior specification is a work in progress and may change . . . ]

- For $a = 1, \ldots, m$ and $b = 1, \ldots, m - 1$ and $j = 1, \ldots, P$:

$$\mathbb{E}[A_j^{a,b}] = \mathbf{0}_{(K_H \times K_H)}$$
$$\mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[(j-1)m + (m - b + a)]^2} \mathbf{1}_{(K_H \times K_H)}$$

- For $a = 1, \ldots, m$ and $b = m$:

$$\mathbb{E}[A_j^{a,b}] = diag(\rho_H^a)_{(K_H \times K_H)} \qquad j = 1$$
$$\mathbb{E}[A_j^{a,b}] = \mathbf{0}_{(K_H \times K_H)} \qquad j = 2, \ldots, P$$
$$\mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[(j-1)m + a]^2} \mathbf{1}_{(K_H \times K_H)} \qquad j = 1, \ldots, P$$

- For $a = 1, \ldots, m$ and $b = m + 1$ and $j = 1, \ldots, P$:

$$\mathbb{E}[A_j^{a,b}] = \mathbf{0}_{(K_H \times K_L)}$$
$$\mathbb{V}[A_j^{a,b}] = \vartheta_{HL} \frac{\lambda^2}{[(j-1)m + a]^2} \mathbb{S}_{HL}$$

$\vartheta \in (0, 1)$ and $\mathbb{S}_{HL} = [\sigma_{iH}^2 / \sigma_{jL}^2;\ i = 1, \ldots, K_H,\ j = 1, \ldots, K_L]$. The hyperparameter $\vartheta$ governs the extent to which the low-frequency data affect high-frequency data and $\mathbb{S}_{HL}$ captures the difference in scaling between high- and low-frequency data.

**Low-Frequency Block**:

- For $a = m + 1$ and $b = 1, \ldots, m$ and $j = 1, \ldots, P$

$$\mathbb{E}[A_j^{a,b}] = \mathbf{0}_{(K_L \times K_H)}$$
$$\mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{[(j-1)m + (m - b + 1)]^2} \mathbf{1}_{(K_L \times K_H)}$$

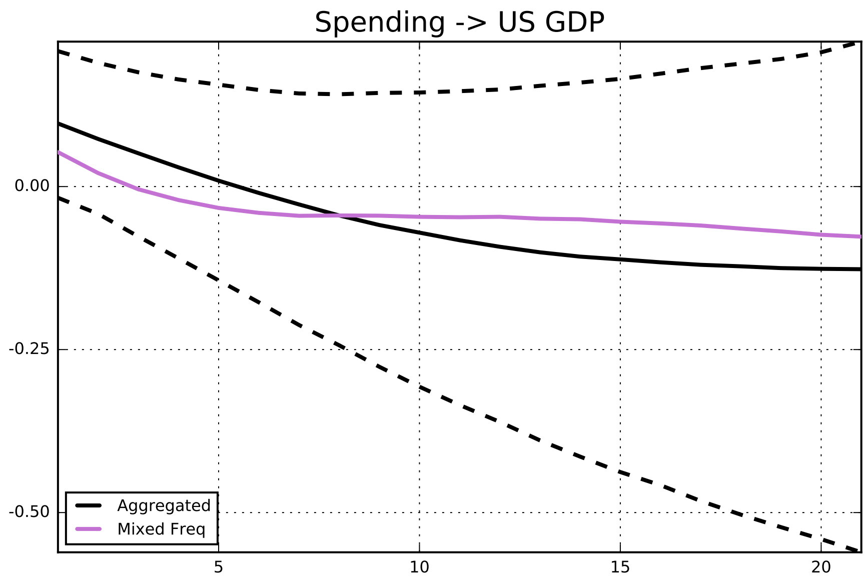
- For $a = m + 1$ and $b = m + 1$ and $j = 1$:

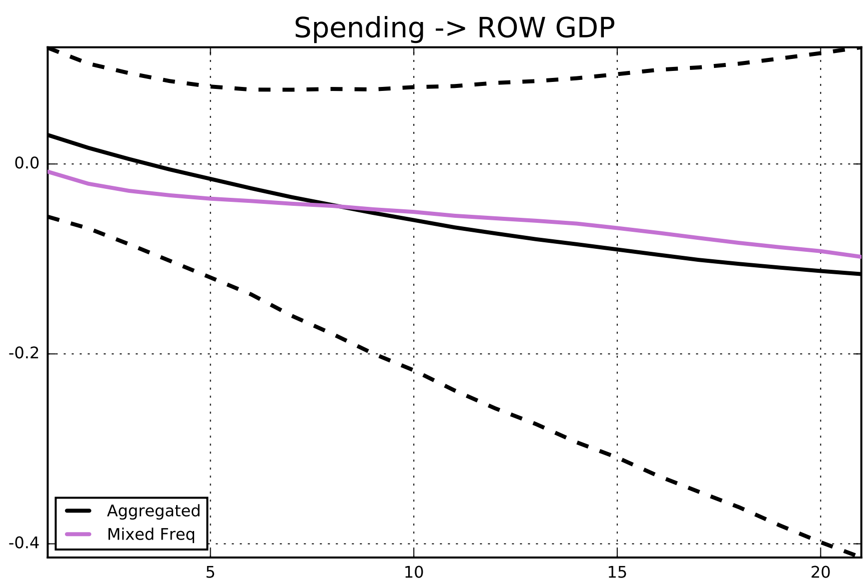
$$\mathbb{E}[A_j^{a,b}] = diag(\rho_L^a)_{(K_L \times K_L)}$$
$$\mathbb{V}[A_j^{a,b}] = \frac{\lambda^2}{m^2} \mathbf{1}_{(K_L \times K_L)}$$

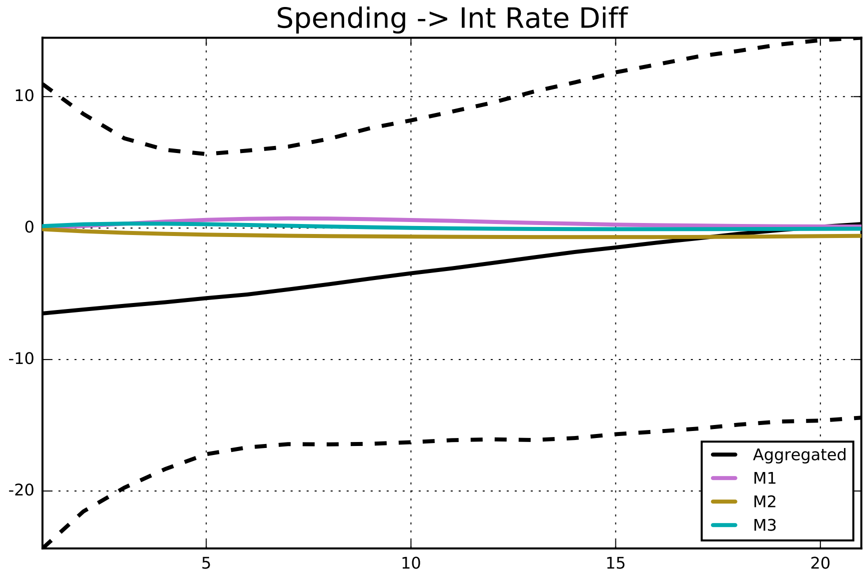
- For $a = m + 1$ and $b = m + 1$ and $j = 2, \ldots, P$:

## 3 Results

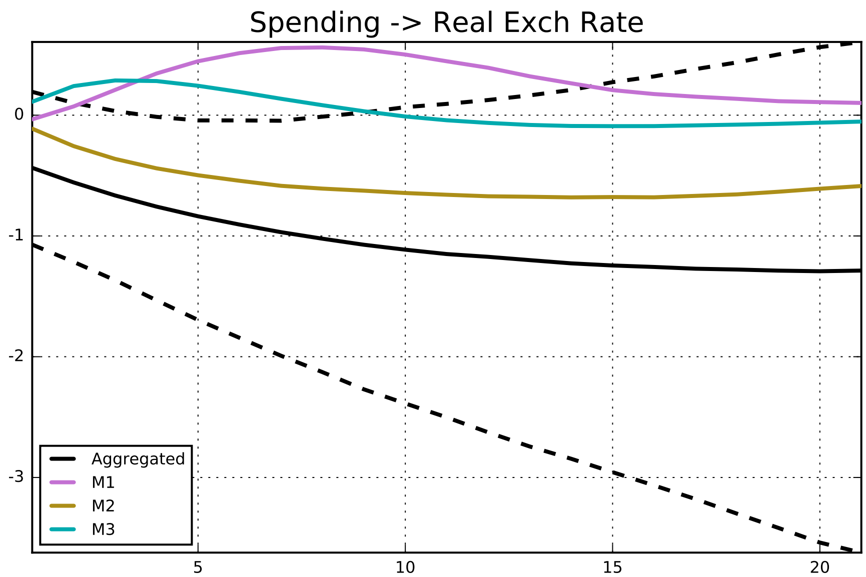
Some preliminary results are shown in the graphs below. In the legends to the graphs, "M1" indicates the response variable at the first month of the quarter, "M2" is the response measured at the second month of the quarter, "M3" is the response at the last month in the quarter.



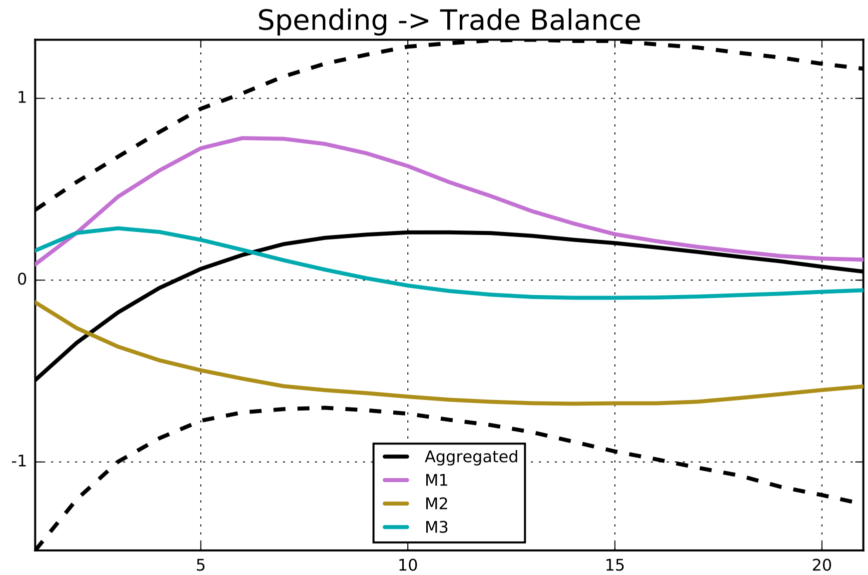





Spending -> Int Rate Diff
10
0
-10
-20
5
10
15
20
Aggregated
M1
M2
M3

Spending -> Real Exch Rate
0
-1
-2
-3
5
10
15
20
Aggregated
M1
M2
M3




## 3.1 Tentative conclusions

- Pattern of responses in mixed-frequency VAR differs from VAR with aggregated data
- In most cases, it's hard to say if the differences are significant
- Exception is the real exchange rate, consistent with another recent study using high-frequency data

## 3.2 Open Questions/Future Work

- Explore different specifications/robustness checks: Different identification for spending shocks
- Try MIDAS polynomials to reduce parameters
- Interpretation: Effect of shocks to high-freq variables on low-freq variables has a natural interpretation. Effect of shocks to low-freq variables on *intra-period* high-freq variables harder to interpret

# References


Andreou E, Ghysels E, Kourtellos A. 2010. Regression models with mixed sampling frequencies. *Journal of Econometrics* **158**: 246–261.

Arin K, Koray F. 2009. Beggar thy Neighbor? The Transmission of Fiscal Shocks from the US to Canada. *Open Economies Review* **20**: 425–434.

Auerbach AJ, Gorodnichenko Y. 2013. Output spillovers from fiscal policy. *American Economic Review Papers and Proceedings* **103**: 141–146.

Auerbach AJ, Gorodnichenko Y. 2016. Effects of Fiscal Shocks in a Globalized World. *IMF Economic Review* **6**: 177–215.

Beetsma R, Giuliodori M, Klaassen F. 2006. Trade Spill-Overs of Fiscal Policy in the European Union: A Panel Analysis. *Economic Policy* **21**: 639–687.

Boileau M, Normandin M. 2012. Do tax cuts generate twin deficits? A multi-country analysis. *Canadian Journal of Economics/Revue canadienne d'économique* **45**: 1667–1699.

Canzoneri MB, Cumby RE, Diba B. 2003. New Views on the Transatlantic Transmission of Fiscal Policy and Macroeconomic Policy Coordination. In Buti M (ed.) *Monetary and Fiscal Policies in EMU: Interactions and Coordination.* Cambridge University Press, 283–311.

Cook D, Devereux MB. 2011a. Cooperative fiscal policy at the zero lower bound. *Journal of the Japanese and International Economies* **25**: 465–486.

Cook D, Devereux MB. 2011b. Optimal fiscal policy in a world liquidity trap. *European Economic Review* **55**: 443–462.

Corsetti G, Meier A, Müller GJ. 2010. Cross-border spillovers from fiscal stimulus. *International Journal of Central Banking* **6**: 5–37.

Corsetti G, Müller GJ. 2006. Twin Deficits: Squaring Theory, Evidence and Common Sense. *Economic Policy* **21**: 597–638.

de Castro F, Garrote D. 2015. The effects of fiscal shocks on the exchange rate in the EMU and differences with the USA. *Empirical Economics* **49**: 1341–1365.

Enders Z, Müller GJ, Scholl A. 2011. How do fiscal and technology shocks affect real exchange rates?: New evidence for the United States. *Journal of International Economics* **83**: 53–69.

Faccini R, Mumtaz H, Surico P. 2015. International Fiscal Spillovers. *Journal of International Economics* **99**: 31–45.

Foroni C, Marcellino M, Schumacher C. 2015. Unrestricted mixed data sampling (midas): Midas regressions with unrestricted lag polynomials. *Journal of the Royal Statistical Society Series A* **178**: 57–82.

Fujiwara I, Ueda K. 2013. The fiscal multiplier and spillover in a global liquidity trap. *Journal of Economic Dynamics and Control* **37**: 1264–1283.

García-Solanes J, Rodríguez-López J, Torres JL. 2011. Demand Shocks and Trade Balance Dynamics. *Open Economies Review* **22**: 739–766.

Ghysels E. 2016. Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics* **193**: 294–314.

Giuliodori M, Beetsma R. 2005. What are the Trade Spill-Overs from Fiscal Shocks in Europe? An Empirical Analysis. *De Economist* **153**: 167–197.

Kim S, Roubini N. 2008. Twin Deficit or Twin Divergence? Fiscal Policy, Current Account, and Real Exchange Rate in the U.S. *Journal of International Economics* **74**: 362–383.

Monacelli T, Perotti R. 2010. Fiscal Policy, the Real Exchange Rate and Traded Goods. *The Economic Journal* **120**: 437–461.

Nicar SB. 2015. International Spillovers from U.S. Fiscal Policy Shocks. *Open Economies Review* **26**: 1081–1097.
URL `http://link.springer.com/10.1007/s11079-015-9364-x`

Ravn MO, Schmitt-Grohé S, Uribe M. 2007. Explaining the Effects of Government Spending Shocks on Consumption and the Real Exchange Rate. Working Paper 13328, National Bureau of Economic Research.