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TESIS DOCTORAL

An analysis of exogenous shocks using structural vector autoregressions identified with sign restrictions

MEMORIA PARA OPTAR AL GRADO DE DOCTOR

PRESENTADA POR

Luciano Campos

Director

Jesús Ruiz Andújar

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Facultad de Ciencias Económicas y Empresariales

Departamento de Economía Cuantitativa

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Luciano Campos

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0.1 Resumen

El análisis macroeconómico llevado a cabo por los bancos centrales y otras instituciones de investigación a tendido a ubicarse entre los modelos teóricos y el análisis empírico durante las últimas décadas. Haciendo ésto, los macroeconomistas aplicados han sido capaces de responder preguntas de sumo interés para quienes toman decisiones de política económica. La herramienta analítica utilizada para brindar dichas respuestas ha dado en llamarse el vector autoregresivo estructural (o SVAR, según sus siglas en inglés). Investigaciones acerca de, por ejemplo, shocks monetarios o fiscales son ahora frecuentemente hechas utilizando esta herramienta. Un análisis donde se utiliza un vector autoregresivo estructural típicamente deriva en tres elementos que son de suma utilidad a la hora de realizar un estudio macroeconómico: las funciones de impulso respuesta a shocks exógenos, la incertidumbre alrededor de estas funciones de impulso respuesta y un análisis de descomposición de la varianza que indica la contribución de diferentes disturbios a las fluctuaciones de las variables macroeconómicas.

La novedad de este método es que es un área gris entre el análisis econométrico y la teoría económica, pues comienza con la estimación de un modelo en su forma reducida (el vector autoregresivo -VAR-) y finaliza con un modelo estructural (el vector autoregresivo estructural -SVAR-). Yendo del primero al último es, precisamente, donde reside la conexión entre la realidad y la teoría. O bien, como lo señala Fry and Pagan [2011],'el VAR es la forma reducida que *resume* los datos; mientras que el SVAR provee una *interpretación* de los mismos'.

Ahora bien, para obtener un SVAR desde un VAR estimado, es necesario identificar los shocks estructurales. Este proceso de identificación aislará los efectos de una innovación determinada y nos dará una interpretación de la misma en forma de funciones de impulso respuesta o de descomposiciones de la varianza. Diferentes tipos de identificación se utilizan en la literatura de VARs: o bien se impone el *supuesto recursivo*, como el usado en la identificación tipo Cholesky (Sims [1980]), o se consideran los efectos de los shocks que se presume se tendrá en el corto plazo (como en Galí [1992]) o bien en el largo plazo (como en Blanchard and Quah [1989]).

Más recientemente, un nuevo método de identificación a venido utilizándose donde ciertas *restricciones de signo* son impuestas, generalmente en el impacto, a las funciones de impulso respuesta de los shocks exógenos. A este novedoso método de identificación se lo puede dividir a *grosso modo* entre quienes apican las *restricciones de signo* siguiendo un criterio informal (como en Faust [1998] y Uhlig [2005]) o uno formal, donde se suele utilizar un modelo teórico para justificar la selección específica de los signos impuestos (como en Canova and de Nicolo [2002]). En este trabajo, utilizo

la identificación formal.

El presente trabajo está dividido en tres capítulos que pueden ser considerados como tres diferentes, mas relacionados, artículos. Lo que los une es que, en todos ellos, la metodología usada es la misma. En los artículos hago un análisis cuantitativo de los efectos de diferentes innovaciones utilizando vectores autoregresivos estructurales identificados mediante *restricciones de signo* donde los signos impuestos en el impacto provienen de modelos dinámicos y estocásticos de equilibrio general (los llamados modelos DSGE, de acuerdo a sus siglas en inglés), que son estándar en la literatura.

En este trabajo, no realizo ningún aporte teórico, pues mi intención es sólo utilizar modelos teóricos simplemente para justificar los signos que impongo en impacto a las funciones de impulso respuesta de las innovaciones analizadas. Tampoco hay una contribución metodológica, ya que las técnicas aquí utilizadas ya han sido desarrollas y se suelen implementar con frecuencia en estudios aplicados. La principal contribución del presente trabajo es cuantitativa. En este sentido, está en línea con los *documentos de trabajo* que se pueden encontrar en los bancos centrales, o bien en revistas de análisis empírico, y mi intención es contribuir a esta literatura de macroeconomía aplicada. Mi principal motivación para realizar dicha tarea es que no he encontrado ningún trabajo empírico como el presentado aquí en el cual se analicen los casos de estudio que he elgido mediante *restricciones de signo*. Probablemente porque se debe a una técnica nueva. En otras palabras, mi intención aquí es enriquecer, no el entendimiento, sino la precisión con la que se miden los shocks exógenos, y responder preguntas relevantes cuantitativas que podrían enfrentar quienes toman decisiones en materia de política económica. Creo sinceramente en lo esencial de esta tarea.

En el primer capítulo de este trabajo, analizo los efectos de un shock monetario exógeno sobre el producto y la inflación en España. En primer lugar, identifico el shock mediante una descomposición de Cholesky de los residuos de la forma reducida, lo cual implica el *supuesto recursivo*. De esta forma, y en línea con la literatura, presumo que una innovación monetaria tiene un efecto contemporáneo en la tasa nominal de interés, pero afecta al producto y a la inflación sólo un trimestre luego del shock. Mediante este primer análisis, obtengo resultados contraintuitivos: observo que tanto los precios como el producto crecen luego de una contracción monetaria. Ahora bien, el efecto sobre precios está muy documentado en la literatura y a dado en llamarse el *price puzzle*. Mas la respuesta obtenida del producto no es tan usual, con lo que la considero un aporte secundario de este trabajo. En todo caso, como la identificación de Cholesky arroja resultados contraintuitivos, procedo a identificar el SVAR mediante *restricciones de signo* donde los signos impuestos en impacto se derivan de un modelo Neo Keynesiano prototípico. Obtengo una serie de estos modelos asignándole a sus parámetros valores frecuentes en la literatura y construyo una distribución de matrices de impacto con todos ellos. Finalmente, utilizo esta distribución para justificar la imposición de signos en el SVAR. Concluyo que una contracción monetaria carece de efectos relevantes en el producto pero sí reduce significativamente la inflación en España.

En el segundo capítulo, analizo los efectos de un shock fiscal sobre el producto y las exportaciones netas en Argentina utilizando un SVAR donde impongo los signos que se derivan de un modelo de ciclo real (Real Business Cycle model) estimado/calibrado que replica adecuadamente algunos momentos clave en la muestra de datos del país. Éstos son, en orden de importancia, una volatilidad del consumo mayor a la del producto, gastos gubernamentales procíclicos y exportaciones netas fuertemente contracíclicas. Estas características no están presentes en economías desarrolladas pero son típicas en las naciones en desarrollo, como es mi caso de estudio. Concluyo que una expansión fiscal tiene un impacto significativo aumentando el producto y disminuyendo las exportaciones netas. Sin embargo, los efectos son de corto plazo, pues duran poco más de un año, y no encuentro pruebas suficientes sobre la existencia de un multiplicador fiscal, con lo que deduzco que hay un fuerte *efecto desplazamiento* del consumo e inversión privadas.

Finalmente, en el tercer capítulo, analizo los efectos de un shock de términos de intercambio sobre el producto y la inflación en Argentina. Para hacerlo, utilizo un SVAR cuyos signos impuestos en impacto provienen de un modelo Neo Keynesiano estándar para una economía pequeña y abierta. Dicho modelo es estimado/calibrado y replica satisfactoriamente ciertos momentos *objetivo* del país. De acuerdo a mis resultados, una mejora en los términos de intercambio no afecta significativamente el producto pero sí provoca inflación. Estos resultados difieren de buena parte de la literatura aplicada y, particularmente, cuestionan la tesis de los llamados economistas *estructuralistas* que consideran a los términos de intercambio como una importante casua de variación en el producto en lo países en desarrollo.

En pocas palabras, mi trabajo se resume así: utilizo un SVAR donde ciertos modelos DSGE estándar y muy diseminados en la literatura me sirven para imponer ciertas *restricciones de signo* en las respuestas de las variables analizadas. Mediante este procedimiento, concluyo que una contracción monetaria incrementa los precios pero no tiene efectos reales significativos en España, una expansión fiscal tiene un impacto importante mas de corto plazo en el crecimeinto del producto y la reducción de las exportaciones netas argentinas, y una mejora en los términos de intercambio genera prácticamente sólo inflación en Argentina sin un aumento sustancial en el producto.

0.2 Summary

Macroeconomic analysis performed by central banks and other research institutions has tended to place itself somewhere between theory and empirics during the last decades. By doing so, applied macroeconomic researchers have been able to provide practical information to policy makers. The analytical tool used to reach this information is called structural vector autoregression. Inquiries about the consequences of, for example, monetary or fiscal shocks are now frequently answered using this tool. A structural vector autoregression typically derives in three elements that are very useful to perform macroeconomic analysis: the impulse response functions to exogenous shocks, the uncertainty about these impulse response functions and variance decomposition analysis that indicate the contribution of different disturbances to macroeconomic variable's fluctuations.

The novelty of this framework is that it is a gray area between econometrics and theory, because it starts with the estimation of a reduced form model (the vector auto regression -VAR-) and it ends up with a structural model (the structural vector autoregression -SVAR-). Going from the latter to the former is where the link between reality and theory resides. Or as Fry and Pagan [2011] put it, 'the VAR is a reduced form that *summarizes* the data; the SVAR provides an *interpretation* of the data'.

Now, in order to get a SVAR from an estimated VAR one needs to identify the structural shocks. This identifications process isolates a particular innovation and allows the analysis of its effects in the form of impulse response functions and variance decompositions. There are different ways of identifying exogenous shocks: one popular choice used during the last decades is the *recursiveness assumption*, as with the Cholesky identification scheme (Sims [1980]). Other ones are according to the presumed effects of the shocks in the short-run (as in Galí [1992]) or in the long-run (as in Blanchard and Quah [1989]).

More recently, a new method of identification has been used where *sign restrictions* are imposed, generally on impact, to the impulse response functions of the exogenous shocks. This newer method can be widely divided into those who apply the *sign restrictions* following an informal criteria (like Faust [1998] and Uhlig [2005]), or a formal one by means of using a theoretical model to justify the specific choice of the signs imposed (like Canova and de Nicolo [2002]). Here, I use the formal identification as all signs imposed are justified by theoretical models.

The present work is divided into three chapters that can be considered as three different, though related, articles. What they have in common is that, in all three of them, the methodology applied is the same. In these papers, I give a quantitative answer to the effects of different innovations using SVARs identified with *sign restrictions* where the signs imposed on impact come from standard dynamic stochastic general equilibrium (DSGE) models find in the literature.

There is no theoretical contribution whatsoever in this work as my intention is just to use

theoretical models merely to justify the signs I impose on impact to the impulse response functions of the disturbances analyzed. There is no methodological contribution either, as techniques used here are already being practiced to some extent, mainly in central banks. The main contribution of this work is, then, quantitative. In this sense, it is in line with working papers found in central banks, or empirical economic journals, and my intention is to contribute to these applied macroeconomic literature. My main motivation to perform this task is that I have not been able to find any empirical work like the one performed here analyzing the case studies I have chosen using *sign restrictions*. This is probably due to the relative novelty of this technique. In other words, I intend here to enrich not the understanding but the precision in the measurement of exogenous shocks and answer relevant quantitative questions policy makers might face. I truly believe this task to be essential.

In the first chapter of this work, I analyze the effects of an exogenous monetary shock on output and inflation in Spain. In order to identify the disturbance, I first do a Cholesky decomposition of the reduced form residuals, which implies the *recursiveness assumption*. According to it, and as usually assumed in the literature, I suppose that a monetary innovation has a contemporaneous effect on the nominal interest rate but only affects output and inflation one quarter after the shock. I reach a *price* and an *output puzzle*, as I find that a money contraction that raises the interest rate, increases both inflation and output. Now, the first puzzle is widely documented in the literature, but the second one is not. So I consider it a contribution of this paper, though not the main one. In any case, as the Cholesky identification scheme results in counterintuitive responses, I discard it and proceed with a second empirical model where I use instead the *signs restriction* identification scheme. The signs imposed on impact are justified by the responses reproduced by a prototypical New Keynesian model whose parameter's values lie over plausible intervals. The main conclusion of this chapter is that a monetary contraction has no relevant effect on output but it does reduce inflation significantly.

In the second chapter, I analyze the effect of a fiscal shock over output and net exports in Argentina using a SVAR imposing the signs implied by a Real Business Cycle model estimated/calibrated that replicates fairly well some key moments of the country's data sample. These are, in order of importance, a consumption volatility that exceeds the output one, procyclical government expenses and strong countercyclical net exports. These characteristics are not presented in developed economies, but are typical in developing ones, as my case study. I find that a fiscal expansion has a significant effect increasing output and reducing net exports. However, the effects are short-termed, as they last little more than one year, and the fiscal multiplier is way below one, so there must be a strong *crowding out* effect over private consumption and/or investment.

Finally, in the third chapter, I analyze the effects of a terms of trade shock on output and inflation in Argentina. To do so, I use a SVAR whose signs imposed on impact come from a standard New

Keynesian Small Open Economy model estimated/calibrated that replicates well enough Argentinian targeted sample moments. According to my results, terms of trade improvements do not affect significantly output but they do have an important impact increasing inflation. These findings differ from some related articles and question the thesis of the so-called *structuralists* economists who typically consider terms of trade as an important source of product volatility in developing countries.

In a few lines, I can summarize my work like this: I perform a SVAR analysis imposing signs in variable's responses conditional on standard DSGE models widely used in the literature. With this procedure, I find that a monetary contraction rises prices but has no significant real effect in Spain, a fiscal expansion has an important but short-termed impact increasing Argentinian GDP and decreasing net exports, and a terms of trade improvement has only a nominal influence in Argentina as it generates inflation but no relevant output growth.

Chapter 1

An analysis of monetary shocks in Spain

1.1 Abstract

I analyze the effects of a monetary shock in Spain over output and inflation by looking at the Impulse-Response Functions of a Structural Vector Autoregression identified with two different methods. The first one is the Cholesky factorization of the reduced form residuals, which implies the *recursiveness assumption*. The Impulse-Response Functions obtained with Cholesky are counter-intuitive: I reach both a *price* and an *output puzzle*. The second identification scheme is *sign restrictions*. In order to justify the election of signs imposed on impact, I use a New Keynesian Model whose parameters' values are defined over plausible intervals. The Impulse-Response Functions obtained using *sign restrictions* are the main results of this work. They show that a negative monetary shock in Spain significantly reduces inflation but has no important effect on output.

Keywords: General equilibrium, Monetary Policy, Identification, Structural VARs, Spain.
JEL Classification: C32, C68, E32, E52

1.2 Introduction

When Spain joined the euro in 1999, it lost its monetary independence. The European Central Bank (ECB) is now the organism that, offering *repo* contracts, fixes the interest rate at the Eurozone[1]. Undoubtedly, the decisions taken by the ECB in Frankfurt about the monetary policy have effects in the Eurozone countries, including Spain. The question is then if these effects are real or just nominal. And, if there is a real impact, like a change in the Spanish real GDP, what is its magnitude.

In this work I analyze the effect of an exogenous monetary innovation in the Eurozone on both Spanish inflation and output. I care about the qualitative but, more importantly, quantitative response to the disturbance. I focus on checking when is the peak effect and when does the return to steady state values occur. These issues are worth being studied as it is extremely relevant to know when a monetary disturbance will have its major effect and how do inflation and output respond in the medium and long term. Will there be any significant impact on the output level? Or will a money shock produce just a short-lived variation in output, while most of the effect traduces into a price response?

In order to perform this investigation, I analyze the Impulse-Response Functions (IRFs) generated by two Structural Vector Autoregression (SVAR), each one identified differently. The first one is identified with Cholesky and the second one with *signs restriction*. The Cholesky identification implies the *recursiveness assumption*, which consists on presuming that only the interest rate responds contemporaneously to the monetary shock while inflation and output react one period after the innovation. In this sense, we can say that the analysis performed with the Cholesky SVAR is mostly empirical, with minimal theory. The IRFs generated by this first SVAR are counter-intuitive: both inflation and output increase after a monetary contraction. This shape in the price response is widely documented in the literature and it is called the *price puzzle*. However, there is little record of the counter-intuitive output response. So I consider it as a first (but not the main) contribution of this work and call it the *output puzzle*.

The second SVAR is identified with *signs restriction* which are based on a New Keynesian (NK) model whose parameters are defined over plausible intervals. So it is accurate to say that this SVAR relies more heavily in theory than the one identified with Cholesky. The IRFs generated by this model are the main result of the present work. I conclude that a negative monetary shock reduces inflation significantly around 90% the size of the disturbance on impact, reaching a peak response at the second quarter. However, the effect dies out fast and is completely muted after the first year. By the other hand, I cannot verify a significant response of output. Well that it decreases around 30% the size of the shock on impact, there is no trace of its effects lasting beyond the second quarter.

[1] In order to fix the interest rate at a desired level, the ECB offers repurchase agreement (*repo*) contracts to around 500 eligible banks of the Eurosystem.

Based on my results, I conclude that a monetary disturbance in Spain affects mostly the price level but has, at the most, a modest effect over real activity.

My results are in line with the vast majority of the empirical literature that analyzes monetary shocks. As the work of Faust [1998] states, 'the recent progress has brought some modest claims of victory by VAR practitioners. Responses of real variables to monetary policy shifts are estimated as modest or nil, depending on the specification.'

Analyzing the monetary innovation using a SVAR implies that I am following a twofold approach: an empirical and a theoretical one. It is empirical since I estimate a Vector Autoregression (VAR) with time series data of the variables under study. And it is theoretical in the sense that the identification of the SVAR relies on theory. Nevertheless, the present work is far from more structural studies as the ones performed by Andrés et al. [2006], Burriel et al. [2010] and Boscá et al. [2010]. These authors estimate NK models specially designed for Spain and they analyze the effects of different shocks. Here, I use a theoretical model to provide me only with the qualitative effect of exogenous shocks, while the quantitative analysis is done with a less structured SVAR. In this sense, this paper is in line with Canova and de Nicolo [2002] who use a limited participation, sticky price model to justify the signs imposed on impact to the VAR in order to analyze a monetary shock in G-7 countries.

The present work is an empirical contribution that intends to serve to policy analysis in Spain. It can be argued that, since the adoption of the Euro at 1999, there should be less interest in studying the effects of monetary innovations because the country cannot decide by itself its monetary policy. But I believe that, even if the country has no more monetary independence, it is worth knowing the effects of a monetary shock in the local economy.

There are several works in the VAR literature that analyze monetary disturbances in Spain. Andrés et al. [1999] use a SVAR identified with long run restrictions including not only interest rate, prices and output, but also exchange rate. They find that a monetary contraction has a modest effect reducing output but a stronger one reducing inflation, so their results are similar to the ones presented here for the second empirical model. Camarero et al. [2002] use a cointegrated SVAR identified with long-run restrictions and concludes that a monetary contraction weakly reduces both inflation and output in the short run (less than 20%), so their result differ quantitatively from mines. van Aerle et al. [2003] use a SVAR informally identified with long run restrictions to study the effects of monetary and fiscal policy and find evidence of substantial differences of monetary policy transmissions across selected European countries. For the case of Spain, they find a moderate decrease of output after a monetary shock and a slight increase in price. Lastly, de Córdoba and Torres [2011] combine VAR estimations and an RBC model to forecast real variables in Spain. The present work is novel in the sense that, to my true knowledge, there are no monetary SVAR analysis identified with *sign restrictions*, whether informal or formally, for Spain.

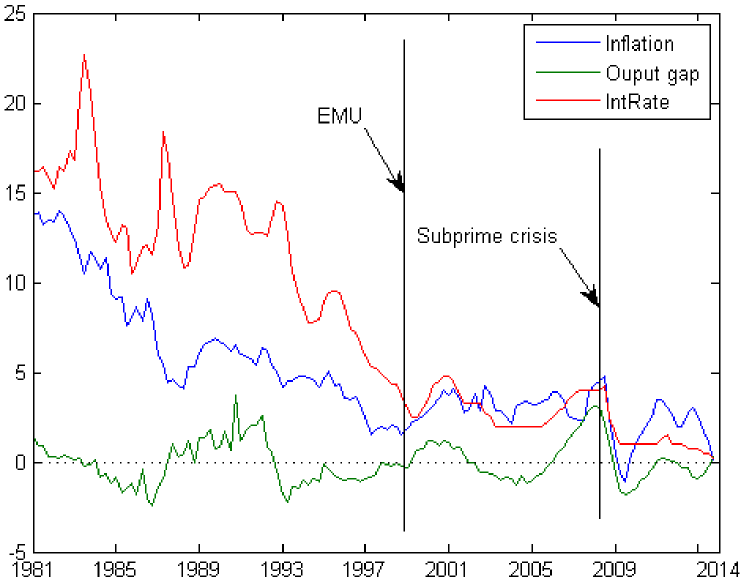
This work is structured as follows: in section 1.3, I show some empirical characteristics of the Spanish economy and explain my interest on monetary shocks. In section 1.4, I analyze the effects of a monetary disturbance on output and inflation using a SVAR identified with Cholesky, my first empirical model. The IRFs generated by this first SVAR are counter-intuitive: I reach both a *price* and an *output puzzle*. The former is widely documented in the literature, but the latter is not, so I consider it as a secondary contribution of this paper. In section 1.5, I describe the theoretical model that I use to justify the signs impose to the identification scheme used in the second empirical model. The theoretical model is an NK model whose parameters are defined over plausible intervals according to related literature. In section 1.6, I analyze a monetary shock in Spain using a SVAR identified with *sign restrictions* according to the signs obtained in section 1.5. The IRFs generated by this second empirical model are the main result of this work. I conclude that a negative monetary innovation has an important but short-lived effect reducing inflation, but a pretty moderate contractive impact on output.

1.3 Empirical characteristics

During the last three decades, there have been substantial changes in the Spanish macroeconomic picture: an important reduction in the level of interest rate and inflation has taken place. The commitment of the country to a well managed macroeconomic policy and the ascription to the Euro, certainly played a major role in this evolution. As a consequence, the volatility of output has also been significantly reduced.

The data sample starts at 1980, right after the restoration of democracy that took place in 1978. From then on, Spain transition to an open and developed country happened considerably fast. Nowadays, the country shows macroeconomic characteristics which are typical of developed countries. Focusing just on GDP growth, inflation and interest rate, we find in the last two decades low volatilities and low levels in all of them. These facts are quite clear from Figure 1.1 presented below. I also present selected sample moments for both Spain and US in Table 1 to show there are no significant differences among the countries.

At the early 1980's, there was a recession in Spain which was overcome by the second half of the decade. Spanish GDP growth became steady but volatile back then. During the 1990's, the tight monetary control exercised by local authorities brought down both inflation and output and reduced significantly their volatility. Once the adjustment was made, and thanks to the devaluation of the *peseta*, the country was back on a growth path. With the exception of the 2001 deceleration, GDP growth steadily until 2008, when Spain got hit hard by the world wide crisis.



See Data Appendix on page 23 for details.

Figure 1.1: Spanish time series

Spanish macroeconomic performance has improved during the last twenty years, so the transmission mechanisms of monetary policy might have changed lately. One natural question that arises is if the real effects of a monetary shock can be stronger nowadays.

Table 1 presents selected sample moments for Spain and US in order to put in perspective my case study. There is no significance difference among output volatilities (σ_y) nor in the autocorrelations ($\rho(\pi_t, \pi_{t-1}), \rho(y_t, y_{t-1})$ and $\rho(r_t, r_{t-1})$). There seems to have been non-negligible differences between inflation and nominal interest rate volatilities (σ_π and σ_r), but the relative volatility of inflation and nominal interest rate (σ_π/σ_r) is fairly similar. So the differences among real rates must have been small[2].

[2]Actually, for the period under study, the real rate mean was 1.47 for US and 2.88 for Spain.

Table 1: Sample correlations

	Spain	US
σ_y	1.19	1.36
σ_π	3.39	1.77
σ_r	5.92	3.32
σ_π/σ_r	0.57	0.53
$\rho_{\pi,y}$	0.11	0.37***
$\rho_{r,y}$	0.13	0.27**
$\rho_{\pi,r}$	0.82***	0.73***
$\rho(\pi_t, \pi_{t-1})$	0.95	0.84
$\rho(y_t, y_{t-1})$	0.85	0.86
$\rho(r_t, r_{t-1})$	0.97	0.95

$^{***}p < 0.01,^{**} p < 0.05$. See Data Appendix on page 23 for details.

The correlation between inflation and output ($\rho_{\pi,y}$) has the expected sign but it is quite low. The one between interest rate and output ($\rho_{r,y}$) is also weak and the sign is counter-intuitive. The only significant correlation is the one that exists between inflation and interest rate ($\rho_{\pi,r}$) and is counter-intuitive as well. These facts are behind the results I get in the empirical analysis carried on in the next section.

1.4 First empirical model

In this work, I define an empirical model as a Structural Vector Autoregression (SVAR) that comes from an identified Vector Autoregression (VAR). So, I need to estimate a VAR first and then identify it to get a SVAR. Once I get the SVAR, I analyze its Impulse Response Functions (IRFs). In other words, the empirical analysis of shocks using SVARs consists basically on three steps: first, the estimation of a reduced-form VAR. Second, the identification of the VAR so that it turns into a SVAR. Third, the analysis of a particular shock using the IRFs generated by the SVAR.

Here, I use two empirical models (this is, two SVARs) by following these three steps to analyze the effects of a monetary shock over output and inflation in Spain. The only difference between these two SVARs is the way each of them is identified. This section presents the first empirical model which uses the Cholesky identification and section 1.6 develops the second empirical model, which is identified with *signs restrictions*.

Initially, most studies identified monetary shocks using innovations in money stock. But it was observed that a loosening in money raised, rather than lowered, the interest rate. This observation is known as the *liquidity puzzle* and it was suggested that this happened because, as noted by Shioji

[1997], 'a large fraction of innovations in money stock in fact reflects shocks to money demand, rather than money supply shocks. This is true when the central bank tries to smooth the movement of the interest rate in the face of fluctuating money demand, by supplying money in an accommodating way.' It was then proposed to use innovations in the short term interest rate instead of money stock. But this lead to another counterintuitive observation pointed by Sims [1992] named as the *price puzzle*. As shown in the following pages, I am faced with this puzzle when analyzing a money disturbance for Spain. This is not as surprising as the response I find for output, which is not frequent at all in the literature.

1.4.1 The reduced-form VAR

I use a three-dimension fixed-coefficients VAR as empirical model to analyze the evolution of selected macroeconomic variables. Its reduced form is represented as:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + \mu_t$$

where Y_t is a 3x1 vector of time series including (in this order) inflation (π_t), output gap (y_t) and interest rate (r_t). The coefficients are represented by B_0 which is a 3x1 constants' vector whereas B_i are 3x3 matrices of variables' coefficients. Lastly, μ_t is a 3xT Gaussian white noise process vector with zero mean and variance Σ.

Before estimating the VAR, I need to define its lag order, which I do by applying the Akaike information criterion (AIC). It results in a two-lag order, so the VAR has the following form:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \mu_t \tag{1.1}$$

I estimate the VAR(2) using Ordinary Least Squares (OLS) and obtain the following coefficients matrices[3]:

$$\hat{B}_0 = \begin{bmatrix} 0.10 \\ 0.09 \\ -0.07 \end{bmatrix} \qquad \hat{B}_1 = \begin{bmatrix} 1.05 & 0.15 & 0.04 \\ 0.08 & 0.68 & 0.11 \\ 0.00 & 0.19 & 1.31 \end{bmatrix} \hat{B}_2 = \begin{bmatrix} -0.13 & -0.15 & -0.01 \\ -0.12 & 0.18 & -0.09 \\ 0.13 & -0.18 & -0.39 \end{bmatrix}$$

I get as well the reduced-form residuals μ_t that have zero mean and the following variance-covariance matrix:

$$\Sigma = \begin{bmatrix} 0.44 & 0.08 & 0.00 \\ 0.08 & 0.38 & 0.05 \\ 0.00 & 0.05 & 0.84 \end{bmatrix} \tag{1.2}$$

[3]See Appendix on page 24 for estimation results details.

In order to check that the VAR process is stationary I need to transform the VAR(2) into a VAR(1), which I accomplish by obtaining the so-called *companion form* of the VAR, which is defined as:

$$\hat{Y}_t = f + F\hat{Y}_{t-1} + \hat{\mu}_t$$

where the matrices are:

$$\hat{Y}_t = \begin{bmatrix} \pi_t \\ y_t \\ r_t \\ \pi_{t-1} \\ y_{t-1} \\ r_{t-1} \end{bmatrix} \quad ; \quad f = \begin{bmatrix} 0.10 \\ 0.09 \\ -0.07 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad ; \quad F = \begin{bmatrix} 1.05 & 0.15 & 0.04 & -0.13 & -0.15 & -0.01 \\ 0.08 & 0.68 & 0.11 & -0.12 & 0.18 & -0.09 \\ 0.00 & 0.19 & 1.31 & 0.13 & -0.18 & -0.39 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

I need the eigenvalues of F matrix to be less than one in absolute value to have a stable and, as a consequence, stationary process[4]. Stationarity is indeed satisfied in this case.

The residuals of the VAR are the unexplained part of the empirical model, so I have there all that affects the evolution of the variables which is not explained by their own past. In order to study the effects of an exogenous money shock, I need to breakdown the reduced-form residuals into fundamental shocks. This is precisely what I do when I identify the empirical model.

1.4.2 From VAR to SVAR: the identification problem

The reduced form model (1.1) can be expressed as:

$$\begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} = B_0 + B_1 \begin{bmatrix} \pi_{t-1} \\ y_{t-1} \\ r_{t-1} \end{bmatrix} + B_2 \begin{bmatrix} \pi_{t-2} \\ y_{t-2} \\ r_{t-2} \end{bmatrix} + \begin{bmatrix} \mu_t^{\pi} \\ \mu_t^{y} \\ \mu_t^{r} \end{bmatrix}$$

where the reduced form residuals μ_t can be matched to structural shocks e_t by finding a 3x3 matrix A_0 such that:

$$\begin{bmatrix} \mu_t^{\pi} \\ \mu_t^{y} \\ \mu_t^{r} \end{bmatrix} = A_0 \begin{bmatrix} e_t^{s} \\ e_t^{d} \\ e_t^{M} \end{bmatrix} \tag{1.3}$$

Then it is clear that each reduced form shock is a linear combination of a structural shock where the elements of the A_0 matrix represent the amounts by which a particular structural shock contributes

[4]As referred in Lutkepohl [1993], stability (all eigenvalues less than one in absolute value) implies stationarity (time invariant first and second moments).

to the variation in each residual. Structural innovations are interpreted as supply, demand and monetary shocks (e_t^s, e_t^y and e_t^M, respectively). Now, if it is assumed that structural disturbances are unit variance, then:

$$\begin{aligned} Var(\mu_t) &= Var(A_0 e_t) \\ &= A_0 Var(e_t) A_0' \\ &= A_0 I A_0' \\ &= A_0 A_0' \end{aligned} \tag{1.4}$$

which means that we can decompose the variance-covariance matrix of the reduced form residuals by finding a matrix that I call A_0. In the present work, I use subsequently two ways of obtaining this matrix: in this section I do a Cholesky decomposition and in section 1.6 I use *sign restrictions*. Once obtained, this matrix allows to perform a structural analysis by plotting IRFs or building variance decompositions.

Equation (1.4) is key here, as it relates the estimated residuals with the structural impact matrix A_0. In other words, it is the link between data and theory[5]. However, there is not enough information to solve the system of equations (1.3) because there are nine parameters to estimate in matrix A_0 but only six free parameters in (1.2) (the three variances and three covariances, because of symmetry), so the system is underidentified. More generally, the covariance structure Σ leaves $n(n-1)/2$ degrees of freedom (where n is the dimension of Σ) in specifying A_0 and hence further restrictions are needed to achieve identification. Exact identification of system (1.3) can be achieved by reducing the amount of free parameters in A_0 to match those of the reduced form residuals variance-covariance matrix (1.2). In the VAR literature there are typically two ways of achieving identification: Cholesky or eigenvalue-eigenvector decomposition of the reduced form residuals variance-covariance matrix Σ.

1.4.3 The Structural VAR identified with Cholesky

In this section, I use the Cholesky identification scheme that, on one hand, provides us with a matrix A_0 such that (1.4) is fulfilled and, on the other hand, solves the identification problem mentioned before. This is thanks to the fact that this particular identification scheme implies that A_0 is a lower triangular matrix. Then we are left with only six parameters to estimate at system (1.3), so it is exactly identified. The advantage of using Colesky is precisely that we can get the desired impact matrix A_0 and, at the same time, solve the identification problem. But at the same time, we can

[5]The SVAR system relates observable VAR-based residuals to unobserved structural shocks (See Bernanke and Mihov [1998]).

only identify one shock (the monetary, here). And this is one of the weaknesses of this identification scheme.

At the same time, whenever Cholesky decomposition is used, there is an underlying economic assumption in the timing of the responses to the variables' shocks. This is the so-called *recursiveness assumption*. In the particular case analyzed in this work, I am assuming that a monetary shock which hits the economy today will impact on interest rate in the current period, but the rest of the variables will only be affected at the second quarter.

The *recursiveness assumption* has been used since Sims [1980] and it implies that a money shock affects the *policy variable* (the interest rate) immediately but the *pre-determined variables* (output and inflation) are only affected from the second quarter on. As discussed by Canova and Pina [2005], this assumption, that is performed by ordering the variables in the VAR in a specific way, has a strong theoretical counterpart: inflation and output take as long as a quarter to react when there is an unexpected change in the interest rate. We might ask ourselves if firms and households take that much time to react, which is the typical critique done to this identification scheme.

As Christiano et al. [1999] pointed out, 'assumptions must be made about the nature of the interaction of the policy shock with the variables in the feedback rule. One assumption is that the policy shock is orthogonal to these variables. Throughout, we refer to this as the recursiveness assumption. Along with linearity of the Fed's feedback rule, this assumption justifies estimating policy shocks by the fitted residuals in the ordinary least squares regression of the Fed's policy instrument on the variables in the Fed's information set. The economic content of the recursiveness assumption is that the time t variables in the Fed's information set do not respond to time t realizations of the monetary policy shock. As an example, Christiano et al. [1996] assume that the Fed looks at current prices and output, among other things, when setting the time t value of its policy instrument. In that application, the recursiveness assumption implies that output and prices respond only with a lag to a monetary policy shock.'

Also, Christiano et al. [1996] mention that 'this is consistent with our basic identifying assumption that policy shocks have no contemporaneous impact on aggregate output. Put differently, any contemporaneous correlation between the VAR disturbance to the policy variable and the indicator of aggregate production is assumed to reflect causation from production to the policy variable, and not the other way around.'

Considering (1.3), the reduced-form VAR(2) described in (1.1) turns into the following SVAR:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + A_0 e_t \tag{1.5}$$

where A_0 is a 3x3 lower triangular matrix with the standard errors of the series' residuals in its main diagonal and e_t is a 3x1 vector of unit variance shocks by definition. The only shock identified here is the monetary one, while the other two are left unidentified. As it stands, the SVAR will look like this:

$$\begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} \equiv \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \underbrace{\begin{bmatrix} 0.66 & 0.00 & 0.00 \\ 0.13 & 0.60 & 0.00 \\ 0.01 & 0.08 & 0.91 \end{bmatrix}}_{A_0} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{1.6}$$

It is important to notice that by placing 1 in the bottom of the shock vector ($e_{3,t}$'s position), I am assuming that the interest rate is the only variable affected in the current period by the monetary shock, while the rest of the variables will only be affected in the subsequent quarters. This *recursive structure* to which I impinge the economy with, implies the existence of frictions so that π_t and y_t respond one quarter after the shock *via* the lagged components of the SVAR[6].

1.4.4 Impulse-Response Functions Analysis

In order to analyze the effects of a monetary shock on output and inflation I look at the IRFs generated by the SVAR (1.6). But, for convenience, I set the unconditional mean to 0 so that I can express it as[7]:

$$\begin{bmatrix} \pi_t \\ y_t \\ r_t \end{bmatrix} \equiv \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \underbrace{\begin{bmatrix} 0.66 & 0.00 & 0.00 \\ 0.13 & 0.60 & 0.00 \\ 0.01 & 0.08 & 0.91 \end{bmatrix}}_{A_0} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{1.7}$$

IRFs computed based on (1.7) have the pattern shown in Figure 1.2.

Figure 1.2 presents the IRFs' obtained after a one standard deviation increase in the interest rate. The IRFs generated by the first empirical model are puzzling: both prices and output rise after a negative monetary shock, while we would expect a decrease in them. Now, the *inflation puzzle* is well documented in the VAR literature. The works of Sims [1992] and Eichenbaum [1992] explain that this puzzle can be solved by including the prices of commodities in the VAR. By the other hand, there is almost no record of an *output puzzle*, so it can be considered as a secondary contribution of this work.

The work of Mojon and Peersman [2001] that uses, like here, a recursive identification, manages to solve the *price puzzle* by including other endogenous variables into the VAR like the exchange rate and the German interest rate. As explained by the authors, the reason for the *price puzzle* 'is that if one does not control for increases in the domestic interest rate that are a response to increases in

[6]Regarding the order of inflation and output in the VAR, there is no difference in placing them in first or second positions (See Primiceri [2005]).

[7]For details in how to get from (1.6) to (1.7) go to the Apendix on page 24.

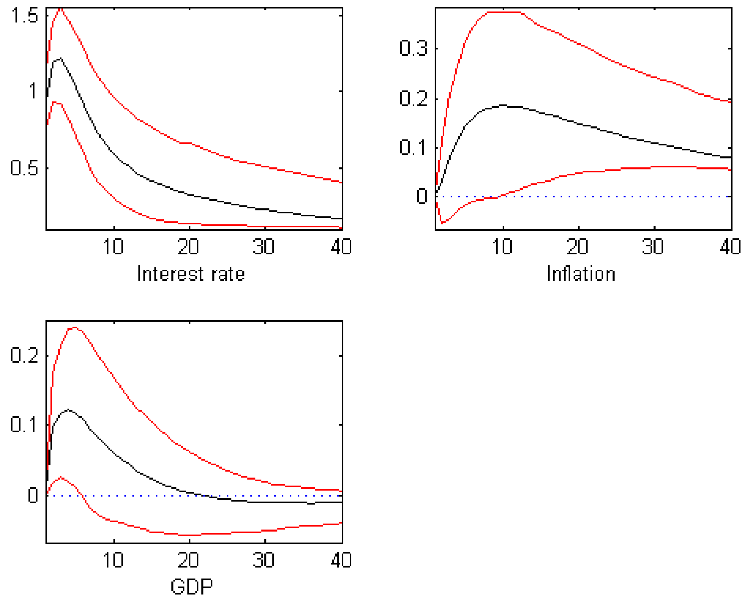


Figure 1.2: Cholesky IRFs after a negative monetary shock with 90% confidence bands

the German rate, such changes may be associated with a depreciation of the exchange rate. This in turn puts upward pressure on prices'. More recently, Castelnuovo and Surico [2010] show that the price puzzle arises when the central bank does not react by raising interest rate sufficiently to halt inflation.

In order to characterize uncertainty around the estimates I plot the IRFs with their confidence bands. Point estimates are presented in black while confidence intervals for 90% are shown in red. I built confidence bands by bootstrapping the estimated model for 1000 replications. This is, I generate artificial data using the estimated model as Data Generating Process (DGP). As described in Berkowitz and Kilian [2000], the logic of bootstrapping is: Making inference on the statistical properties of the data generation process and therefore computing confidence intervals, etc. based on the estimated model, and the estimated residuals, rather than on the time series asymptotic formulas. As mentioned by the authors, bootstrapping is extremely helpful when working with small samples, as is my case in this work. The logic behind this procedure is to infer the properties of the DGP based on the estimated model. Bootstrapping consists in estimating the VAR for a given lag order, obtain the VAR's residuals and, lastly, randomly draw the residuals, and feed them to the VAR. That is, treat them as shocks thus generating artificial, bootstrapped series. It is important to run a pre-sample equal to around 100 observations, which will be discarded to eliminate the influence of initial conditions.

Considering the confidence bands shown in Figure 1.2, the *price puzzle* is attenuated on impact by the fact that inflation response is not significantly different from 0. But the output IRF is significant, so the *output puzzle* is quiet robust. These puzzling response in output has been recently documented by Gertler and Karadi [2014], who find that industrial production actually increase after a negative monetary shock in US. However, this is the only reference where this phenomena can be found, as far as I am concern. So I consider the *output puzzle* in Spain as a secondary contribution of this work.

In resume, due to the presence of *puzzles* in both inflation and output IRFs, I conclude that the *recursiveness assumption* is of no use to analyze the response of these variables to a monetary disturbance in the Spanish economy. I proceed then to analyze the effects of such a shock using *signs restrictions* as identification scheme. As a first step, I check in section 1.5 the responses of inflation, output and interest rate to demand, supply and money innovations using a New Keynesian model whose parameter's values lie inside plausible intervals. Using this results, I impose a pattern of signs in section 1.6 to build my second SVAR and analyze its IRFs.

1.5 Theoretical model

In order to justify the signs imposed on impact to the SVAR analysis of next section, I use a prototypical New Keynesian (NK) model, which comes from the family of the Dynamic Stochastic General Equilibrium (DSGE) models so frequently used nowadays in monetary macroeconomic analysis. The version presented here is obtained from Benati and Surico [2009], which is a simplified version of the model used by Smets and Wouters [2003]. I give here a brief description of the model:

$$R_t = \rho R_{t-1} + (1-\rho)[\phi_\pi \pi_t + \phi_y y_t] + \epsilon_{R,t} \tag{1.8}$$

$$\pi_t = \frac{\beta}{1+\alpha\beta}\pi_{t+1|t} + \frac{\alpha}{1+\alpha\beta}\pi_{t-1} + \kappa y_t + \epsilon_{\pi,t} \tag{1.9}$$

$$y_t = \gamma y_{t+1|t} + (1-\gamma)y_{t-1} - \sigma^{-1}(R_t - \pi_{t+1|t}) + \epsilon_{y,t} \tag{1.10}$$

The nominal interest rate (R_t), inflation (π_t) and the output gap (y_t) are modeled in these equations. Equation (1.8) is the monetary policy rule, where, as in Woodford [2003], it is assumed that the central bank targets the nominal interest rate R_t following a typical Taylor rule. The systematic component of the monetary policy rule has ρ as the smoothing coefficient while ϕ_π and ϕ_y are, respectively, the coefficients on inflation and output gap. The non-systematic component of the Taylor rule is represented by $\epsilon_{R,t}$, which is interpreted as an exogenous monetary shock.

Equation (1.9) is the Phillips curve and its parameters are β (the subjective rate of time preference), α (price indexation to past inflation) and κ (the slope of the Phillips curve). Expected inflation is represented by $\pi_{t+1|t}$. The structural disturbance that affects the Phillips curve is $\epsilon_{\pi,t}$, which is interpreted as a cost-push or (negative) supply shock.

Finally, equation (1.10) represents the intertemporal IS curve with coefficients γ (price setters' forward looking component) and σ (the elasticity of intertemporal substitution in consumption). Expected output gap is represented by $y_{t+1|t}$. The structural disturbance that affects the dynamic IS curve is $\epsilon_{y,t}$, which is interpreted as a demand shock.

All structural disturbances follow AR(1) *iid* processes:

$$\epsilon_{R,t} = \rho_R \epsilon_{R,t-1} + \tilde{\epsilon}_{R,t} \quad ; \quad \tilde{\epsilon}_{R,t} \sim \mathcal{N}(0, \sigma_R^2) \tag{1.11}$$

$$\epsilon_{\pi,t} = \rho_\pi \epsilon_{\pi,t-1} + \tilde{\epsilon}_{\pi,t} \quad ; \quad \tilde{\epsilon}_{\pi,t} \sim \mathcal{N}(0, \sigma_\pi^2) \tag{1.12}$$

$$\epsilon_{y,t} = \rho_y \epsilon_{y,t-1} + \tilde{\epsilon}_{y,t} \quad ; \quad \tilde{\epsilon}_{y,t} \sim \mathcal{N}(0, \sigma_y^2) \tag{1.13}$$

As explained in An and Schorfheide [2007], the so-called measurement errors are added to address a potential model misspecification:

$$\pi_t = \pi_{t-1|t} + \eta_{\pi,t} \tag{1.14}$$

$$y_t = y_{t-1|t} + \eta_{y,t} \tag{1.15}$$

All parameter values are taken from Canova and Paustian [2010], except for $\beta = e^{-r_{ss}/400}$, where the real interest rate at steady state of Spain is $r_{ss} = 2.88$ and the Phillips curve slope κ, which I get from the OLS estimation of:

$$\pi_t = \beta_0 + \beta_1 \pi_{t-1} + \beta_2 y_t + \epsilon_{\pi,t} \tag{1.16}$$

The function (1.16) can be considered as a good approximation of the Phillips curve (1.9) if $\pi_{t+1|t} = \pi_t$. Then parameters to estimate are $\beta_0, \beta_1 = \frac{\alpha}{1-\beta(1-\alpha)}$ and $\beta_2 = \frac{(1+\alpha\beta)\kappa}{1-\beta(1-\alpha)}$. The results of the estimation are:

Table 2: Phillips curve slope estimation

Variables	π_t
π_{t-1}	0.96^{***}
	(54.94)
y_t	0.10^{**}
	(1.98)
constant	0.10
	(0.98)
Observations	131
R-squared	0.96

t-statistics in parentheses

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Now, given that $\alpha \sim \mathcal{U}(0,1)$ and $\beta = 0.99$, then $\kappa \approx 0.05$. So, I consider this parameter to have a uniform distribution around this value, as noted in Table 3.

Table 3: Parameter values

Name	Symbol	Plausible interval
Monetary rule parameters		
Smoothing coefficient	ρ	$\mathcal{U}$**(0,1)**
Inflation coefficient	ϕ_π	$\mathcal{U}$**(0,3)**
Output coefficient	ϕ_y	$\mathcal{U}$**(0,2)**
Phillips curve parameters		
Preference rate	β	**0.99**
Price indexation parameter	α	$\mathcal{U}$**(0,1)**
Phillips curve slope	κ	$\mathcal{U}$**(0,0.05)**
IS curve parameters		
Output forward looking component	γ	$\mathcal{U}$**(0,1)**
Price indexation parameter	α	$\mathcal{U}$**(0,1)**
Elasticity of substitution	σ	$\mathcal{U}$**(0,20)**
Shocks parameters		
Monetary shock persistence	ρ_R	$\mathcal{U}$**(0,1)**
Monetary shock volatility	σ_R	$\mathcal{U}$**(0,2)**
Demand shock persistence	ρ_π	$\mathcal{U}$**(0,1)**
Demand shock volatility	σ_π	$\mathcal{U}$**(0,2)**
Supply shock persistence	ρ_y	$\mathcal{U}$**(0,1)**
Supply shock volatility	σ_y	$\mathcal{U}$**(0,2)**

I put the model into the Sims [2002] form and solve it as in Lubik and Schorfheide [2003] and Lubik and Schorfheide [2004][8]. Then, I randomly draw 1,000 parameters vectors according to values of Table 3. For each draw, there will be a specific dynamic process like (1.5) with its corresponding A_0 matrix. So I will have 1000 of these matrices. The distribution of the elements of these matrices is presented in Figure 1.3.

As it is clear from this figure, the signs of the shocks on impact are indeed robustly either positive or negative in the majority of the cases. Consequently, I can impose these signs to the empirical model in the following section. In particular, notice that, as shown at the first column of Figure 1.3, the money innovation increases the interest rate and decreases both inflation and output, which is completely consistent with common economic wisdom. Or as Christiano et al. [1996] put it 'there

[8]For a detailed description of the model solution refer to the Appendix on page 25.

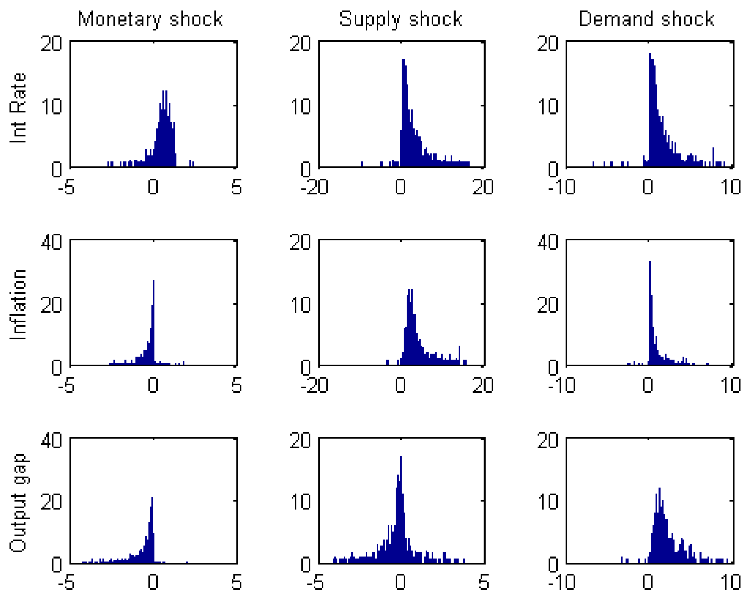


Figure 1.3: Distribution of impacts conditional on the DSGE model

is considerable agreement about the qualitative effects of a monetary policy shock in the sense that inference is robust across a large subset of the identification schemes that have been considered in the literature. The nature of this agreement is as follows: after a contractionary monetary policy shock, short term interest raise rise, aggregate output fall, the aggregate price level responds very slowly and fall.' Regarding the supply disturbance, it generates a rise on interest rate and inflation and a reduction in output gap. So it can be interpreted as a cost-push or negative supply shock. Finally, the demand shock increases all variables.

1.6 Second empirical model

In this section I analyze the effect of a monetary shock on Spanish output and inflation by looking at the IRFs generated by a SVAR identified with *sign restrictions*. In order to perform this analysis I need to follow three steps: first, estimate the reduced-form VAR model (already done at section 1.4.1). Second, identify the VAR, which I do now using *sign restrictions*, so that it turns into a SVAR. Third, analyze the IRFs of output and inflation after a monetary innovation.

1.6.1 The reduced-form VAR

As in the first empirical model, I define the lag-order of the VAR, estimate it and check that it is stationary. All these calculations are described in detail at subsection 1.4.1. The only difference here is that the order of the variables is changed. The VAR(2) model estimated is:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \hat{\mu}_t \tag{1.17}$$

where, now:

$$Y_t = \begin{bmatrix} r_t \\ \pi_t \\ y_t \end{bmatrix}$$

Again, identifying the VAR means transforming the reduced form residuals ($\hat{\mu}_t$) in (1.17) into $A_0 e_t$, where the condition (1.4) is satisfied. However, obtaining the A_0 matrix under the *signs restrictions* scheme is much more complex than under the Cholesky one, which consisted only on doing a Cholesky decomposition of the reduced form variance-covariance matrix as explained above.

1.6.2 The Structural VAR identified with *sign restrictions*

As explained in section 1.4.2, I need to identify the VAR described at (1.17) so that it turns into:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + A_0 e_t \tag{1.18}$$

I would now try a different identification scheme. Instead of obtaining the A_0 matrix from the Cholesky decomposition, as in the first empirical model, I get such matrix imposing *sign restrictions.* A microfunded justification of the signs pattern is needed if I want the analysis to be immune to the Lucas [1976] critique. This is why I use the distribution of the signs of the impact matrices conditional on the DSGE model shown in Figure 1.3. As a consequence, I will impose the following signs to the A_0 matrix:

$$\begin{bmatrix} r_t \\ \pi_t \\ y_t \end{bmatrix} = \begin{bmatrix} + & + & + \\ - & + & + \\ - & - & + \end{bmatrix} \begin{bmatrix} e_t^M \\ e_t^S \\ e_t^D \end{bmatrix} \tag{1.19}$$

where e_t^M, e_t^S, e_t^D are a monetary, a (cost-push) supply and a demand shock, respectively. I interpret the money shock as unexpected monetary contraction that rises the nominal rate and decrease both inflation and output. The supply shock is interpreted as a negative one as it rises both prices and interest rate and decreases output. Lastly, a positive demand shock increases all variables. All these responses are justified by the distributions of impacts shown in Figure 1.3. It is of extreme importance to notice that every shock has a unique pattern of signs. If this were not the case, then it would not be possible to identify shocks separately.

In order to get the desired A_0 matrix, I use the following procedure:

1. I do the Cholesky (or eigenvalue-eigenvector) decomposition of the reduced form residuals such that the variance-covariance matrix is $\Sigma = CC'$ and so exact identification is achieved. Notice that under Cholesky identification scheme, we would use $C = A_0$, so this step was also the final one.

2. I obtain a sufficiently large amount of K_{3x3} matrices making draws from a normal distribution.

3. I do the QR decomposition of K matrices by using the algorithm from Rubio-Ramirez et al. [2010] such that $K = Q \cdot R$ and $QQ' = I$. I also normalize the elements in Q such that the diagonal entries of R are positive.

4. Finally, I get candidate impact matrices $A_0 = C'Q'$. Only those A_0 matrices that satisfy the signs in 1.19 are held, while the others are discarded.

In a few words, the algorithm presented in steps 1 to 4, provides me with a series of A_0 matrices such that condition (1.4) holds (this is, $Var(\mu_t) = A_0 A_0'$) and the pattern of sign is as in 1.19. A precise description of the algorithm used is as follows: after the estimation of the reduced form VAR, I generate 5000 simulations for parameter matrices $\hat{B}_0$ and $\hat{B}_1$, as well as for the variance-covariance matrix Σ, by bootstrapping the estimated model. Once stationarity is checked for the bootstrapped data, I center the estimations around the median of the distribution. I get the Cholesky decomposition of the 5000 variance-covariance matrices such that exact identification is achieved and $\Sigma = CC'$ (this can be done also with an eigenvalue-eigenvector decomposition of the reduced form residuals). Then I generate 10.000 draws from a normal distribution to build 10.000 3x3 matrices called K. Afterwards, I perform QR decomposition of matrix K so I obtain 10.000 orthonormal matrices Q that satisfy $K = Q \cdot R$ and $Q * Q' = I$. I also normalize the elements in Q such that the diagonal entries of R are positive.

Finally, I get a candidate impact matrix $A_0 = C' * Q'$ where Q is called a rotation matrix because it allows us to *rotate* the initial Cholesky (recursive) matrix while maintaining the property that shocks are uncorrelated. In other words, it helps us generate new *weights*. If the candidate impact matrix A_0 satisfies the signs in (1.19), I keep it. If not, I discard it. At the end, I am left with a distribution of 5000 matrices that satisfy both $Var(\mu_t) = A_0 A_0'$ and the desired pattern of signs. The distribution of these A_0 matrices is presented in Figure 1.4[9].

It is important to notice that the pattern of signs imposed on impact produce distributions of elements in the A_0 matrices that are nearly normal. This means that the pattern of signs is easily

[9]Strictly speaking, as noted by Baumeister and Hamilton [2014], the set of impact matrices A_0 is not a distribution. They should rather be considered as 5.000 different models, all fulfilling the same pattern of signs. Taking this into account, it is not accurate to refer to the IRFs obtained as median and confidence intervals. Instead, we should consider them as ranges of possible responses, each one coming from a specific admissible model based on an accepted draw. This being said, I will still refer to my results as if they came from a distribution, as is usually done in the literature.

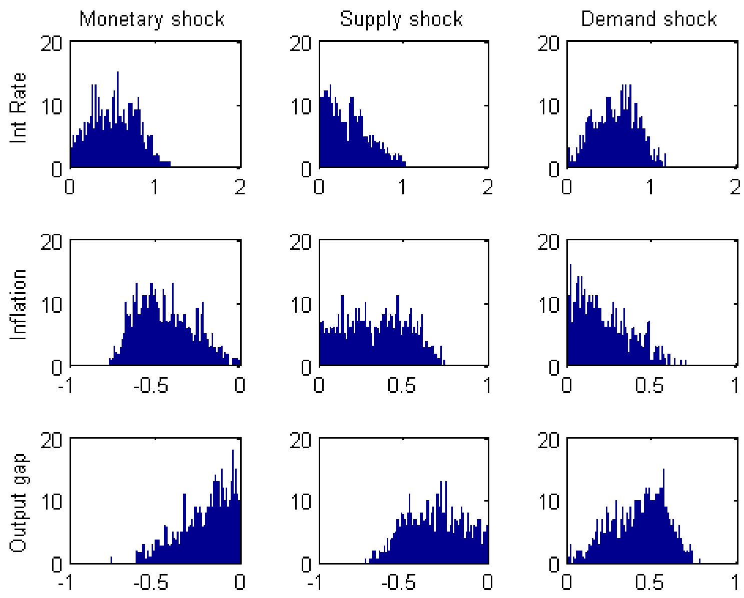


Figure 1.4: Distribution of impacts

traced back using the real data which is contained in the variance-covariance matrix of reduced form residuals. If this were not the case, then one or more of the distributions of A_0 elements in Figure 1.4 would be far from normality.

1.6.3 Variance decomposition analysis

To do a forecast error variance decomposition analysis, I use the 5000 A_0 matrices obtained in the previous section and I build a distribution of variance decomposition matrices using the variance of the first step forecast error. Table 4 presents the mean of this distribution:

Table 4: Variance decomposition

	Interest rate	Inflation	Output gap
Shock:			
Monetary	38.03	50.49	15.01
	[1.80, 87.02]	[6.32, 95.99]	[0.05, 52.38]
Supply	18.01	34.89	31.82
	[0.08, 69.58]	[0.60, 83.89]	[0.49, 84.04]
Demand	43.96	14.62	53.16
	[4.33, 92.70]	[0.07, 49.91]	[6.61, 96.90]

Means and 90% intervals (in brackets)

Although there is a lot of uncertainty around the estimates, we can reach some statements based on the mean of the estimations. Monetary shocks are an important source in the variation of prices (around 50%) but not so much on aggregate activity (around 15%), which is mainly driven by demand (53%) and supply (32%) disturbances.

1.6.4 Impulse-Response Functions Analysis

In this section I report the IRFs which are calculated using the 5000 A_0 matrices, as well as the 5000 parameter matrices $\hat{B}_0$ and $\hat{B}_1$ following the SVAR model (1.18). The range of IRFs obtained is used to calculate the effects of the three shocks on the three variables. A plot of the median and the 90% confidence interval of these IRFs are shown in Figure 1.5. The first column of this figure is the main result of this work. It shows that a negative monetary shock that increases the interest rate reduces significantly inflation but has a weak effect on output. Secondary results are the effects of negative supply and positive demand innovations presented in second and third columns of Figure 1.5, respectively. The second column presents the effect of a negative supply (or positive cost push) shock that raises inflation and interest rate and decreases output, though responses are non-significant. The third column presents the effect of a positive demand shock that increases significantly all variables.

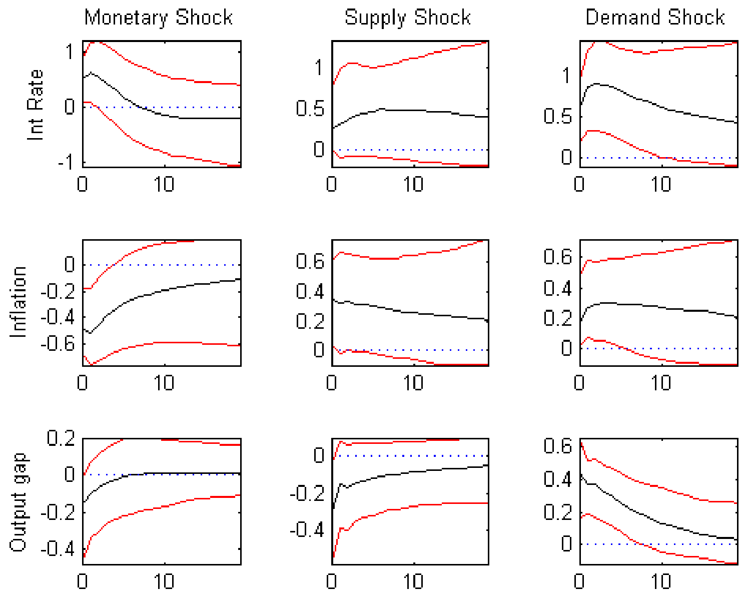


Figure 1.5: *Sign restrictions* IRFs

Figure 1.6 presents a detailed graph only with the monetary shock IRFs. We can see that a negative monetary disturbance reduces on impact both inflation and output around 90% and 30%

the size of the shock, respectively. The peak effect is at the second quarter for inflation and on impact for output. The effect is not significant for output but it actually is for inflation during one year. Giving this results, my main conclusion is that a monetary disturbance has an important effect on inflation but a negligible one on output in Spain.

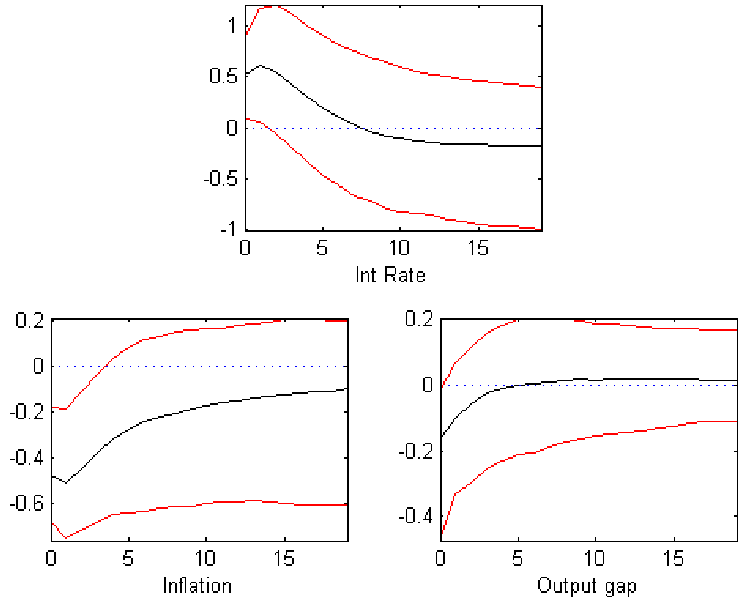


Figure 1.6: Just the Monetary Shock

1.7 Conclusion

In this work, I evaluate the effect of a monetary shock on Spanish's output and inflation by analyzing the Impulse Response Functions (IRFs) generated by two different empirical models (Structural Vector Autoregression -SVARs-). To begin with, I use a SVAR with inflation, output and interest rate where Cholesky decomposition serves as the identifying restriction scheme. By using Cholesky, I assume that the economy has a *recursive structure*. This is, interest rate is the only variable that changes contemporaneously to a monetary shock, whereas output and inflation are affected from the second quarter on.

The results reached using this identifying restrictions are counter-intuitive: the IRFs of output and inflation increase after a negative monetary shock. There is, then, a *price* and an *output puzzle*. The *price puzzle* is well documented in the monetary literature, but the *output puzzle* is not, so I consider it a secondary contribution of this work. The reasons behind this last puzzle are not investigated here, and are left for future research.

The second empirical model is a SVAR that uses *sign restrictions* as identification scheme. The imposition of the signs on impact are justified by the results obtained with a New Keynesian model whose parameter's values are defined over plausible intervals. The IRFs generated by this second empirical model are the main result of this work. They show that a negative monetary shock has non-negligible effect reducing inflation but, at the most, a modest one reducing output.

1.8 Appendix

1.8.1 Data sources

All series sample goes from 1980:1 to 2013:4. For Spain, GDP is taken from Oxford Economics at constant 2008 prices, quarterly frequency and are seasonally adjusted. I apply logarithm to the series and remove its trend using the Hodrick-Prescott decomposition with $\lambda = 1600$ as smoothing parameter. To obtain inflation series I use the CPI Index (2011=100) from Oxford Economics which is at quarterly frequency and non-seasonally adjusted. I take the log-difference of interanual Quarter-to Quarter data values. I am then left with four less data values for the whole sample. So the data sample size is 132. For the interest rate, I use the Spanish three-month (weighted average) interbank rate until 1999:Q1 taken from the Spanish Ministry of the Economy and Finance, and the short term euro *repo* rate from then on that comes from the European Central Bank. Raw data has monthly frequency.

For US, GDP is taken from Bureau of Economic Analysis at constant 2009 prices, quarterly frequency and are seasonally adjusted. I apply logarithm to the series and remove its trend using the Hodrick-Prescott decomposition with $\lambda = 1600$ as smoothing parameter. To obtain inflation series I use the CPI Index (1982-1984=100) from the Bureau of Labor Statistics which is at monthly frequency and seasonally adjusted. I take the log-difference of interanual Quarter-to Quarter data values. I am then left with four less data values for the whole sample. So the data sample size is 132. For the interest rate, I use the T-bill three-month rate from the Federal Reserve. Raw data has monthly frequency.

1.8.2 VAR estimation results

Table 5: VAR estimation results

Variables	π_t	y_t	r_t
π_{t-1}	1.05***	0.08	0.00
	(11.63)	(0.89)	(0.01)
π_{t-2}	-0.13	-0.12	0.13
	(-1.47)	(-1.42)	(1.02)
y_{t-1}	0.15	0.68***	0.19
	(1.56)	(7.52)	(1.42)
y_{t-2}	-0.15	0.18**	-0.18
	(-1.55)	(2.05)	(-1.36)
r_{t-1}	0.04	0.11*	1.31***
	(0.58)	(1.95)	(15.88)
r_{t-2}	-0.01	-0.09^{*}	-0.39^{***}
	(-0.14)	(-1.66)	(-4.83)
constant	0.10	0.09	-0.07
	(0.89)	(0.87)	(-0.48)
Observations	130	130	130
R-squared	0.96	0.74	0.98

t-statistics in parentheses

$^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$

Table 6: Granger casualty test (F-statistics)

Variables	π	y	r
π	442.23***	1.82	4.44**
y	1.31	159.36***	1.05
r	1.11	2.13	714.85***

$^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1.$

1.8.3 Cholesky Impulse-Response Functions detail

To get the IRFs I need to assume that the economy is on its long run equilibrium. To obtain the long run equilibrium I proceed as:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \hat{\mu}_t$$

$$Y_t - \hat{B}_1 Y_{t-1} - \hat{B}_2 Y_{t-2} = \hat{B}_0 + \hat{\mu}_t$$

$$Y_t[I_k - \hat{B}_1 L - \hat{B}_2 L^2] = \hat{B}_0 + \hat{\mu}_t$$

where L is the lag operator. As the process is indeed stationary, I can invert the matrix to obtain:

$$Y_t = [I_k - \hat{B}_1 L - \hat{B}_2 L^2]^{-1}\hat{B}_0 + [I_k - \hat{B}_1 L - \hat{B}_2 L^2]^{-1}\hat{\mu}_t$$

Or in its structural form:

$$Y_t = \underbrace{[I_k - \hat{B}_1(1) - \hat{B}_2(2)]^{-1}\hat{B}_0}_{(UM)} + \underbrace{[I_k - \hat{B}_1(1) - \hat{B}_2(2)]^{-1}A_0}_{(LRI)} e_t \tag{1.20}$$

In 1.20 I have the SVAR's unconditional mean (UM) and the matrix I will use to capture the long-run impact of structural shocks (LRI).

For convenience, I will set unconditional mean to 0. Then, I can express 1.20 as

$$Y_t = [I_k - \hat{B}_1 L - \hat{B}_2 L^2]^{-1} A_o e_t$$

or, what is the same:

$$Y_t = \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + A_o e_t \tag{1.21}$$

Given the identification restrictions I have imposed to A_0 and that the interest rate is the only variable affected by the monetary shock in my model, 1.21 is actually:

$$Y_t = \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \begin{bmatrix} 0.66 & 0.00 & 0.00 \\ 0.13 & 0.60 & 0.00 \\ 0.01 & 0.08 & 0.91 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \tag{1.22}$$

1.8.4 Model solution under determinancy and indeterminancy

The system of equations (1.8)-(1.15) is a Linear Rational Expectations (LRE) model that can be put into the Sims [2002] form:

$$\Gamma_0(\theta)\Sigma_t = \Gamma_1(\theta)\Sigma_{t-1} + \Psi(\theta)\varepsilon_t + \Pi(\theta)\eta_t \tag{1.23}$$

where the state vector is:

$$\Sigma_t = [R_t \quad \pi_t \quad y_t \quad \pi_{t+1/t} \quad y_{t+1/t} \quad \epsilon_{R,t} \quad \epsilon_{\pi,t} \quad \epsilon_{y,t}]'$$

the structural shocks vector is:

$$\varepsilon_t = [\tilde{\epsilon}_{R,t} \quad \tilde{\epsilon}_{\pi,t} \quad \tilde{\epsilon}_{y,t}]'$$

the forecast errors vector is:

$$\eta_t = [\eta_{\pi,t} \quad \eta_{y,t}]'$$

and θ collects the structural parameters of the model:

$$\theta = [\rho \quad \phi_\pi \quad \phi_y \quad \beta \quad \alpha \quad \kappa \quad \gamma \quad \sigma \quad \rho_R \quad \rho_\pi \quad \rho_y \quad \sigma_R^2 \quad \sigma_\pi^2 \quad \sigma_y^2]'$$

The matrices of the canonical form are:

$$\Gamma_0 = \begin{bmatrix} 1 & -(1-\rho)\phi_\pi & -(1-\rho)\phi_y & 0 & 0 & -1 & 0 & 0 \\ 0 & 1 & -\kappa & -\frac{\beta}{1+\beta\alpha} & 0 & 0 & -1 & 0 \\ \frac{1}{\sigma} & 0 & 1 & -\frac{1}{\sigma} & -\gamma & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Gamma_1 = \begin{bmatrix} \rho_R & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{\alpha}{1+\beta\alpha} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \frac{\delta}{1+\beta\delta} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \rho_R & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho_\pi & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho_y \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

$$\Psi = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \qquad \Pi = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

The model solution under both determinancy and indeterminancy can be achieved following Lubik and Schorfheide [2003] and Lubik and Schorfheide [2004] by doing the QZ decomposition which allows to deal with singularity in the Γ_0 matrix. I, then, proceed by doing the following factorization:

$$Q'\Lambda Z' = \Gamma_0 \tag{1.24}$$

$$Q'\Omega Z' = \Gamma_1 \tag{1.25}$$

where $Q'Q = Z'Z = I$ and both Λ and Ω are upper triangular matrices with the generalized eigenvalues as their diagonal elements. The QZ decomposition always exists, no matter the singularity of Γ_0.

I proceed next by pre-multiplying (1.23) by Q:

$$Q\Gamma_0\Sigma_t = Q\Gamma_1\Sigma_{t-1} + Q\Psi\varepsilon_t + Q\Pi\eta_t \tag{1.26}$$

Considering both (1.24) and (1.25), (1.26) turns into:

$$\underbrace{QQ'}_{I}\Lambda Z'\Sigma_t = \underbrace{QQ'}_{I}\Omega Z'\Sigma_{t-1} + Q\Psi\varepsilon_t + Q\Pi\eta_t \tag{1.27}$$

By replacing $w_t = Z'\Sigma_t$, I could rewrite (1.27) as:

$$\Lambda w_t = \Omega w_{t-1} + Q\Psi\varepsilon_t + Q\Pi\eta_t \tag{1.28}$$

Now, (1.28) can be expressed in matrix form as:

$$\begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ 0 & \Lambda_{22} \end{bmatrix} \begin{bmatrix} w_{1t} \\ w_{2t} \end{bmatrix} = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ 0 & \Omega_{22} \end{bmatrix} \begin{bmatrix} w_{1t-1} \\ w_{2t-1} \end{bmatrix} + \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} (\Psi\varepsilon_t + \Pi\eta_t) \tag{1.29}$$

Where the unstable eigenvalues of Λ matrix (those who are $|\lambda_{ij}| \geq 1$) have been placed in the lower right and are represented by Λ_{22}. I would then have two blocks: the explosive and the non-explosive one.

To solve for the explosive block, I consider the second row in 1.29:

$$\Lambda_{22}w_{2t} = \Omega_{22}w_{2t-1} + Q_2\Psi\varepsilon_t + Q_2\Pi\eta_t \tag{1.30}$$

By defining $\Psi_x^* = Q_2\Psi$ and $\Pi_x^* = Q_2\Pi$, then 1.30 turns into:

$$w_{2t} = \Lambda_{22}^{-1}\Omega_{22}w_{2t-1} + \Lambda_{22}^{-1}(\Psi_x^*\varepsilon_t + \Pi_x^*\eta_t) \tag{1.31}$$

In order to obtain a stable solution, I need 1.31 to be 0. This can be accomplished by setting $w_{20} = 0$ and by choosing the measurement errors vector η_t in a way such that the second member of 1.31 is equal to 0.

The Blanchard and Kahn [1980] conditions says that, in order to achieve a determinate solution, the number of $|\lambda_{ij}| \geq 1$ have to be equal to the number of non-predetermined variables, which is 2 in my case ($\pi_{t+1|t}$ and $y_{t+1|t}$). If, by the other hand, the number of unstable roots is lower than that of the non-predetermined variables, then the solution is indeterminate, which allows for the presence of sunspot shocks.

To solve for the non-explosive block, I consider the first row in 1.29:

$$\Lambda_{11}w_{1t} + \Lambda_{12}w_{2t} = \Omega_{11}w_{1t-1} + \Omega_{12}w_{2t-1} + Q_1\Psi\varepsilon_t + Q_1\Pi\eta_t \tag{1.32}$$

Whenever the solution is stable $w_{2t} = w_{2t-1} = 0$. Then, 1.32 comes down to:

$$\Lambda_{11}w_{1t} = \Omega_{11}w_{1t-1} + Q_1(\Psi\varepsilon_t + \Pi\eta_t)$$

$$w_{1t} = \Lambda_{11}^{-1}\Omega_{11}w_{1t-1} + \Lambda_{11}^{-1}Q_1(\Psi\varepsilon_t + \Pi\eta_t) \tag{1.33}$$

From (1.31) and (1.33), the solution of the model is:

$$\begin{cases} w_{1t} = & \Lambda_{11}^{-1}\Omega_{11}w_{1t-1} + \Lambda_{11}^{-1}Q_1(\Psi\varepsilon_t + \Pi\eta_t) \\ w_{2t} = & \Lambda_{22}^{-1}\Omega_{22}w_{2t-1} + \Lambda_{22}^{-1}(\Psi_x^*\varepsilon_t + \Pi_x^*\eta_t) \end{cases} \tag{1.34}$$

Chapter 2

An analysis of fiscal shocks in Argentina

2.1 Abstract

I analyze the consequences of a fiscal shock in Argentina using a Structural Vector Autoregression (SVAR) identified with *sign restrictions*. This identification is based on the Impulse Response Functions produced by a Real Business Cycle model that replicates some key moments of the Argentinian data sample. These key moments are: a higher volatility in consumption than in output, procyclical government expenses and strong countercyclical net exports. I then use the SVAR to analyze the effect of a positive fiscal shock on output and on net exports and I find that it has an important impact increasing the former and decreasing the latter. However, the effect lasts little more than one year and the fiscal multiplier is way below one. So, there must be a *strong crowding* out effect. The relevance of these findings lies in that they can help to asses quantitatively the fiscal policy in Argentina.

Keywords: General equilibrium, Identification, Real Business Cycles Model, Structural VARs, Fiscal Policy, Open Economy Macroeconomics, Argentina.

JEL Classification: C32, C68, E13, E32, E62, F41

2.2 Introduction

In the last two decades there has been no much room for monetary policy in Argentina: under the fixed exchange-rate regime during the 1990's, money supply depended only on the level of international reserves held by the Central Bank of Argentina (BCRA). At 2002, there was a regime switch to a floating exchange-rate and inflation increased substantially, reducing any potential real effect a monetary policy might have. Hopefully, Argentina will be able to keep inflation under control, regain public confidence in its own currency and, as a consequence, be able to make a better use of the monetary policy. Until then, the fiscal policy will keep its role as the main tool at hand for the government to influence the performance of the economy. It is then of much importance to know the consequences of its use. Will it have a big impact on output? For how long? How will the effect be on net exports? These are the questions I try to answer in this work.

I evaluate in this paper the effect of a fiscal shock over output and net exports in Argentina, using a Structural Vector Autoregression (SVAR) identified by a specific pattern of signs on impact. These signs are based on the Impulse Response Functions (IRFs) generated by a Real Business Cycle (RBC) model that replicates some key moments of the Argentinian data sample. These key moments are, in order of importance: a higher volatility in consumption than in output, procyclical government expenses and strong countercyclical net exports. My main conclusion is that a positive fiscal shock has a significant effect increasing output and reducing net exports with a peak response two quarters after the shock. Nevertheless, variables' responses are short-termed (around one year) and there is no fiscal multiplier (around 0.4 at peak). So, there must be a *strong crowding* out effect over private consumption and investment. The conclusions of this paper are of practical importance as they can be used for economic policy analysis.

The results reached here are in line with the existing literature. Dungey and Fry [2009] analyze a fiscal shock in New Zealand using a SVAR identified with informal *sign restrictions* and imposing a positive response of output on impact. It concludes that a fiscal shock that increases government expenses has a positive effect on output around 60%, which is lower to the value I estimate for Argentina. Mountford and Uhlig [2009] analyze a fiscal shock in US using a SVAR identified with *signs restrictions* but remain agnostic about the effect of a fiscal shock on output and impose no restrictions on the signs of the responses of the key variables of interest. The only restrictions imposed are those of the government spending (and other policy instruments) that is assumed to be positive. They analyze different policy scenarios and find out that deficit spending weakly stimulates the economy and crowds out private investment through a rise in interest rates. Results I reach here are similar to theirs.

Regarding the scarce VAR literature for Argentina, existing works are in line with the zero-restriction identification used in the traditional approach of Blanchard and Perotti [2002]. The works of both Rezk et al. [2006] and Lanteri [2011], the only papers that perform a fiscal VAR analysis for this country to my true knowledge, use a SVAR identified with Cholesky to analyze a fiscal shock on GDP and national savings, respectively. The former concludes that a fiscal shock has, at the most, a moderate and short-lived effect on output, and cast doubts upon some traditionally accepted Keynesian macroeconomic policy prescriptions. So their results are not so far from mines. The latter concludes that government spending shocks impact negatively and permanently on national savings. In any case, to the present there is no SVAR identified with *sign restrictions*, neither informal nor formally, that analyses fiscal shocks in Argentina. This work intends to fill this gap.

Since the seminal work of Sims [1980], SVAR models have been used to evaluate the effect of exogenous shocks on the evolution of economic variables. The main advantage of these models is that they are not as structured as general equilibrium ones are. Nevertheless, in order to draw some conclusions out of the analysis, some restrictions need to be made to identify the disturbances in the SVAR. Lately, *signs restrictions* have been used to perform such identification. This method consists on imposing a pattern of signs on the variables at impact, when the innovation occurs. This is, a given shock is assumed to have a determined effect at period zero over some (or all) of the analyzed variables. The question then is where do these *sign restrictions* come from?

One possibility is to derive the *sign restrictions* from intuition: for example, a positive productivity shock is assumed to have a positive effect on output and a negative one on prices. Nevertheless, a more formal procedure is preferable if the objective is to derive economically relevant statements. Or as Cooley and LeRoy [1985] put it "If the models are interpreted as structural, the restrictions on error distributions adopted in atheoretical macroeconometrics are not arbitrary renormalizations, but prior identifying restrictions. As such, they require justification from theory." In terms of this paper, by imposing *sign restrictions* I am conditioning the empirical SVAR model. This requires a structural justification, which can only come from formal theory by the use of a theoretical model. As the variables analyzed here are output, consumption, investment and net exports, the RBC model seems the correct one to use.

However, the baseline RBC model, pioneered by Kydland and Prescott [1982], was designed to analyze the US and is ill suited to reproduce some common features of the Argentinian economy. Especially, its data generating process (DGP) does not have a private consumption volatility greater than the output one. This is a typical characteristic of developing countries, but it is absent in developed nations. In this paper, I use an RBC model that is able to match this empirical fact. The model used here can also replicate two other key moments of Argentina and of most developing countries: the countercyclical net exports and the procyclical government expenses. The rest of the data moments are matched quiet satisfactorily by the model's DGP.

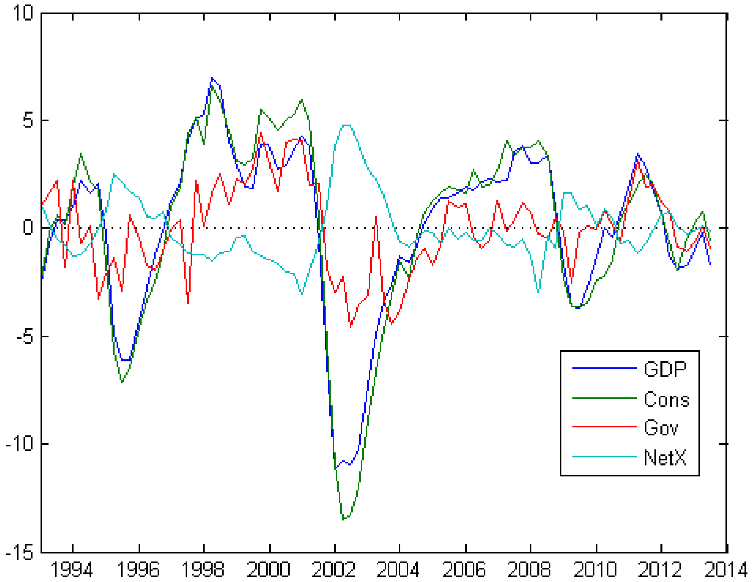
Using this RBC model, which suits fairly well for Argentina, I analyze the shape of the IRFs generated by it after a fiscal, productivity and net exports shocks. According to these IRFs, a fiscal expansion generates an increase in output and a decrease in net exports; a productivity improvement boosts both government expenses and net exports; and a positive shock to net exports increases output but decreases government consumption. I use these responses as a justification for the qualitative identification scheme I impose to the SVAR at time 0. By doing so, the *sign restrictions* used to identify the empirical model (SVAR) are not arbitrary impositions but formal constraints that come from a theoretical model (RBC).

Once the SVAR is identified, I proceed to the quantitative evaluation of a fiscal shock in Argentina, the main goal of this paper. The SVAR built is limited to three variables: government consumption, output and net exports. Looking at the distribution of the SVAR'IRFs generated after a positive fiscal shock is how I derive its effect on output and on net exports. Secondary results are the responses of endogenous variables to productivity and net exports innovations.

The work is organized as follows: section 2.3 presents some empirical regularities of Argentina for the last two decades. The variables chosen to describe the country's macroeconomic performance is in line with the policy analysis carried out in this work and the theoretical model used. Along with Argentinian data sample characteristics, I show also those of the US. This comparison is relevant as it reveals why we need to modify the standard RBC model (originally designed to match US data) in order to analyze a developing country like Argentina.

In section 2.4, I extend the RBC model developed in Aguiar and Gopinath [2007] by including the government sector. I present there the equilibrium as well as the steady state conditions. I also show some simulated key moments together with the IRFs obtained from the model simulation. IRFs show a clear pattern of response on impact following the structural shocks, as mentioned above. So I can use these responses to impose the *sign restrictions* in the following section.

In section 2.5, I estimate a reduced-form VAR with the following variables: government consumption, output gap and net exports. I then identify the SVAR with a *sign restriction* scheme that comes from the signs on impact of the RBC model' IRFs. Once identification is achieved, I reach analyze the SVAR'IRFs which show that a positive fiscal innovation has a non-negligible impact on both output and net exports with a peak response two quarters after the shock. However, the effect does not last much longer than one year and there is no fiscal multiplier. I also perform a forecast error variance decomposition that show that fiscal disturbances explain an important part of output and net exports volatilities, at least at the first period horizon.



See Data Appendix on page 57 for details.

Figure 2.1: Argentinian HP-filtered time series

2.3 Stylized facts

Since the late 1970's, developed nations have experienced a drop in their macroeconomic variables' volatilities (a phenomenon known as "The Great Moderation"). In contrast, developing countries have not shown such reduction in volatility. Actually, it has even increased during the economic opening to financial markets that took place in many emerging nations during the last three decades. This macroeconomic instability suffered by developing countries might come from more volatile shocks, such as terms of trade or country risk premium shocks; from a worse macroeconomic policy management by the authorities, or from other source of institutional instability that can amplify the effect of fundamental innovations.

Far from being an exception, Argentina has experienced a high volatility in all its macro-variables during the last twenty years. This fact is presented in Figure 2.1, where evolution of output, private consumption, government consumption and net exports are shown. Private investment is not presented in the graph because of its extreme volatility.

To evaluate the magnitude of the volatility in these series, I compare them to those of the US in Table 1. The data sample goes from 1993:Q1 up to 2013:Q3, which implies more than 20 years of quarterly data or 83 observations for each country. The standard deviations of all the variables are higher in Argentina. Most notably, consumption is at least 4 times more volatile than in the US. It is a special characteristic of Argentina, as of most developing countries, that the volatility of private consumption is even higher than the output one ($\sigma_c/\sigma_y = 1.14$). This empirical regularity implies that there is less consumption smoothing in emerging countries, which contradicts a widely known stylized fact of rich nations. This characteristic shown in the data is one of the key moments in this article.

Another relevant moment for the purpose of this work is the correlation between output and government consumption. As documented by Ilzetzki and Végh [2008], government consumption is procyclical in developing countries while it is countercyclical (or acyclical) in advanced nations. This puzzling phenomenon has been called "when it rains it pours" by Kaminsky et al. [2004]. It is puzzling in the sense that it contradicts the classic Keynesian stabilization rule of boosting (reducing) the share of government consumption during economic contractions (expansions). This stylized fact is present in Argentina, where there is a procyclicality in government consumption of $\rho_{g,y} = 0.62$ as opposed to countercyclicality in US of $\rho_{g,y} = -0.60$ for the given data sample.

Table 1: **HP-filtered Business Cycles (1993-2013)**

Statistic	Argentina	US
Standard Deviations		
σ_y	3.86	1.20
σ_c	4.41	1.01
σ_i	13.17	5.51
σ_g	2.05	1.12
σ_{nx}	1.49	0.32
σ_c/σ_y	1.14	0.84
σ_i/σ_y	3.41	4.59
σ_g/σ_y	0.53	0.93
σ_{nx}/σ_y	0.39	0.27
Correlations with y		
$\rho_{c,y}$	0.98	0.92
$\rho_{i,y}$	0.97	0.92
$\rho_{g,y}$	0.62	-0.60
$\rho_{nx,y}$	-0.90	-0.60
$\rho_{nx,g}$	-0.59	0.41
Serial Correlations		
y	0.91	0.89
c	0.92	0.93
i	0.90	0.94
g	0.63	0.79
nx	0.84	0.82

Standard deviations are reported in percentage points. See Data Appendix on page 57 for details.

Lastly, net exports are more countercyclical in developing nations than in developed ones. Table 1 shows that this is actually the case for the two representative countries taken here: Argentina has stronger than US countercyclality in net exports ($\rho^{Ar}_{nx,y} = -0.90$ and $\rho^{US}_{nx,y} = -0.60$). This fact has been analyzed by Calvo [1998], among others, and it is known as the *sudden stop* phenomenon. It consists in a dramatic current account reversal that occurs in developing economies whenever there is an economic crisis. In 2002 one *sudden stop* occurred in Argentina. As it becomes clear from Figure 2.1, the country suffered then an important drop in output that was followed by an improvement of net exports.

Regarding the serial correlations of both countries, they do not seem to differ as much. With the exception of government consumption, the persistence parameter is quite high in all of the variables.

To avoid the use of space, I only present the first autocorrelation parameter for each of the countries.

In sum, there are three stylized facts of Argentina that have been highlighted here. In order of importance, these are: the higher than output consumption volatility, the procyclical government expenses and the strong countercyclical net exports. These empirical regularities are present in most of the developing countries and any model that intends to explain their behavior should be able to replicate these facts. In the next section, I present a model that is quite successful in generating the above mentioned characteristics so typical in a developing country like Argentina.

2.4 The theoretical model

Since the seminal work of Kydland and Prescott [1982], dynamic stochastic general equilibrium (DSGE) models have been used to explain economic aggregate fluctuations. The so-called Real Business Cycle (RBC) model represents a useful tool because of its simplicity and good fit to data of developed economies. Nevertheless, the standard RBC model needs some adjustments if it intends to represent macroeconomic fluctuations in emerging countries. I use here an RBC model that suits well some key moments of developing countries in general and Argentina in particular.

Recent literature has focused on capturing developing nations' aspects using RBC models. Kydland and Zarazaga [2002], for example, calibrate one of these models to explain the Argentinian depression in the 1980's while Neumeyer and Perri [2005] calibrate another that incorporates a country risk component through the emerging economies' interest rates to match Argentinian macro variables in the period 1983-2001. An RBC model that features trend shocks with calibrated deep parameters and estimated shocks' coefficients is used by Aguiar and Gopinath [2007] to replicate some empirical regularities of both emerging and small open developed economies.

I extend this last model with the inclusion of the government sector, I estimate some of its parameters and calibrate others, and simulate it to verify if the model is able to match Argentinian time series presented before. The targeted moments are, in order of importance: the higher than output private consumption volatility, the procyclical government consumption and the strong countercyclical net exports. As it is shown below, the success of the RBC model to replicate these moments, allows me to use the theoretical responses of structural shocks to impose *signs restrictions* in the next section.

Starting with the description of firm's behavior, the inclusion of trend shocks to productivity is the basic difference with a standard RBC model. Technology is then characterized as:

$$Y_t = e^{z_t} K_{t-1}^{\alpha} (\Gamma_t L_t)^{1-\alpha} \tag{2.1}$$

where output (Y_t) uses capital (K_t) and labor (L_t) as inputs. The capital share of output is $\alpha \in (0, 1)$

while z is a productivity AR(1) process described as:

$$z_t = \rho_z z_{t-1} + \epsilon_t^z \qquad ; \qquad |\rho_z| < 1 \qquad ; \qquad \epsilon_t^z \sim \mathcal{N}(0, \sigma_z^2) \tag{2.2}$$

where ρ_z is the productivity persistence parameter and σ_z^2 is the variance of the shock. The novelty of the model is the incorporation of Γ_t, which represents the cumulative product of *growth shocks* and it is described as:

$$\Gamma_t = e^{\theta_t}\Gamma_{t-1} = \prod_{s=0}^{t} e^{\theta_s} \tag{2.3}$$

where θ is the *growth shock* since it constitutes the stochastic trend of productivity. This disturbance can be interpreted as an impressive change in fiscal, monetary, exchange rate or trade policy that sometimes occurs in developing countries and implies an important regime switch. There has been many of such episodes during recent economic history of Argentina. Although, the only example present in the data sample used here is the one that corresponds to the 2002 crisis, as mentioned when presenting the empirical regularities.

This *growth shock* (or shock to the trend) is described as the following AR(1) process:

$$\theta_t = (1-\rho_\theta)\ln(\mu) + \rho_\theta\theta_{t-1} + \epsilon_t^\theta \qquad ; \qquad |\rho_\theta| < 1 \qquad ; \qquad \epsilon_t^\theta \sim \mathcal{N}(0, \sigma_\theta^2) \tag{2.4}$$

where ρ_θ is the trend shock persistence parameter, μ represents productivity's long-run growth rate and σ_θ^2 is the variance of the shock.

Regarding households, the utility function has Cobb-Douglas preferences which are:

$$u_t(C_t, L_t) = \frac{\left[C_t^\gamma(1-L_t)^{1-\gamma}\right]^{1-\sigma}}{1-\sigma} \tag{2.5}$$

where C_t and L_t are private consumption and labor, respectively. The consumption share is $0 < \gamma < 1$ and σ is the utility curvature. The resource constraint of the agents looks like this:

$$\begin{aligned}(1-\tau_y)Y_t = (1+\tau_c)C_t + K_t - (1-\delta)K_{t-1} + \frac{\phi}{2}\left(\frac{K_t}{K_{t-1}} - \mu\right)^2 K_{t-1} \\ +(1+r_{t-1})B_{t-1} - B_t - T_t\end{aligned} \tag{2.6}$$

where τ_y and τ_c are taxes on income and consumption, respectively, δ is the depreciation rate, ϕ is the capital adjustment cost, r_t is the real interest rate and B_t and T_t are government bonds and transfers, respectively. The households' budget constraint implies that agents' disposable income is used to consume, invest and finance the government.

Private investment is given by:

$$I_t = K_t - (1-\delta)K_{t-1} + \frac{\phi}{2}\left(\frac{K_t}{K_{t-1}} - \mu\right)^2 K_{t-1} \tag{2.7}$$

where quadratic capital adjustment costs are present as:

$$\frac{\phi}{2}\left(\frac{K_t}{K_{t-1}}-\mu\right)^2 K_{t-1}$$

The government budget constraint is:

$$G_t + T_t + (1+r_{t-1})B_{t-1} = \tau_y Y_t + \tau_c C_t + B_t \tag{2.8}$$

where the left hand side are all the expenses of the government and the right hand side represents its income. This is, the government has some current expenses (treated as government consumption -G_t- in this paper), transfers (T_t) and payments of past debt at its corresponding interest rate ($(1+r_{t-1})B_{t-1}$). At the same time, it finances itself taxing household's income ($\tau_y Y_t$) and consumption ($\tau_c C_t$) and issuing bonds (B_t).

The model economy is closed by following Scmitt-Grohé and Uribe [2003] who define real interest rate as:

$$r_t = r^* + \psi\left(e^{B_t - b} - 1\right) \tag{2.9}$$

where r^* is the world interest rate, b represents the steady state level of debt over GDP and $\psi > 0$ is the portfolio adjustment cost. This last parameter can be interpreted as the coefficient on interest rate premium. Its calibration is crucial for the results presented later on. It is important to notice that (2.9) ultimately determines the price of debt.

Finally, the aggregate resource constraint can be represented as:

$$Y_t = C_t + I_t + G_t + NX_t \tag{2.10}$$

where net exports NX_t are related to government debt position as:

$$NX_t = (1+r_{t-1})B_{t-1} - B_t \tag{2.11}$$

This last equation implies that the foreign sector of the economy is in equilibrium whenever current and capital account are equal. In other words, a capital outflow (inflow) needs to have a counterpart with a current account surplus (deficit). In the real world, surplus in both accounts can coexist for some time if there is no adjustment in the exchange rate, which happens if there is an intervention of the Central Bank. But situations of this kind are not contemplated in this model.

Following Blanchard and Perotti [2002] and Chung and Leeper [2007], I add the following fiscal rule:

$$G_t = Y_t^{\eta} B_{t-1}^{\omega} \Gamma_t^{1-\eta-\omega} e^{g_t} \tag{2.12}$$

which illustrates that government consumption is determined by current output and lagged debt with coefficients η and ω, respectively. The only difference here is that the fiscal rule has a trend component represented by $\Gamma_t^{1-\eta-\omega}$. At the same time, g_t is defined as the fiscal shock that follows an AR(1) process:

$$g_t = \rho_g g_{t-1} + \epsilon_t^g \qquad ; \qquad |\,\rho_g\,| < 1 \qquad ; \qquad \epsilon_t^g \sim \mathcal{N}(0, \sigma_g^2) \tag{2.13}$$

2.4.1 Detrended setup

The production function (2.1) implies that a trend shock permanently affects Γ_t, so that output is non-stationary with a stochastic trend. Detrended variables are defined as:

$$\hat{x}_t \equiv \frac{x_t}{\Gamma_{t-1}}$$

Detrending (2.5), (2.6), (2.1) and (2.9), the planner's maximization problem looks like this:

$$\underset{\{\hat{C}_t, L_t, \hat{K}_t, \hat{B}_t\}}{\text{Max}} \; E_0 \sum_{t=0}^{\infty} \beta^t \Gamma_{t-1}^{\gamma(1-\sigma)} \frac{\left[\hat{C}_t^{\gamma}(1-L_t)^{1-\gamma}\right]^{1-\sigma}}{1-\sigma}$$

subject to

$$(1-\tau_y)\hat{Y}_t = (1+\tau_c)\hat{C}_t + \hat{K}_t - (1-\delta)\frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}} + \frac{\phi}{2}\left(e^{\theta_{t-1}}\frac{\hat{K}_t}{\hat{K}_{t-1}} - \mu\right)^2 \frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}}$$
$$+(1+r_{t-1})\frac{\hat{B}_{t-1}}{e^{\theta_{t-1}}} - \hat{B}_t - \hat{T}_t$$

with

$$\hat{Y}_t = e^{z_t}\left(\frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}}\right)^{\alpha}\left(e^{\theta_t}L_t\right)^{1-\alpha} \tag{2.14}$$

$$r_t = r^* + \psi\left(e^{\hat{B}_t - b} - 1\right) \tag{2.15}$$

2.4.2 Equilibrium conditions

I solve the optimization problem by using the recursive Lagrangian:

$$\mathcal{L} = \beta^t E_t \Bigg\{ \Gamma_{t-1}^{\gamma(1-\sigma)} \frac{\left[\hat{C}_t^{\gamma}(1-L_t)^{1-\gamma}\right]^{1-\sigma}}{1-\sigma} + \lambda_t \Bigg[(1-\tau_y)\hat{Y}_t - (1+\tau_c)\hat{C}_t - \hat{K}_t + (1-\delta)\frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}}$$
$$-\frac{\phi}{2}\left(e^{\theta_{t-1}}\frac{\hat{K}_t}{\hat{K}_{t-1}} - \mu\right)^2 \frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}} - (1+r_{t-1})\frac{\hat{B}_{t-1}}{e^{\theta_{t-1}}} + \hat{B}_t + \hat{T}_t \Bigg] \Bigg\}$$

and reach the following first order conditions:

$\hat{C}_t$:

$$\lambda_t = \frac{\gamma \hat{C}_t^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(1-\sigma)}\Gamma_{t-1}^{\gamma(1-\sigma)}}{1+\tau_c}$$

L_t:

$$\lambda_t = \frac{(1-\gamma)\hat{C}_t^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(-\sigma)-\gamma}\,\Gamma_{t-1}^{\gamma(1-\sigma)}}{1-\tau_y}\frac{L_t}{(1-\alpha)\hat{Y}_t}$$

So, the intratemporal condition is:

$$\frac{\hat{C}_t}{(1-L_t)} = \frac{\gamma}{1-\gamma}(1-\alpha)\frac{1-\tau_y}{1+\tau_c}\cdot\frac{\hat{Y}_t}{L_t} \tag{2.16}$$

$\hat{B}_t$:

$$E_t\beta^{t+1}\lambda_{t+1}\frac{1+r_t}{e^{\theta_t}} = \beta^t\lambda_t$$

So, the intertemporal condition is:

$$\frac{\hat{C}_t^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(1-\sigma)}e^{\theta_t[1-\gamma(1-\sigma)]}}{1+r_t} = \beta E_t\left[\hat{C}_{t+1}^{\gamma(1-\sigma)-1}(1-L_{t+1})^{(1-\gamma)(1-\sigma)}\right] \tag{2.17}$$

$\hat{K}_t$:

$$E_t\beta^{t+1}\lambda_{t+1}\left\{(1-\tau_y)\alpha\frac{\hat{Y}_{t+1}}{\hat{K}_t}+1-\delta+\frac{\phi}{2}\left[\left(e^{\theta_t}\frac{\hat{K}_{t+1}}{\hat{K}}\right)^2-\mu^2\right]\right\}$$
$$= \beta^t\lambda_t e^{\theta_t}\left[1+\phi\left(e^{\theta_{t-1}}\frac{\hat{K}_t}{\hat{K}_{t-1}}-\mu\right)\right]$$

So, the arbitrage condition is:

$$\begin{aligned}
&\hat{C}_t^{\gamma(1-\sigma)-1}(1-L_t)^{(1-\gamma)(1-\sigma)}e^{\theta_t[1-\gamma(1-\sigma)]}\left[\phi\left(e^{\theta_{t-1}}\frac{\hat{K}_t}{\hat{K}_{t-1}}-\mu\right)+1\right] = \\
&\beta E_t\left\{\hat{C}_{t+1}^{\gamma(1-\sigma)-1}(1-L_{t+1})^{(1-\gamma)(1-\sigma)}\left\{(1-\tau_y)\alpha\frac{\hat{Y}_{t+1}}{\hat{K}_t}+1-\delta\right.\right. \\
&\left.\left.+\frac{\phi}{2}\left[\left(e^{\theta_t}\frac{\hat{K}_{t+1}}{\hat{K}_t}\right)^2-\mu^2\right]\right\}\right\}
\end{aligned} \tag{2.18}$$

At the same time, detrending equations of investment (2.7), government constraint (2.8), aggregate constraint (2.10), net exports (2.11) and the fiscal rule (2.12) I get, respectively,:

$$\hat{I}_t = \hat{K}_t - (1-\delta)\frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}} + \frac{\phi}{2}\left(e^{\theta_{t-1}}\frac{\hat{K}_t}{\hat{K}_{t-1}} - \mu\right)^2 \frac{\hat{K}_{t-1}}{e^{\theta_{t-1}}} \tag{2.19}$$

$$\hat{G}_t = \tau_y \hat{Y}_t + \tau_c \hat{C}_t + \hat{B}_t - \hat{T}_t - (1+r_{t-1})\frac{\hat{B}_{t-1}}{e^{\theta_{t-1}}} \tag{2.20}$$

$$\hat{Y}_t = \hat{C}_t + \hat{I}_t + \hat{G}_t + \hat{NX}_t \tag{2.21}$$

$$\hat{NX}_t = (1+r_{t-1})\frac{\hat{B}_{t-1}}{e^{\theta_{t-1}}} - \hat{B}_t \tag{2.22}$$

$$\hat{G}_t = \hat{Y}_t^{\eta}\hat{B}_{t-1}^{\omega} e^{\theta_t(1-\eta-\omega)} e^{-\omega\theta_{t-1}} e^{g_t} \tag{2.23}$$

Productivity (2.2), trend (2.4) and fiscal shocks (2.13), together with expressions (2.14)-(2.23) conform a system of 13 equations with 13 variables. State variables are capital and debt stocks $[\hat{K}_t, \hat{B}_t]$, while control variables are private consumption, labor, private investment, output, net exports, public transfers, real interest rate and government expenses $[\hat{C}_t, L_t, \hat{I}_t, \hat{Y}_t, \hat{NX}_t, \hat{T}_t, r_t, \hat{G}_t]$. Exogenous variables are productivity, trend and fiscal shocks $[z_t, \theta_t, g_t]$. We obtain the steady state in the following section. The model is log-linearized to the first order about the steady state, solved and simulated using Dynare software[1]. Results are presented below at Table 3 and Figures 2.2 and 2.3.

2.4.3 Steady state

At steady state, exogenous shocks are at the expectations values are $z = \theta = g = 0$. At the same time, I consider debt, transfers and government expenses ratio to output as constants $b = \hat{B}/\hat{Y}$, $\bar{T} = \hat{T}/\hat{Y}$ and $\bar{G} = \hat{G}/\hat{Y}$, respectively. Additionally, the intertemporal condition (2.17) implies that, at steady state:

$$\mu = [\beta(1+r^*)]^{\frac{1}{1-\gamma(1-\sigma)}}$$

[1]Refer to Adjemian et al. [2011] for a detail of the algorithms implemented by the software.

All these considered, I am left at steady state with a system of seven variables $[\hat{C}_t, L_t, \hat{I}_t, \hat{Y}_t, N\hat{X}_t, r_t, \hat{K}_t]$ and the following seven equations:

$$\begin{aligned}
\frac{\hat{C}}{1-L} =& \frac{\gamma}{1-\gamma}(1-\alpha)\frac{1-\tau_y}{1+\tau_c}\cdot\frac{\hat{Y}}{L} \\
r^* =& (1-\tau_y)\alpha\frac{\hat{Y}}{\hat{K}}-\delta \\
\hat{I} =& \left(1-\frac{1-\delta}{\mu}\right)\hat{K} \\
\hat{Y} =& \left(\frac{\hat{K}}{\mu}\right)^{\alpha}(\mu L)^{1-\alpha} \\
N\hat{X} =& \left(\frac{1+r^*}{\mu}-1\right)b\hat{Y} \\
(1-\tau_y) =& (1+\tau_c)\frac{\hat{C}}{\hat{Y}}+\left(1-\frac{1-\delta}{\mu}\right)\frac{\hat{K}}{\hat{Y}}+\left(\frac{1+r^*}{\mu}-1\right)b-\bar{T} \\
r =& r^*
\end{aligned}$$

which lead to the following steady state solutions:

$$\begin{aligned}
\hat{Y} =& \Omega\hat{K} \\
\hat{L} =& \Omega^{\frac{1}{1-\alpha}}\mu^{\frac{2\alpha-1}{1-\alpha}}\hat{K} \\
\hat{C} =& \frac{\gamma}{1-\gamma}(1-\alpha)\frac{1-\tau_y}{1+\tau_c}\left(\Omega^{\frac{\alpha}{\alpha-1}}\mu^{\frac{1-2\alpha}{1-\alpha}}-\Omega\hat{K}\right) \\
\hat{K} =& \frac{\frac{\gamma}{1-\gamma}(1-\alpha)(1-\tau_y)\Omega^{\frac{1}{\alpha-1}}\mu^{\frac{1-2\alpha}{1-\alpha}}}{1-\tau_y+\frac{\gamma}{1-\gamma}(1-\alpha)(1-\tau_y)+\left(\frac{1-\delta}{\mu}-1\right)\frac{1}{\Omega}+\left(1-\frac{1+r^*}{\mu}\right)b+\bar{T}} \\
N\hat{X} =& \left(\frac{1+r^*}{\mu}-1\right)b\hat{Y} \\
\hat{I} =& \left(1-\frac{1-\delta}{\mu}\right)\hat{K} \\
r =& r^*
\end{aligned}$$

where:

$$\Omega = \frac{r^*+\delta}{(1-\tau_y)\alpha}$$

2.4.4 Estimation and calibration

The model presented in the previous section has 22 parameters which are:

$$\alpha, \beta, \gamma, \delta, \phi, \sigma, \psi, \mu, \bar{T}, \bar{G}, b, r^*, \tau_c, \tau_y, \rho_z, \rho_\theta, \rho_g, \eta, \omega, \sigma_z, \sigma_\theta, \sigma_g$$

I estimate the parameters of the productivity process (α, ρ_z and σ_z), trend parameters (ρ_θ and σ_θ) and those of the fiscal rule (η, ω and σ_g) by the procedure explained in this section. Government parameters ($b, \bar{T}, \bar{G}, \rho_g, \tau_c$ and τ_y) and world interest rate (r^*) are calibrated according to long term relations observed in the data sample. The rest of the parameters ($\beta, \gamma, \delta, \phi, \sigma$ and ψ) are calibrated following the related literature.

In order to estimate technology parameters, the production function (2.1) is expressed in per-capita terms:

$$y_t = e^{z_t} k_{t-1}^{\alpha} \Gamma_t^{1-\alpha}$$

where lower case letters represent per-capita variables. The function is reexpressed in log terms as:

$$\ln(y_t) = \alpha \ln(k_{t-1}) + (1-\alpha) \ln(\Gamma_t) + z_t$$

In order to obtain detrended variables, I need to get an estimation of the trend ($\ln(\Gamma_t)$) which is not observable. To do so, I assume that it can be represented fairly well by the Hodrick-Prescott filtered trend component of the output ($\ln(y_t)$). With this assumption, I can then obtain detrended per-capita output and capital. These are defined as:

$$\begin{aligned} \ln(\tilde{y}_t) &= \ln\left(\frac{y_t}{\Gamma_t}\right) \\ \ln(\tilde{k}_{t-1}) &= \ln\left(\frac{k_{t-1}}{\Gamma_t}\right) \end{aligned}$$

Finally, I get the cycle components of the Hodrick-Prescott decomposition from both detrended output ($\ln(\tilde{y}_t)$) and capital ($\ln(\tilde{k}_{t-1})$) and define them as C_{yt} and C_{kt}, respectively. I reach then the following model:

$$\begin{aligned} C_{yt} &= \alpha C_{kt} + z_t \\ z_t &= \rho_z z_{t-1} + \epsilon_t^z \qquad ; \qquad | \rho_z | < 1 \qquad ; \qquad \epsilon_t^z \sim \mathcal{N}(0, \sigma_z^2) \end{aligned}$$

which I use to estimate α, ρ_z and σ_z with OLS by applying the Cochrane-Orcutt procedure. Convergence of estimated parameters is achieved after 12 iterations[2]. The estimated parameters α, ρ_z and σ_z are presented in Table 2.

I am left now with the estimation of trend shock parameters of equation (2.4). To perform this estimation, I start by applying logs to (2.3) so that it turns into:

$$\ln\left(\frac{\Gamma_t}{\Gamma_{t-1}}\right) = \theta_t$$

[2]See Appendix on page 57 for data details.

which are series in differences that are possible to build because I already have the unobservable $\ln(\Gamma_t)$, as explained previously. Consequently, I can estimate the parameters $\rho_\theta, \sigma_\theta$ and μ of the trend shock equation (2.4) by OLS from:

$$\theta_t = \beta_0 + \beta_1 \theta_{t-1} + \epsilon_t^\theta$$

where $\hat{\beta}_0 = (1 - \rho_\theta)\ln\mu, \hat{\beta}_1 = \rho_\theta$ and $std\left(\hat{\epsilon}_t^\theta\right) = \sigma_\theta$. The estimated parameters ρ_θ and σ_θ are presented in Table 2.

In order to estimate the parameters η, ω and σ_g, the fiscal rule (2.23) can be expressed as

$$g_t = \eta y_t + \omega b_{t-1} + (1 - \eta - \omega)\theta_t - \omega\theta_{t-1} + \varepsilon_t^g$$

where $x_t \equiv \ln \hat{X}_t$ and $\varepsilon_t^g \equiv \ln e_t^g$. Then

$$g_t = \eta \tilde{y}_t + \omega \tilde{b}_{t-1} + \theta_t + \varepsilon_t^g \tag{2.24}$$

where $\tilde{y}_t \equiv y_t - \theta_t$ and $\tilde{b}_{t-1} \equiv b_{t-1} - \theta_t - \theta_{t-1}$. From an econometric point of view, I can use OLS to estimate (2.24) because $E\left(\varepsilon_t^g, \tilde{b}_{t-1}\right) = 0$. But I am also assuming that $E\left(\varepsilon_t^g, \tilde{y}_t\right) = 0$ and $E\left(\varepsilon_t^g, \theta_t\right) = 0$. This is, the errors are not related to any of the exogenous variables, so there are no endogeneity problems (like simultaneity or reverse causality). The other assumption is that $\tilde{y}_t, \tilde{b}_{t-1}$ and θ_t are linearly independent. The estimated parameters η, ω and σ_g are presented in Table 2.

Regarding government parameters, they come from long term averages found in the data sample. The coefficients $b, \tau_y, \bar{T}$ and $\bar{G}$ are set at the average ratio of debt, income taxes, transfers and government expenses over output, respectively, while τ_c represents the average ratio of consumption taxes over aggregate private consumption. World interest rate r^* is the average of the rate on three months US treasuries[3].

[3] See Appendix on page 58 for data details.

Table 2: Parameter values

Name	Symbol	Value	Remarks
Preference parameters			
Discount factor	β	0.99	calibrated
Consumption share	γ	0.5	calibrated
Risk aversion	σ	2	calibrated
Technology parameters			
Capital share	α	0.25**	estimated
Depreciation rate	δ	0.05	calibrated
Capital adjustment cost	ϕ	4	calibrated
Coefficient on interest rate premium	ψ	0.005	calibrated
Steady-state normalized debt	b	0.66	calibrated
World interest rate	r^*	0.02	calibrated
Government parameters			
Steady-state Government transfers	$\bar{T}$	0.02	calibrated
Steady-state Government expenses	$\bar{G}$	0.13	calibrated
Consumption taxes	τ_c	0.1	calibrated
Income taxes	τ_y	0.02	calibrated
Shocks parameters			
Productivity persistence	ρ_z	0.75***	estimated
Productivity volatility	σ_z	0.005	estimated
Trend persistence	ρ_θ	0.99***	estimated
Trend volatility	σ_θ	0.06	estimated
Fiscal rule parameters			
Output elasticity	η	0.34***	estimated
Debt elasticity	ω	-0.05**	estimated
Government expenses persistence	ρ_g	0.63	calibrated
Volatility	σ_g	1.44	estimated

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

2.4.5 Simulation results

In order to assess the fit of the model to Argentinian data, I analyze the statistical properties of its DGP. Simulated data is hp-filtered with a smoothing parameter of $\lambda = 1600$. So it is treated exactly the same way as sample data. Table 3 shows DGP' statistical properties of the simulated RBC model: it fits data qualitatively well, but it is quantitatively poor in many aspects. Specifically, the cross correlations are much lower than those present in real data[4]. Nevertheless, the targeted moments that I intend to replicate are matched quite satisfactorily. The model can reproduce a higher than output private consumption volatility and an important procyclical government consumption. It can also generate countercyclical net exports, the other key moment of this work, although not as well as the other two targeted moments.

Table 3: Actual vs Simulated data

Statistic	Actual data	Simulated data
Targeted moments		
σ_c/σ_y	1.14	1.15
$\rho_{g,y}$	0.62	0.38
$\rho_{nx,y}$	-0.90	-0.37
Non-targeted moments		
σ_i/σ_y	3.41	3.83
$\rho_{c,y}$	0.98	0.05
$\rho_{i,y}$	0.97	0.02
$\rho(y_t, y_{t-1})$	0.91	0.95
$\rho(c_t, c_{t-1})$	0.92	0.72
$\rho(i_t, i_{t-1})$	0.90	0.73

Even if the model does not fit real data perfectly, the success in reproducing the targeted moments mentioned before are enough for the purpose of the present work: to use the model as a justification for the *signs restrictions* identification of a less structural analysis, as the one carried on with a SVAR in next section.

Figure 2.2 shows the IRFs, calculated for 20 quarters, of a fiscal shock that results from simulating the RBC model calibrated/estimated for Argentina. The key aspects to be notice are the responses on impact of both output and net exports as shown in subplots $3x2$ and $3x3$, respectively. Although the dynamic of output is mostly a contraction, the response is positive on impact. Regarding net exports, there is a negative response on impact to the fiscal expansion. In the next section, I use these IRFs to identify the signs of the SVAR.

The dynamics observed in Figure 2.2 are standard for an RBC model, where variable's responses are driven mainly by the *wealth effect*. Each of the subplots is presented in order, according to the following explanation of the dynamics: when there is a positive fiscal shock, like an unexpected increase in government consumption, G increases at period 0. If government expenditure is debt financed, as is the case here, public debt (B) increases, so private saving must rise in order to match

[4] A misspecification of the model can be responsible for failing to reproduce closer to real time series moments, as critized by García-Cicco et al. [2010].

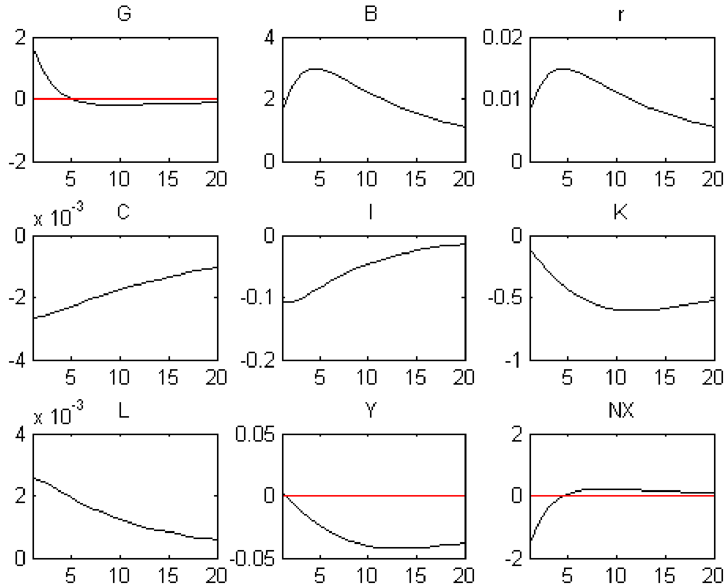


Figure 2.2: RBC' IRFs after a fiscal shock

public dis-saving. This means that the real interest rate (r) must go up in order to induce an increase in private savings. Consequently, private consumption (C) and investment (I) fall after an increase in government expenditure. The drop in investment produces a reduction of the capital stock (K) in the economy. At the same time, agents feel poorer as there are (or there will be) less resources available for private use. Hence, they work harder and increase the hours worked (L), which implies that there is a negative *wealth effect*. Finally, less leisure and more work leads to a rise in output (Y), as is presented in the subplot $3x2$. However, the persistent contraction in consumption and investment imply the rise in output to be ephemeral.

The real rate of interest is crucial in determining the dynamics of private consumption and investment. It is possible to obtain a weaker decrease in the responses of both of them by increasing, respectively, the parameters of risk aversion (σ) and of the capital adjustment cost (ϕ). But the model is not able to reproduce a positive impact on neither of these two variables. Using different model specifications might change their responses. When public expenditure yields utility, which can be modeled by including G in the household's utility function, the effect of a fiscal shock on investment may change, but consumption still falls. Regarding consumption, one way of achieving a positive response has been provided by Ravn et al. [2007] who modeled deep habits formation on a variety of consumption goods and firm's monopolistic competition. These types of models can produce a stronger impact on aggregate output by changing dynamics of consumption and investment. Nevertheless, their greater complexity makes them less practical to the goal of this paper, which is just to derive the sign of the responses on impact. In other words, I consider good enough the simpler model used here as long as the response of output is the expected one.

The last subplot ($3x3$ in Figure 2.2) shows that there is a decrease in net exports on impact, followed by an increase around the forth quarter after the disturbance. As it is clear from (2.22), net exports fall on impact because of the increase in public debt used to finance the government. The subsequent rise in net exports is related to the reduction in debt and it depends both on the interest rate and the trend shock. Intuitively, a debt financed fiscal shock generates initially a capital inflow that, according to the model, has a counterpart with a current account deficit. But in the following periods, debt has to be payed, so there is a capital outflow compensated by a current account surplus. The shape of the net exports response to a fiscal shock is widely dependent on the coefficient of interest rate premium ψ, as it is evident from the equilibrium condition for net exports (2.22) that, at the same time, depends crucially on the evolution of the real interest rate, as described in (2.15). Calibration of the parameter at $\psi = 0.005$ allows the model to reproduce a drop in net exports on impact. This shape in the response of net exports is insensitive with respect to the calibration used in the related literature (Aguiar and Gopinath [2007] or Neumeyer and Perri [2005] set $\psi = 0.001$).

It is important to remark that all IRFs ultimately return to steady state. The only reason for some responses to seem to be divergent in Figure 2.2 is that I am doing simulations just for 20 periods to focus on the impact response. If simulations were done over a higher number of periods the graphs would show a return to steady state for all of these variables.

Figure 2.3 presents the IRFs of all three shocks (fiscal, productivity and net exports innovations) over government expenses, output and net exports. The fiscal shock (ϵ_t^g) is defined at (2.13) and the productivity shock (ϵ_t^z) at (2.2). Regarding net exports shock, we interpret it as a negative innovation to (ϵ_t^θ) at (2.4). Because, according to (2.22), this will imply a positive shock to net exports. Figure 2.3 provides all the signs that are needed to impose on impact in the following section. It shows that a fiscal shock increases government expenses and output while it decreases net exports; the productivity innovation increases all variables and a net export disturbance decreases government expenses while it increases output and net exports.

2.5 The empirical model

In this section I use a Structural Vector Autoregression (SVAR) model to evaluate the impact of a positive fiscal shock in Argentina. I interpret the shock as an unexpected increase in the amount of government consumption, as in Kaminsky et al. [2004], and check which is the behavior

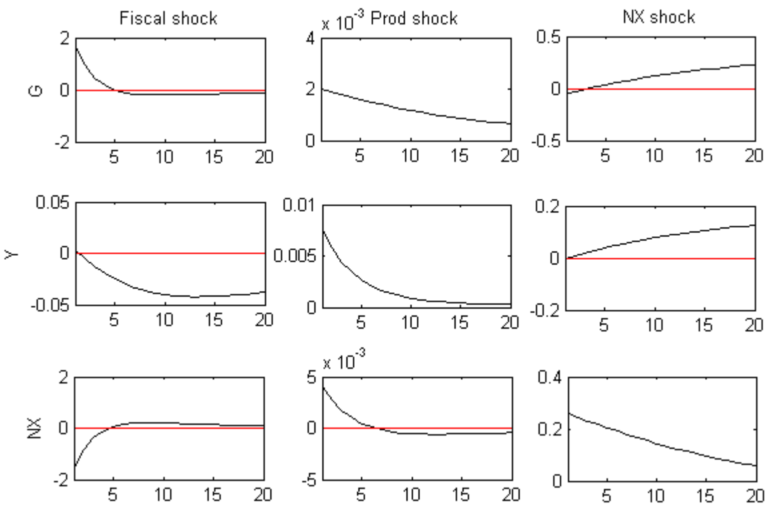


Figure 2.3: RBC' IRFs for the three shocks

of output and net exports by analyzing their IRFs. Secondary results consist on the effects of productivity and net exports innovations on endogenous variables. In order to perform such analysis, I first estimate a reduced form VAR composed of government consumption, output and net exports. Secondly, I identify the structural shocks that affect the three variables by adopting a *sign restrictions* identification scheme conditional on the responses of structural shocks of the RBC model presented above. And, finally, I study the effect of exogenous shocks plotting the IRFs of the SVAR and perform a forecast error variance decomposition analysis.

2.5.1 The reduced form VAR

I use a fixed-coefficients VAR as an empirical model to analyze the effect of a fiscal shock. Its reduced form is represented as:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + \mu_t$$

where Y_t is a 3x1 vector of time series including the log of government consumption (g_t), the log of output (y_t) and net exports over output (nx_t). All variables are HP-filtered using a smoothing parameter of $\lambda = 1600$. The coefficients are represented by B_0, which is a $3x1$ constants' vector, and B_i, which are $3x3$ matrices of variables' coefficients. Lastly, μ_t is a $3xT$ Gaussian white noise process vector with zero mean and variance Σ.

Before estimating the VAR, I need to define its lag order, which I do by applying the Akaike information criterion (AIC). It results in a two-lag order, so that the VAR has the following reduced form:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \mu_t \tag{2.25}$$

I estimate the VAR using OLS to obtain the following coefficient matrices[5]:

$$\hat{B}_0 = \begin{bmatrix} -0,05 \\ -0,03 \\ 0,01 \end{bmatrix} \qquad \hat{B}_1 = \begin{bmatrix} 0,31 & 0,24 & -0,22 \\ 0,08 & 1,33 & -0,60 \\ -0,04 & -0,32 & 0,61 \end{bmatrix} \hat{B}_2 = \begin{bmatrix} 0,22 & -0,08 & 0,25 \\ -0,09 & -0,42 & 0,72 \\ -0,04 & 0,18 & -0,21 \end{bmatrix}$$

I get as well the reduced-form residuals μ_t that have a zero mean and the following variance-covariance matrix:

$$\Sigma = \begin{bmatrix} 2,15 & 0,38 & -0,08 \\ 0,38 & 1,21 & -0,38 \\ -0,08 & -0,38 & 0,45 \end{bmatrix}$$

2.5.2 The structural VAR identified with *sign restrictions*

In order to identify the VAR I follow a procedure that has two essential ingredients: on one hand, exact identification is achieved by doing a Cholesky decomposition of the reduced form variance covariance matrix. On the other hand, the desired pattern of signs is imposed using a rotation matrix that comes from an orthogonal decomposition of matrices randomly drawn from a normal distribution. At the end of the procedure, I am left with a large number of candidate impact matrices with the desired properties.

More precisely, the algorithm is as follows:

1. It decomposes the reduced form residuals variance-covariance matrix using Cholesky (or egienvalue-eigenvector decomposition): $\Sigma = CC'$.
2. A sufficiently large amount of K_{3x3} matrices are drawn from a normal distribution.
3. I do the QR decomposition of K matrices using the algorithm by Rubio-Ramirez et al. [2010] to obtain rotation matrices Q such that $K = QR$ and $QQ' = I$. This is, Q is an orthogonal matrix.
4. Get the candidate impact matrix: $A_0 = C'Q'$ and keep only those matrices that have the desired pattern of signs.
5. Use the A_0 matrices to plot IRFs and do forecast error variance decomposition analysis.

[5]See Appendix on page 59 for estimation results details.

In the present case, once the algorithm presented on steps 1 to 5 is done, the reduced form model (2.25) turns into:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + A_0 e_t \tag{2.26}$$

where A_0 is a 3x3 matrix and e_t is a 3x1 vector of normally distributed shocks with unit variance by definition. The SVAR system relates observable VAR-based residuals to unobserved structural shocks. In other words, it is the link between data and theory. Additionally, as noted in Canova and Pina [2005], general equilibrium logic implies that impact of all shocks at the initial period should be, in general, non-zero. Indeed, this is exactly what DSGE models, as the one presented previously in this work, reproduce: all the responses of the variables are non-zero at $t = 0$, as shown in Figures 2.2 and 2.3. This fact implies that the elements of the A_0 matrix should typically be non-zero as is the case with the *signs restrictions* approach. By using this identification scheme, I assign the signs conditional on the RBC model to the elements of A_0 matrix:

$$\begin{bmatrix} g_t \\ y_t \\ nx_t \end{bmatrix} = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \underbrace{\begin{bmatrix} + & + & - \\ + & + & + \\ - & + & + \end{bmatrix}}_{A_0} \begin{bmatrix} e_t^F \\ e_t^{Pvty} \\ e_t^{NX} \end{bmatrix} \tag{2.27}$$

where $e_t^F, e_t^{Pvty}, e_t^{NX}$ are interpreted as a fiscal, a productivity and a net exports shock, respectively[6]. The signs of the A_0 matrix at (2.27) are based on the responses generated by the RBC model shown in Figure 2.3. As it stands, the pattern of signs that have been imposed imply that a positive fiscal innovation increases output and decreases net exports, a positive productivity innovation increases all variables, and a positive net exports disturbance decreases government expenses while it increases output.

I give here a brief description of the steps of the algorithm: once the reduced form VAR is estimated, I generate 5000 simulations for parameter matrices $\hat{B}_0$ and $\hat{B}_1$, as well as for the variance-covariance matrix Σ, by bootstrapping the estimated model. Once stationarity is checked for the bootstrapped matrices, I center them using the median of the distribution. Afterwards, I get 5000 A_0 matrices based on sign restrictions satisfying the conditions mentioned above. The distribution of these A_0 matrices is presented in Figure 2.4.

[6] As noted by Kilian [2011], 'in general, structural shocks do not correspond to particular model variables. For example, in a VAR system consisting of only price and quantity, we can think of a demand shock and a supply shock each shifting prices and quantities. In fact, if price and quantity variables were mechanically associated with price and quantity shocks, this would be an indication that the proposed model is not truly structural.' Considering this fact, it can be argued that the net exports shock I identify is not fully structural. I leave this as a task to solve in the future with the with the waiver that this disturbance is not the focus of my analysis.

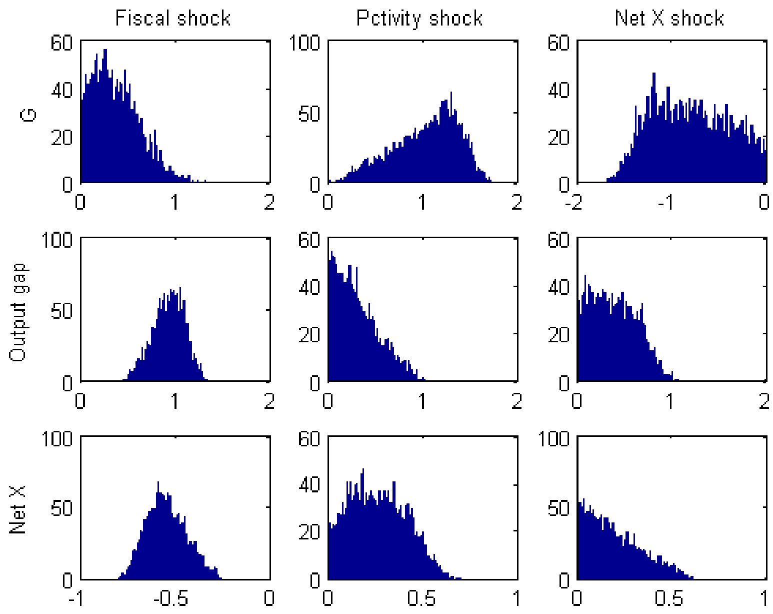


Figure 2.4: Distribution of impacts

It is important to notice that the pattern of signs imposed on impact produce distributions of elements in the A_0 matrices that are nearly normal. This means that the pattern of signs is easily traced back using the real data which is contained in the variance-covariance matrix of reduced form residuals. If this were not the case, then one or more of the distributions of A_0 elements in Figure 2.4 would be far from normality.

2.5.3 Variance decomposition analysis

To do a forecast error variance decomposition analysis, I use the 5000 A_0 matrices obtained in the previous section and I build a distribution of variance decomposition matrices using the variance of the first step forecast error. Table 4 presents the mean of this distribution:

Table 4: Variance decomposition

	Gov exp	Output gap	Net Exports
Shock:			
Fiscal	8.71	72.44	68.01
	[0.08, 28.90]	[37.16, 98.10]	[32.86, 97.21]
Productivity	54.95	11.08	19.68
	[7.84, 95.79]	[0.05, 42.14]	[0.31, 56.72]
Net Exports	36.33	16.48	12.31
	[0.76, 85.37]	[0.13, 49.61]	[0.04, 47.28]

Means and 90% intervals (in brackets)

According to Table 4, fiscal shocks are important in explaining output and net exports variations, at least for the first step forecast error, as they represent 72% and 68% of their volatility, respectively.

2.5.4 Impulse-Response Functions Analysis

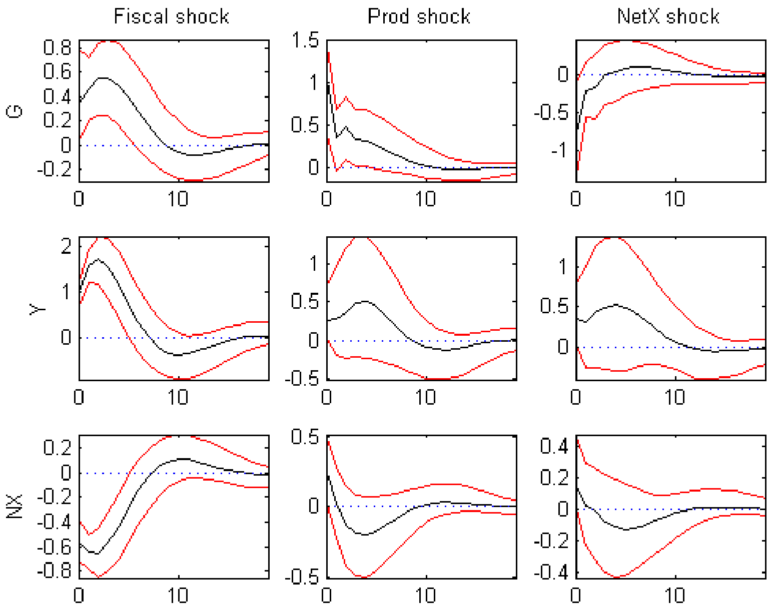
IRFs of fiscal shock are calculated using all 5000 A_0 matrices as well as the 5000 parameter matrices $\hat{B}_0$ and $\hat{B}_1$ following the SVAR model (2.27). The distribution of IRFs obtained is use to calculate the response of a fiscal shock on the three variables. A plot of the median and the 90% confidence interval of the IRFs distribution is shown in Figure 2.5. At the same time, Figure 2.6 presents a detail of just the fiscal shock.

This figure is the main result of this work and it shows that a fiscal shock has an important effect on both output and net exports. The disturbance increases output around 285% and decreases net exports approximately 170%. Both variables reach a peak around the second quarter after the shock and the response is significantly different from 0 for a 90% confidence level, as shown in the graph in red. Nevertheless, the effect dies out fast by the end of the first year. Secondary results are the responses of endogenous variables to productivity and net exports shocks.

At the same time, I can get an approximate measure of the long term fiscal multiplier which is represented by the elasticity of output with respect to government expenses. Considering on impact an increase in government consumption of 33% and in output of 94%, and given an average share of government consumption over GDP for the Argentinian data sample of 13%, the multiplier on impact would be:

$$\frac{\Delta y}{\Delta g} \cdot \frac{g}{y} \approx 0.37$$

While the multiplier at the peak (second quarter), when the increase in output reaches 173% (and considering an increase in government spending of 55%), is approximately equal to 0.40. As the



Median and 90% confidence intervals.

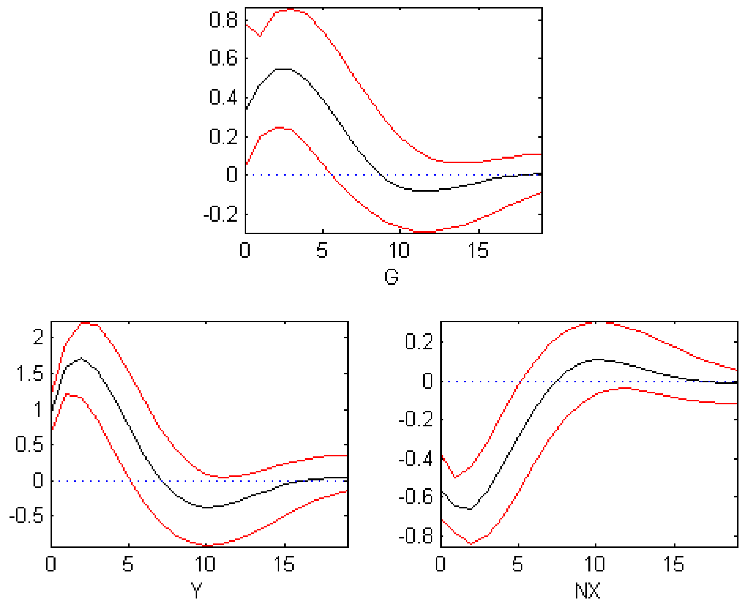
Figure 2.5: SVAR' IRFs

fiscal multiplier is considerably less than one, there must be a strong crowding out effect on private consumption and/or investment. I leave the reasons behind these effects for further research.

2.6 Conclusions

In this work I evaluate the effects of a fiscal shock over output and net exports in Argentina. In order to do so, I perform a Structural VAR analysis with three variables: government consumption, output and net exports, imposing a pattern of signs on impact. These signs come from the IRFs obtained by simulating an RBC model with estimated/calibrated parameters. This theoretical model serves as a justification for the *signs restrictions* approach used here because it replicates quiet satisfactorily some key moments of Argentinian data sample. These are, in order of importance: higher than output private consumption volatility, procyclical government consumption and countercyclical net exports.

My main result is that a positive fiscal shock has an important effect increasing output and decreasing net exports with a peak at the second quarter. However, the effect is mostly short termed, as it lasts little more than one year, and there is no fiscal multiplier. This result has important implications as it helps to assess quantitatively the fiscal policy in Argentina.



Median and 90% confidence intervals.

Figure 2.6: SVAR' IRFs after a fiscal shock

2.7 Appendix

2.7.1 Data

Figure 1, Table 1 & actual data of Table 3: The variables used are y (GDP), c (personal consumption), i (personal investment-GFCF-), g (government consumption), x (exports of goods and services) and m (imports of goods and services). Argentinian data comes from the Economic Ministry (MECON) while US data was taken from the US Bureau of Economic Analysis (BEU). The data is expressed at constant prices and at quarterly frequency from 1993:Q1 to 2013:Q3. All series used are seasonally adjusted. Net exports is trade balance over output. All series but net exports are taken in logs. All series are Hodrick-Prescott filtered with a smoothing parameter of 1,600.

Technology: Labor series corresponds to number of urban workers. They are taken from the Encuesta Permanente de Hogares (EPH) of the Argentinian Economic Ministry (MECON). From 1993 until 2002 they are bianual, and quarterly from then on. In order to transform bianual into quarterly data I apply the following procedure:

$$\Delta L_t = \alpha + \sum_{j=1}^{20} \beta_j D_{j,t} + e_t \tag{2.28}$$

where ΔL_t are labor series expressed in difference and $D_{j,t}$ are 20 dummy variables I use to fill missing values, which are the 2nd and 4th quarters from 1993 until 2002 (inclusive). Each dummy variable is a $(1xT)$ zero vector (where T is the number of observations), which has a 1 in the row corresponding to each specific missing quarter. As a result of the application of (2.28), original values are kept and missing values are created. I then transform the series back into levels in order to estimate productivity parameters.

Capital series are real capital stock at constant prices obtained from MECON. Both labor and capital series are not seasonally adjusted. I filter them with the Stable Seasonal Filter subrutine of Matlab[7].

Fiscal rule: GDP and government consumption series are described above. Series of Argentinian debt are in % of GDP and they are from Mecon. They go from 1994:Q4 to 2012:Q2 and they are seasonally adjusted using Matlab subrutine.

Taxes and transfers: Consumption and income taxes are value added and gross income taxes, respectively. The former is at constant prices while the latter is at current prices. Both series are non seasonally adjusted and they go from 1993:Q1 to 2012:Q4. Transfers are reported in current prices from 2002:Q1 until 2012:Q4. Taxes and transfers are from *Finanzas Públicas* report of MECON.

US T-bill 3 month rates are from the Federal Reserve (FRB H15).

[7]Available at www.mathworks.com.

2.7.2 VAR estimation results

Table 5: VAR estimation results

Variables	g_t	y_t	nx_t
g_{t-1}	0.31^{***}	0.08	-0.04
	(2.70)	(0.90)	(-0.71)
g_{t-2}	0.22^{**}	-0.09	-0.04
	(1.95)	(-1.01)	(-0.85)
y_{t-1}	0.24^{*}	1.33^{***}	-0.32^{***}
	(1.69)	(12.25)	(-4.81)
y_{t-2}	-0.08	-0.42^{**}	0.18
	(-0.57)	(-3.93)	(2.80)
nx_{t-1}	-0.21	-0.60^{***}	0.61^{***}
	(-0.76)	(-2.76)	(4.57)
nx_{t-2}	0.25	0.72^{***}	-0.21
	(0.88)	(3.31)	(-1.55)
constant	-0.05	-0.03	0.01
	(-0.30)	(-0.22)	(0.06)
Observations	81	81	81
R-squared	0.52	0.92	0.81

t-statistics in parentheses

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$

Table 6: Granger casualty test (F-statistics)

Variables	g	y	nx
g	9.36^{***}	0.65	1.04
y	1.69	90.39^{***}	11.68^{***}
nx	0.47	6.51^{***}	10.57^{***}

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1.$

Chapter 3

An analysis of terms of trade shocks in Argentina

3.1 Abstract

I analyze the effects of terms of trade shocks over aggregate output and inflation in Argentina using a Structural Vector Autoregression model identified with *sign restrictions* conditional on an estimated/calibrated New Keynesian Small Open Economy model. Results presented as variance decomposition and impulse response functions show that terms of trade shocks do not have a significant impact on output while they mainly affect inflation. These findings can be due to the fact that sample data is split into two: during the first part the country had a fixed exchange rate, while it acquired a flexible one during the second part. In any case, evidence presented here discard terms of trade as an important driver of business cycles in Argentina which is in contrast to an extended believe among some economists who believe that output performance depends crucially on them.

Keywords: Terms of trade shocks; Structural VARs; Signs restrictions identification; Small open economy New Keynesian models; Argentina.

JEL Classification: C32; E12; F41

3.2 Introduction

In the past twenty years, Argentina, as well as many other emerging countries, has suffered important business cycles fluctuations. Volatility in developing countries has been widely studied in small-open-economy macroeconomics. Broadly, the available theoretical explanations fall into two categories: one is that emerging market economies are subject to more volatile shocks than are developed countries. The second category of explanations argues that in emerging countries government policy tends to amplify business-cycle fluctuations whereas in developed countries public policy tends to mitigate aggregate instability. In other words, these explanations hold responsible either foreign or domestic shocks for local output performance in emerging countries. In this paper I check the relevance of foreign disturbances in Argentinian macroeconomic outlook by studying the effect terms of trade improvements have on output and inflation.

Since Prebisch [1959], terms of trade have been seen as a major source of business cycles in developing economies. The Singer-Prebisch hypothesis of the 1950's assigned an important role to deteriorating terms of trade as the main reason of the under-performance of emerging nations. This thesis was also called *structural* in opposition to an inquiry that allegedly leaves aside relevant features when undertaking economic analysis. *Structuralism* is still very popular among economists in Argentina who rely on their premises to do policy recommendations. However, there is not much applied literature trying to quantify the effect of terms of trade variations in this country.

This paper conducts an empirical examination of the effect of terms of trade shocks in Argentina using both a theoretical and an empirical model. The former is a New Keynesian Small Open Economy (NK SOE) model and the latter is a Structural Vector Autoregression (SVAR) model identified with *sign restrictions*. Some of the parameters of the NK SOE model are estimated, while others are calibrated using Argentinian data for the period 1993:1 to 2013:3. Model's data generating process (DGP) resembles fairly well those of Argentinian sample data, so a quite accurate analysis can be performed. Additionally, qualitative responses to exogenous disturbances in this theoretical model can be used to perform a quantitative analysis with an empirical model. This is precisely what I do when using the SVAR, whose results can be considered as more realistic than those obtained with a purely theoretical investigation.

The conclusion of this work is that terms of trade (TOT) shocks have an important effect on inflation but not on output. According to the results obtained here, a positive TOT shock increases output less than 10% on impact, reaching a peak response by the first quarter. Nevertheless, this effect is barely significant. By the other hand, inflation is significantly affected by a terms of trade shock as it increases around 45% on impact, and its effects lasts at least half a year. At the same time, according to a variance decomposition analysis, TOT disturbances account only for 10% of observed the output variability while they explain more than 50% of the inflation one. Mi conclusions provide evidence to discard terms of trade as an important source of business cycles' drivers in Argentina.

It is known since Friedman [1953] that an advantage often attributed to flexible exchange rate regimes over fixed regimes is their ability to insulate more effectively the economy against external shocks. Since then, a number of theories have confirmed this original intuition and it has become one of the least disputed arguments in favor of flexible exchange rate regimes[1]. As analyzed by Broda [2001], there are smoother real output paths after terms of trade shocks. At the same time, the author concludes that these disturbances are inflationary in floating regimes. The findings obtained here can be explained by the fact that Argentina during more than half of the sample data had a floating exchange rate regime.

To my truly knowledge, the present article is original as I am not aware of any similar work done to analyze terms of trade shocks in Argentina. The closer VAR analysis available is that of Broda [2004] that analyzes terms of trade shock effects for several developing countries. The author uses a panel VAR identified with *zero restrictions* and concludes that under a fixed exchange regime impact of TOT shocks on output is higher than under flexible one. He estimates a 10% response in output to terms of trade shocks and that these disturbances are responsible for a 10% of total output variability, so my results are similar to his.

Mendoza [1995] is a common reference in the literature of open macroeconomics that analyses the effect of terms of trade on business cycles. With a calibrated Real Business Cycles (RBC) model, the author concludes that terms of trade shocks explain 37% of GDP variability in developing economies. So my results differ somehow from his and are even further from those of Kose [2002] who also calibrates an RBC model and concludes that almost 90% of output variability is explained by terms of trade shocks. By the other hand, Lubik and Teo [2005] and Lubik and Schorfheide [2007] perform a bayesian estimation of an RBC and a NK model, respectively, and find evidence of an explanatory power of terms of trade around 10%, which is in line with the results obtained here.

Escudé [2009] builds an NK SOE model and incorporates direct foreign exchange intervention where there are two alternative corner regimes: a floating exchange regime where the monetary authority abstains from intervening in the currency market and a pegged exchange regime where it abstains from intervening in the money market. The goal of the author's paper is to get the optimal monetary and exchange rate policies. Some parameters of the model are calibrated using steady state values for the Argentine economy, others are estimated with Bayesian techniques using data for the period 2002:3 to 2007:4.

Finally, Berkmen [2009] study the impact of TOT shocks on Argentina over the period 2003 to 2007 using the IMF's Global Integrated Monetary and Fiscal (GIMF) model, which incorporates overlapping generation households and nominal rigidities. They are particularly interested in

[1] See for example Corsetti and Pesenti [2001].

checking whether counter-cyclical monetary and fiscal policies can reduce inflationary pressures in inflation after a positive TOT shock, which they represent by a commodity price shock. Results are similar to those presented here, as the author finds a higher response in inflation than in output to a TOT shock.

A main distinction with respect to the cited literature is that here I use a SVAR identified with *sign restrictions* to derive quantitative conclusions about an improvement in terms of trade. In this sense, the techniques used here are in the spirit of those used in works like Fry and Pagan [2011]. This type of structural analysis is quite new and its use is beginning to extend in macroeconometric research. Its main advantage is that it is based on a reduced form analysis, with the difference that some interpretation needs to be given to the data. Additionally, *signs restrictions* are much less restricted than other forms of identification (like Cholesky). But this advantage is also a disadvantage in the sense that *signs restrictions* imply only weak information. So it is important to impose restrictions in the highest number of elements in order to get results with some extent of precision.

On section 3.3, I present some stylized facts of the last two decades of the Argentinian economy. Even if the intention of this section is purely descriptive, some transformations need to be made to original series. Economic contraction of the late 1990's, as well as the posterior currency devaluation and debt default that occurred in 2002, constituted a traumatic event that marked the ending of one economic regime and the beginning of a new one. What particularly distinguished both regimes was that exchange rate was fixed until devaluation and it became moderately flexible after. Now, during the years when devaluation hit harder (from the end of 2001 to the beginning of 2003) macroeconomic series had completely unusual values. This fact needs to be taken into account, specially, when using nominal variables in the research. In order to deal with this problem I get rid of outliers data values from problematic years with the method explained below. I then present targeted sample moments for the whole period as well as for before and after the devaluation event. I also show sample moments for the US, in order to compare Argentinian data to that of a developed country.

Section 3.4 presents the theoretical model. I take the NK SOE model used by Lubik and Schorfheide [2007], which is a simplified version of Galí and Monacelli [2005]. This is a prototypical New Keynesian model properly suited to perform an open economy analysis as it explicitly introduces variables such as exchange rate and terms of trade. Judging from the interests that motivate this study, this model seems the correct one to use. Some of the parameters are calibrated while others are estimated. On one side, calibration comes from long term Argentinian or US data, as it corresponds, with the exception of the intertemporal substitution elasticity and the Phillips curve slope which come from the optimization of a function that minimizes differences of selected theoretical and sample moments of Argentinian. On the other side, estimated parameters are those of the policy rule and the production function. These estimations are done by OLS and Cochrane-Orcutt procedure, respectively, using Argentinian sample data.

Simulation results presented in Section 3.4 show that the theoretical model fits fairly well Argentinian series. Targeted empirical moments are replicated by the model quiet successfully. Unfortunately, this is not the case for non-targeted moments, as there are some quantitative and, more disturbing, qualitative differences between data and model's DGP. This underperformance of the model do not weaken my findings as I just use the theoretical model to get the signs imposed on impact to the SVAR analysis performed later on. This is, here I perform a quantitative analysis that relies only qualitatively on the theoretical model. In any case, it is left for further research to change the theoretical model in order to improve the fit to data.

On section 3.5, I present the empirical model which consists on a SVAR with three variables: output gap, inflation and terms of trade variations. The identification of the SVAR is done by imposing the signs conditional on the responses generated by the theoretical model of the previous section. The terms of trade shock generates positive responses in all endogenous variables. Regarding the shocks to inflation and output they are interpreted as supply and demand shocks, respectively. As these two innovations are not specified in the theoretical model used here, I impose the restrictions informally. However, they are in line with the responses observed in other DSGE frameworks that do model these shocks. As it stands, I impose a positive response of output and inflation and a negative one of terms of trade to a demand shock and negative response of output, positive of inflation and negative of terms of trade to a supply disturbance. With Montecarlo methods, I build a distribution of impact matrices (A_0) satisfying the *sign restrictions*. This distribution is used to get the median and 90% interval IRFs of demand, cost-push and TOT shocks as well as to perform a variance decomposition analysis. The conclusion is that terms of trade shocks can only account for important effects in inflation but not in real activity.

3.3 Data analysis

3.3.1 Recent economic events and data transformation

A widely known stylized fact is that emerging market economies are about twice as volatile as developed economies. Argentina is far from being the exception. During the last twenty years, the country has experienced important variability in its macroeconomic variables as shown in Figure 3.1. As presented in the figure, a first difficulty that arouses when analyzing Argentinian time series is the huge exchange rate devaluation that occurred at 2002 and that divides Argentinian recent economic history into two markedly different periods: the *fixed exchange rate regime* (also known as the *Convertibility model*) and the *administrated exchange rate regime* installed after the devaluation

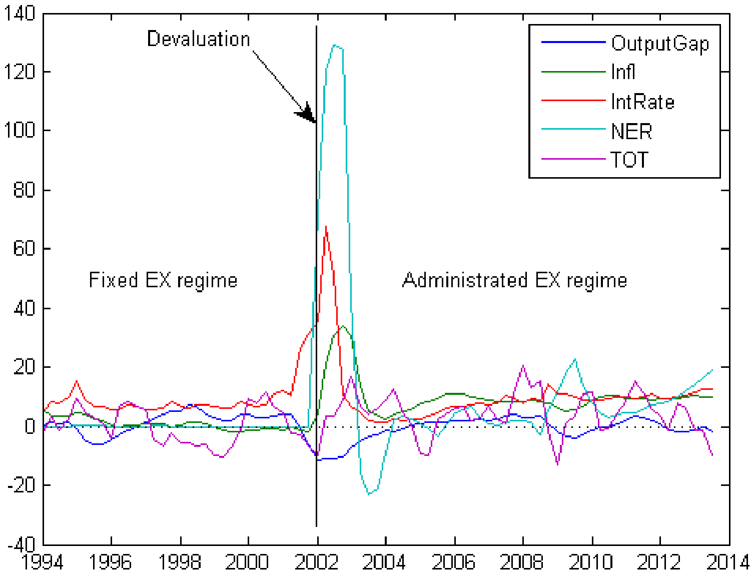


Figure 3.1: Argentinian time series

took place. Variability along the whole sample period is very high (around ±20%). But from 2001 to 2003, when the devaluation effects hit harder, macroeconomic volatility exploded beyond usual levels.

An analysis of Argentinian time series can be misleading if variability of the presented variables is not softened to lighten the effect of the violent devaluation episode of 2002. In order to do so, I follow Stock and Watson [2002] and get rid of outliers by applying the following criteria:

- Output gap: Outliers are identified as observations that differ from the sample median by more than two times the sample interquartile range. I replace these observations with the median of the eight adjacent values. As a result, four data values are transformed (from 2002:1 to 2002:4).

- Inflation: Outliers are identified as observations that differ from the sample median by more than two times the sample interquartile range. I replace these observations with the median of the six adjacent values. As a result, three data values are transformed (from 2002:3 to 2003:1).

- Nominal interest rate: Outliers are identified as observations that differ from the sample median by more than four times the sample interquartile range. I replace these observations with the median of the eight adjacent values. As a result, five data values are transformed (from 2001:3 to 2002:3).

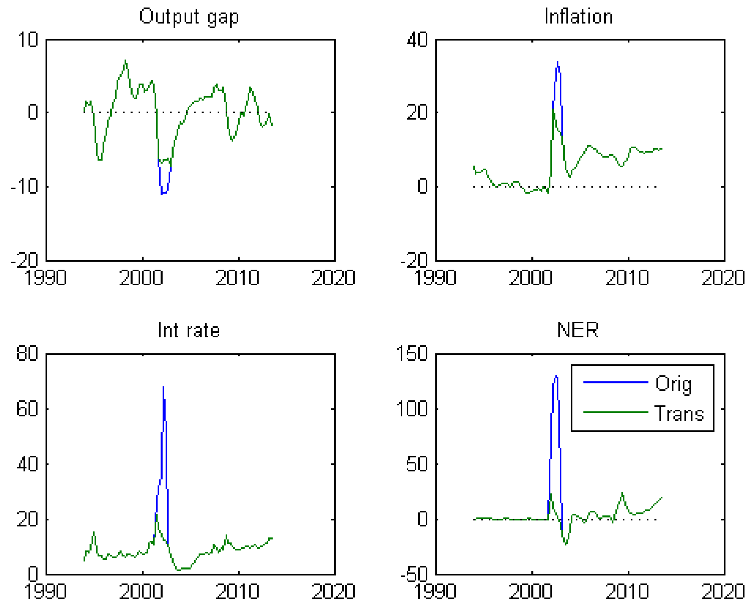


Figure 3.2: Argentinian time series (original and transformed)

- Nominal exchange rate (NER): Outliers are identified as observations that differ from the sample median by more than six times the sample interquartile range. I replace these observations with the median of the eight adjacent values. As a result, five data values are transformed (from 2002:1 to 2003:1).

As terms of trade do not present outliers, I keep original values. The data transformation detail can be seen in Figure 3.2.

As a result of this data transformation, I obtain sample series that are still extremely volatile but benefit from the lack of outliers values occurred around the devaluation event. The transformed series are shown in Figure 3.3 from where some observations can be derived. However, before analyzing empirical regularities in Argentina, I will describe briefly major economic events that took place during the last twenty years.

In order to grasp recent economic history in the country, it is important to distinguish among both regimes that settled before and after the devaluation event of 2002. *Fixed* and *administrated exchange rate regimes* were completely different in nature and responded to the circumstances of their times. Fixed exchange rate was implemented on 1991 to face hyper-inflationary episodes that had been damaging Argentina since the late 1980's. It was very successful in halting inflation and fostering output during most of the 1990's, but it turned out to be ill suited to cope with economic downturns. The reason behind this was that the *fixed exchange rate* regime was mainly a

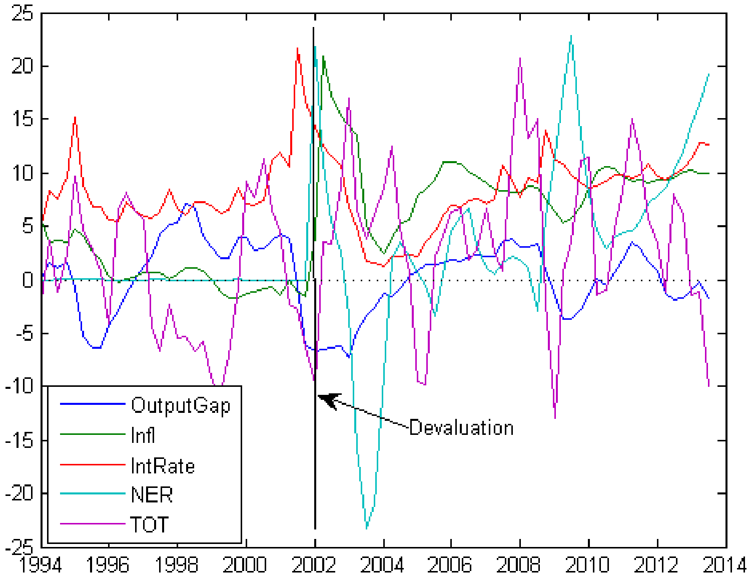


Figure 3.3: Argentinian time series (without outliers)

capital-inflow led growth model: foreign reserves came mostly from the capital account, while the country frequently run current account deficits. Output growth during the first half of 1990's was sustained by FDI, which consisted basically on private investment in the privatization of services state owned companies. But growth during the second half of the 1990's was based mainly on portfolio investment, which was very volatile and highly influenced by other emerging markets outlooks. A first warning of the fragility of the *fixed exchange rate* regime was the impact of Mexican *peso* devaluation in 1995 (known as the *Tequila* effect). But it wasn't until Brazilian currency devaluation in 1999 that the system started to crumble.

During 2001, Argentinian government aimed to save the *fixed exchange rate* system. The country borrowed two loans of 40 and 30 billion US$ (known as the *Blindaje* and *Megacanje* loans, respectively), provided mostly by the IMF because private investors were reluctant to keep on lending to the country. A *zero deficit* policy, that inhibited fiscal deficits by law, was also implemented some months before the breakdown in an endeavor to regain private investors' confidence. However, all these attempts were fruitless. The main reason was that Argentina had become to expensive under the *fixed exchange rate* regime. The Central Bank was unable to devaluate the currency because it was forbidden by the *Convertibility* law, and the speed of deflation in internal prices, which was assumed to be the solution for the lack of competitiveness at the time, was just never fast enough.

Excluded from international financial markets, Argentina had no choice other than debt default and local currency devaluation on January 2002. This marked the end of the *fixed exchange rate* regime and the beginning of the *administrated* one. The immediate effect of the devaluation was an important gain in competitiveness of the country. Argentina had traditionally been considered one of the most advanced countries in the region, so it had both the industrial potential and a skillful workforce to undergo a fast recovery. Economic performance improved steadily since the devaluation episode: GDP growth has remain quite high during most of the *administrated exchange rate* regime. The difference with the previous regime, was that now it had become mainly an export led growth model: foreign reserves came mostly from the current account surplus. At the same time, terms of trade improved significantly for Argentina (as for many commodity exporting countries) during the past ten years driven mostly by China's increasing demand. Considering that since 2002 Argentina's GDP growth is mainly lead by exports, this fact has improved even more the country's performance.

Nevertheless, economic perspective for the country has worsen significantly during the last three years. Argentina has been unable to tackle inflationary pressure and it is now in danger of falling into stagnation. Local authorities have not only been powerless to reduce inflation, they have also been unwilling to recognize that rising prices were actually taking place at unusual speed[2]. In a country were inflation has been out of control several times in the recent past, government's attitude has eroded private sector trust regarding economic outlook, with a consequent drop in private investment. Additionally, high inflation has turned the country more expensive and less competitive. And, to get things worse, commodity exports prices have decreased in the last two years. Consequently, the export led growth model has been seriously weakened.

3.3.2 Empirical regularities

Looking at Figure 3.3, we can see there are some distinctions between the *fixed* and *administered exchange rate* regimes. More specifically, volatilies and TOT correlations with the rest of the variables seem to be different before and after devaluation. Table 1 presents relevant sample data moments for the whole sample as well as for both periods. The same moments are shown for US as a representation of a developed country.

[2]A brief description of this serious issue is given at page 72.

Table 1: Argentinian vs US sample moments

	Argentina			US
Statistic	Whole sample	Fixed EX regime	Administrated EX regime	
σ_q	7.14	6.23	7.31	3.15
σ_y/σ_q	0.48	0.60	0.42	0.46
σ_π/σ_q	0.71	0.32	0.46	0.26
σ_r/σ_q	0.49	0.58	0.47	0.70
σ_e/σ_q	1.03	0.01	1.26	2.24
$\rho(q_t, q_{t-1})$	0.60	0.69	0.46	0.72
$\rho(q, y)$	-0.06	-0.20	0.15	-0.41***
$\rho(q, \pi)$	0.29***	0.12	0.10	-0.81***
$\rho(q, r)$	-0.07	0.07	-0.15	-0.06
$\rho(q, ner)$	-0.15	-0.01	-0.30**	0.44***

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. See Data Appendix on page 85 for details.

The table shows that there are important differences both between Argentina's subsequent regimes and between this nation and US. A first salient feature is that terms of trade volatility (σ_q) in Argentina more than doubles that of the US. As most developing countries, Argentina is basically a commodity exporter and a capital goods importer. In 2013, commodities represented 66% of total exports and capital goods represented 74% of total imports for the country[3]. Consequently, terms of trade for the country are mainly driven by the prices of these products. Being an important player in world commodity market (specially for products like soya, wheat, corn, barley, leather, meat, fruits, vegetables, biodiesel, copper and gold), Argentina is a price taker for the goods it exports. It follows that the terms of trade can be regarded as an exogenous source of aggregate fluctuations for the country. Because primary commodities display large fluctuations over time, terms of trade have the potential of being an important source of business cycles in the country.

A second important observation is that terms of trade go from weakly counter-cyclical to weakly pro-cyclical with the subsequent exchange regimes in Argentina, while they are strongly counter-cyclical in US. Now, the counter-cyclicality in the US can be explained by the size of its economy, such that the high imports demand during booms can affect worldwide prices and deteriorate US terms of trade. But for Argentina, being a small world market player, this explanation is not satisfactory. Countercyclical terms of trade during the fixed *exchange rate regime* are hard to explain, while them being procyclical during *administrated exchange rate regime* can be due to the export led growth during that period.

[3]Source: Argentian statistic national institute (Indec).

Finally, correlation of terms of trade with both inflation and nominal exchange rate are qualitatively different between the countries. For Argentina, there seems to be a non-negligible impact of the improvement of terms of trade rising internal prices and appreciating the nominal exchange rate. These features are replicated successfully by the theoretical model as explained below.

3.3.3 Problems with Argentinian data

The credibility of macroeconomic series measurement has been seriously damaged during the last years in Argentina. It is known that the consumer price index (CPI) has been systematically underestimated since the national statistics institute's intervention in 2007. Since then, official inflation has been lower than the one estimated by private consultants. But it was not until the last three years that the gap between both estimations has widened. It is also suspected that GDP series have been overestimated lately. This is said to be taking place since 2007, according to a group of researchers of the University of Buenos Aires[4]. Finally, Argentinian government has tighten the control on foreign currency reserves since 2011 in an attempt to reduce capital outflow. Since then, official exchange rate has been lower than the market value. But it was not until 2012 that the gap between official and market currency values widened.

This being said, in the present work I use official data. I expect results presented here not to be qualitatively distinct from those obtained if national series would not have been arbitrarily modified, although quantitative differences might arise. Fortunately, the government has recognized real CPI inflation in the last months. So this problem is now being solved.

3.4 The theoretical model

The data description presented above might give us some clues of the dynamics of some variables of interest after a terms of trade innovation. However, the raw data is in principle driven by a multitude of shocks, of which the terms of trade is just one. So, as Ravn et al. [2007] put it, 'an important step in the process of isolating TOT shocks (or any kind of shock, for that matter) is identification. Data analysis based purely on statistical methods will in general not result in a successful identification of TOT shocks. Economic theory must be at center stage in the identification process.'

The model used here is taken from Lubik and Schorfheide [2007], which is a simplified version of Galí and Monacelli [2005]. It features the three key ingredients any New Keynesian (NK) model has: the existence of money, such that nominal prices are present; monopolistic competition, where firms have some market power to set the price of differentiated goods; and nominal rigidities in prices represented by the New Keynesian Phillips curve. At the same time, the model incorporates explicitly

[4]Refer to www.arklems.org for further information.

the exchange rate, the terms of trade, exports, imports and international financial markets. So it is a Small Open Economy (SOE) model. In this sense, the NK framework, which typically consists of a two-equation dynamical system with a NK Phillips curve and a dynamic IS-type equation plus the monetary rule, is augmented with the *law of one price* and a dynamic rule for the terms of trade.

Regarding household's behavior, consumption maximization leads to the Euler equation that can be expressed as an open economy dynamic IS-curve:

$$\begin{aligned} y_t = & E_t y_{t+1} - [\tau + \alpha(2-\alpha)(1-\tau)](R_t - E_t \pi_{t+1}) - \rho_z z_t \\ & - \alpha[\tau + \alpha(2-\alpha)(1-\tau)] E_t \Delta q_{t+1} + \alpha(2-\alpha)\frac{1-\tau}{\tau} E_t \Delta y^*_{t+1} \end{aligned} \tag{3.1}$$

where $0 < \alpha < 1$ is the import share and τ is the intertemporal substitution elasticity between home and foreign goods. Endogenous variables are aggregate output y_t and CPI inflation rate π_t. The terms of trade q_t, defined as the ratio between export and import prices in the same currency, enter in first differences (Δq_t) and will alternatively assumed to be exogenous and endogenous, as described below. R_t is the nominal interest rate, y^*_t is exogenous world output and z_t is the growth rate of the technology process A_t with ρ_z as persistence parameter[5].

With respect to the producer side, domestic firm's maximization leads to the following open economy Phillips curve:

$$\pi_t = \beta E_t \pi_{t+1} + \alpha\beta E_t \Delta q_{t+1} - \alpha \Delta q_t + \frac{\kappa}{\tau + \alpha(2-\alpha)(1-\tau)}(y_t - \bar{y}_t) \tag{3.2}$$

where $0 < \beta < 1$ is the households discount factor, and $\kappa > 0$ is the Phillips curve slope that captures the degree of price stickiness. Additionally, potential output in the absence of nominal rigidities is defined as:

$$\bar{y}_t = \frac{-\alpha(2-\alpha)(1-\tau)}{\tau} y^*_t \tag{3.3}$$

The monetary authority is assumed to follow a policy rule where, besides CPI inflation and output, nominal exchange rate depreciation (Δe_t) is targeted:

$$R_t = \rho_R R_{t-1} + (1-\rho_R)[\phi_\pi \pi_t + \phi_y y_t + \phi_e \Delta e_t] + \varepsilon_{R_t} \qquad ; \qquad \varepsilon_{R_t} \sim \mathcal{N}(0, \sigma^2_R) \tag{3.4}$$

where e_t is the nominal exchange rate and policy coefficients are assumed to be $\phi_\pi, \phi_y, \phi_e \geq 0$. The persistence parameter is $0 < \rho_R < 1$ and ε_{R_t} is an exogenous policy shock which can be interpreted as the non-systematic component of the monetary policy.

Following the *law of one price*, it is assumed that relative PPP holds:

$$\pi_t = \Delta e_t + (1-\alpha)\Delta q_t + \pi^*_t \tag{3.5}$$

[5]In order to guarantee stationarity of the model, all real variables are expressed in terms of percentage deviations from A_t.

where π_t^* is a world inflation shock which is treated as unobservable[6].

Regarding terms of trade, they are treated subsequently as exogenous and endogenous. I use the latter specification to optimize the function that minimizes the differences between theoretical and empirical sample moments when obtaining values for the parameters of the Phillips curve (κ) and the elasticity of substitution (τ), as explained below. For the simulations, I treat terms of trade as exogenous. Whenever TOT are exogenous, they are assumed to follow an AR(1) process:

$$\Delta q_t = \rho_q \Delta q_{t-1} + \varepsilon_{q_t} \qquad ; \qquad \varepsilon_{q_t} \sim \mathcal{N}(0, \sigma_q^2) \tag{3.6}$$

where $0 < \rho_q < 1$ is the persistence parameter and ε_{q_t} is the TOT innovation. By the other hand, when TOT are endogenous, (3.6) is replaced by:

$$[\tau + \alpha(2-\alpha)(1-\tau)]\Delta q_t = \Delta y_t^* - \Delta y_t \tag{3.7}$$

where

$$\Delta y_t^* = y_t^* - y_{t-1}^* \tag{3.8}$$

$$\Delta y_t = y_t - y_{t-1} \tag{3.9}$$

Endogenous terms of trade as defined by (3.7) imply that this is the relative price that clears world market. With this specification, an increase in world output will improve terms of trade, while an increase in domestic output will deteriorate them.

And, lastly, the rest of the exogenous shocks are assumed to follow AR(1) processes:

$$z_t = \rho_z z_{t-1} + \varepsilon_{z_t} \qquad ; \qquad \varepsilon_{z_t} \sim \mathcal{N}(0, \sigma_z^2) \tag{3.10}$$

$$\pi_t^* = \rho_{\pi^*} \pi_{t-1}^* + \varepsilon_{\pi_t^*} \qquad ; \qquad \varepsilon_{\pi_t^*} \sim \mathcal{N}(0, \sigma_{\pi^*}^2) \tag{3.11}$$

$$y_t^* = \rho_{y^*} y_{t-1}^* + \varepsilon_{y_t^*} \qquad ; \qquad \varepsilon_{y_t^*} \sim \mathcal{N}(0, \sigma_{y^*}^2) \tag{3.12}$$

where $0 < \rho_i < 1$ and ε_i are the persistence parameters and innovations of the i_{th} variable, respectively.

As mentioned before, I use two different specifications of the model depending on whether terms of trade are treated exogenously or endogenously. When TOT are treated as exogenous, the system is represented by the 10 equations (3.1)-(3.6), (3.8) and (3.10)-(3.12) which has 10 variables: 2 control variables (π_t, y_t) and 8 state variables ($R_t, \Delta q_t, \pi_t^*, y_t^*, \Delta y_t^*, \Delta e_t, \bar{y}_t, z_t$). There are five innovations that affect this system: $\varepsilon_{R_t}, \varepsilon_{q_t}, \varepsilon_{z_t}, \varepsilon_{\pi_t^*}$ and $\varepsilon_{y_t^*}$. By the other hand, when TOT are solved endogenously, the system is represented by the 11 equations (3.1)-(3.5) and (3.7)-(3.12) which has 11 variables: 3 control variables ($\pi_t, y_t, \Delta q_t$) and 8 state variables ($R_t, \pi_t^*, y_t^*, \Delta y_t^*, \Delta e_t, \bar{y}_t, z_t, \Delta y_t$). There are four innovations that affect this system: $\varepsilon_{R_t}, \varepsilon_{z_t}, \varepsilon_{\pi_t^*}$ and $\varepsilon_{y_t^*}$.

[6] Another interpretation for π_t^* is that it captures deviations from PPP.

Both specifications of the model are linearized around the zero steady state and solved using Sims [2002] method[7]. Linearization, solution and simulation of both models are performed with Dynare software[8].

3.4.1 Empirical implementation

I follow a mixed strategy to obtain model's parameters values: some of them are calibrated while others are estimated using sample data from 1993:1 to 2013:3 of Argentina and US, as it corresponds. Calibrated parameters are the discount factor $\beta = e^{-r_{ss}/400}$, where the real interest rate at steady state is $r_{ss} = 2.58$; Argentinian import share α, that comes from the ratio of average imports over output; TOT persistence ρ_q and volatility σ_q, which are set to match the serial correlation and standard deviation of terms of trade in Argentina; and world output and inflation persistences and volatilities ($\rho_{y^*}, \rho_{\pi^*}, \sigma_{y^*}$ and σ_{π^*}, respectively), which are set to match US serial correlations and standard deviations of output gap and inflation, correspondingly.

In order to calibrate the intertemporal substitution elasticity τ and the Phillips curve slope κ, I minimize the following loss function

$$F = \left(\sigma_q^m - \sigma_q^d\right)^2 + \left[\rho(q,y)^m - \rho(q,y)^d\right]^2 + \left[\rho(q,\pi)^m - \rho(q,\pi)^d\right]^2 + \left[\rho(q,e)^m - \rho(q,e)^d\right]^2 \tag{3.13}$$

where statistics with upper-script m refer to the model and those with upper-script d refer to sample data (just of the *administrated exchange rate* regime). The criteria to include these targeted sample moments, and not others, is that the these are the ones that differ the most from those of the US, as can be seen on Table 1. So, it can be interpreted that these are the sample moments that best explain the special characteristics of Argentina, as a difference from US. I solve the model for determinacy taking terms of trade as endogenous and using the parameter values of Table 2. Initial values assigned for τ and κ are 0.30 for both, which is the estimation obtained for Canada in Lubik and Schorfheide [2007]. I perform 10,000 Monte Carlo simulations for the optimization of (3.13). Each simulation is of size 80, that matches 20 years of quarterly available sample data of Argentina, and get the median of the distributions of τ and κ, which are shown on Table 2.

Policy rule and productivity's parameters are estimated by OLS and Cochrane-Orcutt procedure, respectively. Regarding the former, the rule (3.4) can be expressed as:

$$R_t = \rho_R R_{t-1} + \beta_1 \pi_t + \beta_2 y_t + \beta_3 \Delta e_t + \varepsilon_{R_t} \tag{3.14}$$

[7]It is questionable whether it makes sense to linearize around zero steady state a model that should accurately represent a country like Argentina, where (for example) inflation has been systematically high. A solution to this problem can be the modification of the typical NK model used here as proposed by Ascari and Ropele [2009], that incorporates trend inflation. This being said, I leave this task for further work.

[8]Refer to Adjemian et al. [2011] for a detail of the algorithms implemented by the software.

where $\beta_i = (1-\rho_R)\phi_i$ for the i_{th} variable, respectively. The function (3.14) is estimated only with data of the *administrated exchange rate* period (2002:1-2013:3), as using the whole sample results in implausible values[9]. The estimation results in the following parameter's values:

$$\hat{R}_t = 0.82^{***} R_{t-1} + 0.13^{**} \pi_t + 0.26^{***} y_t + 0.07^{***} \Delta e_t \quad \text{with} \quad \sigma_R = 1.16$$

where *** and ** denote 99% and 95% significance levels, respectively. It is straightforward to recuperate the monetary rule parameters considering $\beta_i = (1-\rho_R)\phi_i$, which are presented in Table 2[10].

To estimate productivity parameters ρ_z and σ_z, I follow Galí and Monacelli [2005] and define the following production function:

$$Y_t = Z_t N_t \tag{3.15}$$

where N_t denotes employment and $z_t = \ln Z_t$ follows the AR(1) process (3.10). I apply logs to the cyclical components obtained by HP-filtering Y_t and N_t and estimate (3.15) together with (3.10) using the Cochrane-Orcutt procedure with whole sample data (1993:1 to 2013:3). Convergence of estimated parameters is achieved after 10 iterations[11]. A detail of calibrated and estimated parameters is present in Table 2.

[9] The estimation of (3.14) using the whole sample data produced the following values: $\rho_R = 0.96, \phi_\pi = 0.63, \phi_y = 5.35$ and $\phi_e = 0.77$. As output parameter value is much higher than it usually is in the literature, these estimation is discarded. In any case, it makes sense to focus on the *administrated exchange rate* regime when fitting a Taylor rule to the monetary authority because during the *fixed exchange rate* regime the Central Bank of Argentina had limited power to set the nominal rate, as explained with the *trilemma* by Obstfeld et al. [2004].

[10] As mentioned by Lubik and Schorfheide [2007], OLS estimation of the policy rule is questionable because of endogeneity problems. Nevertheless, system based estimation methods, like Bayesian, are left for further work.

[11] See Appendix on page 86 for data details.

Table 2: Parameter values

Name	Symbol	Value	Remarks
Discount factor	β	0.99	calibrated
Intertemporal substitution elasticity	τ	0.25	estimated
Import share	α	0.12	calibrated
Phillips curve slope	κ	0.56	estimated
Policy rule parameters			
Inflation parameter	ϕ_π	0.71**	estimated
Output parameter	ϕ_y	1.40***	estimated
Exchange rate parameter	ϕ_e	0.38***	estimated
Interest rate persistence	ρ_R	0.82***	estimated
Interest rate volatility	σ_R	1.16	estimated
Shocks' parameters			
Productivity persistence	ρ_z	0.87*	estimated
Productivity volatility	σ_z	1.34	estimated
TOT persistence	ρ_q	0.60	calibrated
TOT volatility	σ_q	7.14	calibrated
World output persistence	ρ_{y^*}	0.92	calibrated
World output volatility	σ_{y^*}	1.47	calibrated
World inflation persistence	ρ_{π^*}	0.73	calibrated
World inflation volatility	σ_{π^*}	0.83	calibrated

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$. See Data Appendix on page 85 for details.

3.4.2 Simulation results

As mentioned above, there are two different specifications of the model depending on whether terms of trade are treated exogenously or endogenously. I use the former to analyze the responses to a TOT shock and the latter to get parameters κ and τ minimizing the function (3.13).

Starting with the first specification, the model is simulated using TOT as exogenous. Except for the relative volatility of inflation and terms of trade (σ_π/σ_q), targeted moments are well replicated by the model, as shown in Table 3. Nevertheless, some non-targeted moments replication is quantitatively far from those of data and others are even qualitatively different. The worse performance of the model is in replicating cross correlation of output with inflation, nominal interest rate and nominal exchange rate ($\rho(y,\pi), \rho(y,r)$ and $\rho(y,e)$, respectively). Calibrating a lower value for the intertemporal substitution elasticity (τ) can improve the fit of the model to these non-targeted moments, but at the expense of generating implausible values for the targeted relative volatilities

$\sigma_\pi/\sigma_q, \sigma_r/\sigma_q$ and , σ_e/σ_q.

Table 3: Argentinian Data vs simulation

	Data			
Targeted moments	Whole sample	Fixed EX regime	Administrated EX regime	Model
σ_q	7.14	6.23	7.31	8.93
σ_y/σ_q	0.48	0.60	0.42	0.41
σ_π/σ_q	0.71	0.32	0.46	1.25
σ_r/σ_q	0.49	0.58	0.47	0.86
σ_e/σ_q	1.03	0.01	1.26	1.43
$\rho(q, y)$	-0.06	-0.20	0.15	0.19
$\rho(q, \pi)$	0.29***	0.12	0.10	0.13
$\rho(q, r)$	-0.07	0.07	-0.15	-0.02
$\rho(q, ner)$	-0.15	-0.01	-0.30**	-0.50
Non-targeted moments				
$\rho(y_t, y_{t-1})$	0.90	0.80	0.89	0.53
$\rho(\pi_t, \pi_{t-1})$	0.88	0.80	0.60	0.62
$\rho(r_t, r_{t-1})$	0.79	0.56	0.86	0.95
$\rho(e_t, e_{t-1})$	0.78	0.59	0.79	0.61
$\rho(y, \pi)$	-0.33***	-0.26	-0.25*	0.45
$\rho(y, r)$	-0.12	-0.17	-0.11	0.09
$\rho(y, e)$	-0.14	-0.00	-0.10	0.28
$\rho(\pi, r)$	0.11	-0.13	0.38***	0.71
$\rho(\pi, e)$	0.28**	0.51***	0.09	0.79
$\rho(r, e)$	0.51***	-0.07	0.71***	0.63

$^{***}p < 0.01,^{**} p < 0.05,^{*} p < 0.1$. See Data Appendix on page 85 for details.

The dynamics generated after a TOT shock are presented in Figure 3.4. An improvement in terms of trade is followed by a nominal exchange rate appreciation (which is a fall in Δe_t) because, as is clear from (3.5), relative PPP holds. The nominal exchange rate appreciation has a negative effect on nominal interest rate as the monetary authority reacts according to the rule (3.4). Now, using a NK model where rigidities in prices exist, a nominal variation will have real effects, at least in the short run. So, output rises according to (3.1). At the same time, there is an increase in inflation according to (3.2), which mitigates the real effect in the short horizon. The rise in prices is such that there is a rise in the real interest rate and the increase in output is rapidly muted. This fact is key to understand why terms of trade do not play a major role in driving business cycle.

Calibrating the intertemporal substitution elasticity τ for a higher value and the Phillips curve

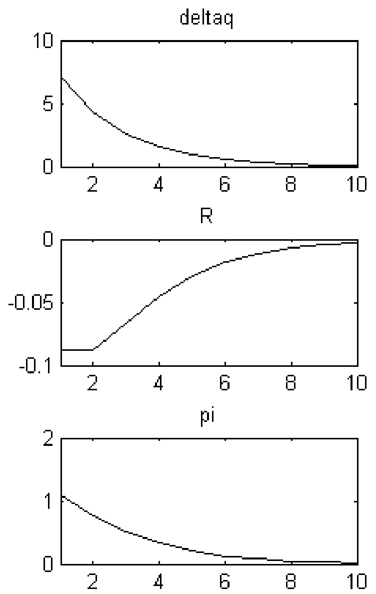


Figure 3.4: NK IRFs to a TOT shock

slope κ for a lower one, increases the weight of TOT shocks as sources of volatility, but at the expense of worsening the fit of the model to some data sample moments. A higher substitution elasticity and a lower Phillips curve parameter decrease the impact that output increment, that follows an improvement of the terms of trade, has on inflation according to the NK Phillips curve (3.2). Intuitively, if local and foreign goods are perfectly substitutable, increment of local prices are moderated when there is an output rise. But still, exchange rate will appreciate as PPP holds and nominal interest rate will fall as is clear from the monetary rule. There is then more room for a persistent rise in output as the real nominal rate decreases.

Interestingly, TOT disturbances have have a higher impact on inflation than they have on output. Again, the elasticity of substitution between home and foreign goods and the Phillips curve parameters are crucial for this result. If both of them were calibrated at higher values, then terms of trade would account for a higher proportion of price variability. Dynamics would follow the usual path: PPP implies that terms of trade improvement are counterbalanced by a nominal exchange rate appreciation; then nominal interest rate falls as it is implied by the Taylor rule; and, as a consequence, output increases. But a high value for the substitution elasticity τ and, specially, for the Phillips curve parameter κ, will amplify the effect on inflation. So, real rate will rise and the initial increment in output will be muted soon.

3.5 The empirical model

In this section I use a Structural Vector Autoregression (SVAR) model to evaluate the impact of a positive TOT shock in Argentina. I interpret the shock as an unexpected increase in the relative price P_x/P_m and check which is the behavior of output and inflation by analyzing their IRFs. In order to perform such analysis, I first estimate a reduced form VAR composed of output gap, CPI inflation and terms of trade variations. Afterwards, I identify the structural shocks that affect both variables by adopting a *sign restrictions* identification scheme. The shapes of the simulated model IRFs of output gap, inflation and terms of trade changes after a TOT improvement come from Figure 3.4 and serve as the justification for the signs imposed on impact to generate the SVAR's IRFs presented below. Regarding the responses to demand and cost-push shocks, they are set informally, though they are consistent with usual DSGE models dynamics.

3.5.1 The reduced form VAR

I use a fixed-coefficients VAR as an empirical model to analyze the effect of a fiscal shock. Its reduced form is represented as:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + ... + B_p Y_{t-p} + \mu_t$$

where Y_t is a 3x1 vector of time series including output gap (y_t), CPI inflation (π) and terms of trade variations (Δq_t). The coefficients are represented by B_0, which is a $3x1$ constants' vector, and B_i, which are $3x3$ matrices of variables' coefficients. Lastly, μ_t is a $3xT$ Gaussian white noise process vector with zero mean and variance Σ.

Before estimating the VAR, I need to define its lag order, which I do by applying the Akaike information criterion (AIC). It results in a two-lag order, so that the VAR has the following reduced form:

$$Y_t = B_0 + B_1 Y_{t-1} + B_2 Y_{t-2} + \mu_t \tag{3.16}$$

I estimate the VAR using OLS to obtain the following coefficient matrices[12]:

$$\hat{B}_0 = \begin{bmatrix} 0.17 \\ 1.04 \\ 0.49 \end{bmatrix} \quad ; \quad \hat{B}_1 = \begin{bmatrix} 1.45 & -0.03 & -0.00 \\ -0.20 & 1.05 & 0.00 \\ 0.61 & -0.13 & 0.72 \end{bmatrix} \quad ; \quad \hat{B}_2 = \begin{bmatrix} -0.61 & 0.01 & -0.00 \\ 0.10 & -0.20 & -0.04 \\ -0.82 & 0.36 & -0.32 \end{bmatrix}$$

I get as well the reduced-form residuals μ_t that have a zero mean and the following variance-covariance matrix:

[12]See Appendix on page 87 for estimation results details.

$$\Sigma = \begin{bmatrix} 1.45 & 0.20 & -0.02 \\ 0.20 & 5.59 & 1.91 \\ -0.02 & 1.91 & 27.02 \end{bmatrix}$$

3.5.2 The structural VAR identified with *sign restrictions*

In order to identify the VAR I follow a procedure that has two essential ingredients: on one hand, exact identification is achieved by doing a Cholesky decomposition of the reduced form variance covariance matrix. On the other hand, the desired pattern of signs is imposed using a rotation matrix that comes from an orthogonal decomposition of matrices randomly drawn from a normal distribution. At the end of the procedure, I am left with a large number of candidate impact matrices with the desired properties.

More precisely, the algorithm is as follows:

1. It decomposes the reduced form residuals variance-covariance matrix using Cholesky (or egienvalue-eigenvector decomposition): $\Sigma = CC'$.
2. A sufficiently large amount of K_{3x3} matrices are drawn from a normal distribution.
3. I do the QR decomposition of K matrices using the algorithm by Rubio-Ramirez et al. [2010] to obtain rotation matrices Q such that $K = QR$ and $QQ' = I$. This is, Q is an orthogonal matrix.
4. Get the candidate impact matrix: $A_0 = C'Q'$ and keep only those matrices that have the desired pattern of signs.
5. Use the A_0 matrices to plot IRFs and do forecast error variance decomposition analysis.

In the present case, once the algorithm presented on steps 1 to 5 is done, the reduced form model (3.16) turns into:

$$Y_t = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + A_0 e_t \tag{3.17}$$

where A_0 is a 3x3 matrix and e_t is a 3x1 vector of normally distributed shocks with unit variance by definition. The SVAR system relates observable VAR-based residuals to unobserved structural shocks. In other words, it is the link between data and theory. Additionally, as noted in Canova and Pina [2005], general equilibrium logic implies that impact of all shocks at the initial period should be, in general, non-zero. Indeed, this is exactly what DSGE models, as the one presented previously in this work, reproduce: all the responses of the variables are non-zero at $t = 0$, as shown in Figures

3.4. This fact implies that the elements of the A_0 matrix should typically be non-zero as is the case with the *signs restrictions* approach. By using this identification scheme, I assign the signs conditional on the RBC model to the elements of A_0 matrix:

$$\begin{bmatrix} y_t \\ \pi_t \\ \Delta q_t \end{bmatrix} = \hat{B}_0 + \hat{B}_1 Y_{t-1} + \hat{B}_2 Y_{t-2} + \underbrace{\begin{bmatrix} + & - & + \\ + & + & + \\ - & - & + \end{bmatrix}}_{A_0} \begin{bmatrix} e_t^D \\ e_t^S \\ e_t^q \end{bmatrix} \tag{3.18}$$

where e_t^D, e_t^S and e_t^q are interpreted as a demand, cost-push (or negative supply disturbance) and a terms of trade shocks, respectively. The signs of the third column of the A_0 matrix at (3.18) are based on the responses generated by the NK model shown in Figure 3.4. As it stands, the pattern of signs that have been imposed imply that a terms of trade improvement increases all variables. Regarding the rest of the sign, they are imposed informally. The reason for this resides in that, given the specification of the theoretical model used here, from where the *signs restrictions* are derived, there is no precision on what exactly are demand and supply innovations. In any case, it makes much sense to impose the signs shown at (3.18). These imply that a positive demand disturbance increases both output and inflation while it worsens terms of trade, and a negative supply shock decreases output, increases prices and also worsens terms of trade. Additionally, these responses are consistent with DSGE models in the monetary literature.

I give here a brief description of the steps of the algorithm: once the reduced form VAR is estimated, I generate 5000 simulations for parameter matrices $\hat{B}_0$ and $\hat{B}_1$, as well as for the variance-covariance matrix Σ, by bootstrapping the estimated model. Once stationarity is checked for the bootstrapped matrices, I center them using the median of the distribution. Afterwards, I get 5000 A_0 matrices based on sign restrictions satisfying the two conditions mentioned above. This distribution is shown in Figure 3.5, where is clear that the sign of the response is whether positive or negative.

Once this distribution is obtained, I can use it to generate output gap, inflation and terms of trade responses to exogenous innovations. The results, which represent the main conclusion of this work, are presented in Figures 3.6 and 3.7.

3.5.3 Variance decomposition analysis

To do a forecast error variance decomposition analysis, I use the 5000 A_0 matrices obtained in the previous section and I build a distribution of variance decomposition matrices using the variance of the first step forecast error. Table 4 presents the mean of this distribution:

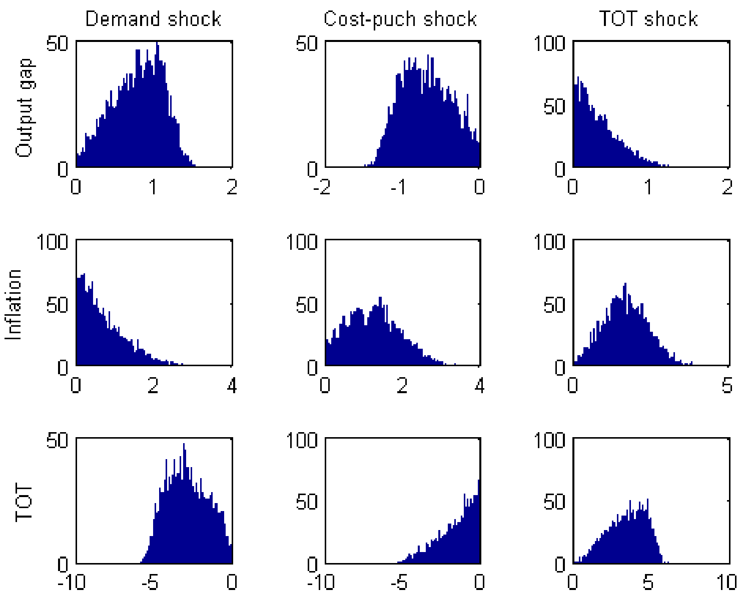


Figure 3.5: Distribution of A_0 matrix' elements

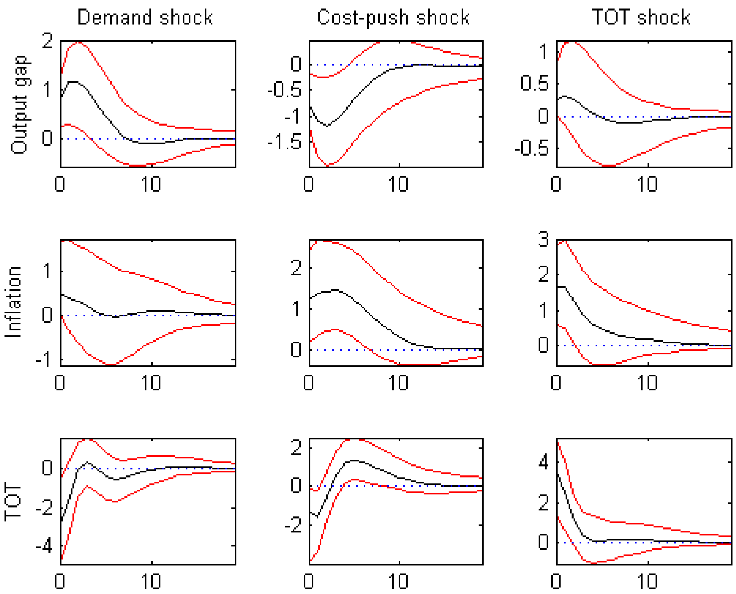
Table 4: Variance decomposition

	Output gap	Inflation	Terms of trade
Shock:			
Demand	48.16	12.51	36.76
	[4.44, 95.07]	[0.04, 50.44]	[1.77, 85.32]
Cost-push	41.27	34.19	13.82
	[1.56, 91.47]	[0.92, 83.95]	[0.04, 56.65]
TOT	10.57	53.31	49.42
	[0.04, 43.12]	[8.46, 95.97]	[7.33, 94.33]

Means and 90% intervals (in brackets)

As is shown in Table 4, TOT shocks can account for only 10.57% of output variability in Argentina. This result has importance in the sense that it contradicts a widely settled believe that says that these shocks are an important driving force of business cycles in the country.

The results obtained here differ from those of Mendoza [1995] and Kose [2002] who assign a much higher relative importance to TOT shocks explaining output variability. These authors calibrate RBC models for developing countries and find that TOT shocks account for 35% and 90% of total output variability, respectively. By the other hand, Lubik and Teo [2005] and Lubik and Schorfheide [2007] perform a Bayesian estimation of an RBC and a NK model, respectively, and find evidence



Median and 90% confidence intervals.

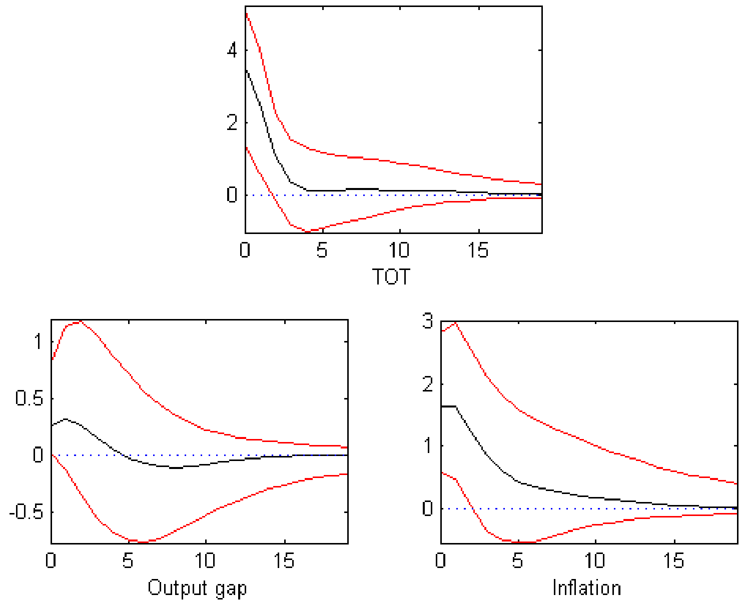
Figure 3.6: SVAR IRFs

of an explanatory power of terms of trade below 10%, which is in line with the results obtained here. My results are also similar to those in Broda [2004]. According to Table 4, major source of output volatility are demand and cost-push disturbances, that, together, explain around 90% of the variation in aggregate output. By the other hand, inflation is indeed importantly affected by TOT shocks, that explain around half of its total variability.

3.5.4 Impulse-Response Functions Analysis

IRFs to exogenous innovations are calculated using all these 5000 A_0 matrices as well as the 5000 parameter matrices $\hat{B}_0$ and $\hat{B}_1$ following the SVAR model (3.18), so a distribution of IRFs is obtained, rather than a single one. A plot of the median and the 90% confidence interval of each IRF distribution is shown Figures 3.6 and 3.7.

These graphs show that a positive terms of trade shock has a significant effect on inflation but not on output. The disturbance increases the former almost 50% but the latter less than 10% on impact, being the peak effect around the first quarter. The influence of the innovation is barely significant for output, while it lasts at least half a year for inflation. According to my findings, terms of trade fluctuations cannot be held responsible for an important source of output variability in Argentina, as they have only a nominal impact on prices.



Median and 90% confidence intervals.

Figure 3.7: SVAR IRFs to TOT shock

3.6 Conclusions

In this work, I analyze the effect of a terms of trade improvement over output and inflation in Argentina using a Structural Vector Autoregression identified with *sign restrictions* conditional on a New Keynesian Small Open Economy model. My main finding is that terms of trade shocks do not have a significant effect over output but they do affect importantly the level of prices in Argentina. These conclusions differ with some of the empirical literature of developing countries that assign a major role to terms of trade as an important source of output variability. It is also in contrast to the widely accepted idea among some *structuralist* economists in Argentina who believe that terms of trade variations can explain output performance in developing countries.

3.7 Appendix

3.7.1 Data

Figure 1, Table 1 & actual data of Table 3: The variables used are y (GDP), q (terms of trade), π (CPI inflation), r (nominal interest rate) and e (nominal exchange rate). Argentinian data comes from the Economic Ministry (MECON) while US data was taken from the US Bureau of Economic

Analysis (BEU).
Argentina:

- GDP original series is at constant prices, quarterly frequency and seasonally adjusted. Source is Mecon. I transform original series into Output Gap by applying an HP filter with smoothing parameter $\lambda = 1600$.

- Terms of trade original series is defined as the ratio of export unit value index over import unit value index ($TOT = 100 * X$average price$/M$average price). The terms of trade fluctuate in line with changes in export and import prices. Clearly the exchange rate and the rate of inflation can both influence the direction of any change in the terms of trade. Quarterly frequency, non seasonally adjusted. Source: Indec. I transform original series by applying interanual Quarter-to-Quarter log differences.

- CPI original series is not seasonally adjusted with base year 2008:M4 and monthly frequency. Source: Indec. To obtain quarterly frequency I use just the second month of each quarter. In order to obtain CPI inflation, I transform original series by applying interanual Quarter-to-Quarter log differences.

- Nominal exchange rate original series are AR$ to US$ at monthly frequency. Source: BCRA. To obtain quarterly frequency I use just the second month of each quarter. I transform original series by applying interanual Quarter-to-Quarter log differences.

- Nominal interest rate is interbank rate up to 15 days at monthly frequency. Source: BCRA.

Technology: Labor series corresponds to number of urban workers. They are taken from the Encuesta Permanente de Hogares (EPH) of the Argentinian Economic Ministry (MECON). From 1993 until 2002 they are bianual, and quarterly from then on. In order to transform bianual into quarterly data I apply the following procedure:

$$\Delta L_t = \alpha + \sum_{j=1}^{20} \beta_j D_{j,t} + e_t \qquad (3.19)$$

where ΔL_t are labor series expressed in difference and $D_{j,t}$ are 20 dummy variables I use to fill missing values, which are the 2nd and 4th quarters from 1993 until 2002 (inclusive). Each dummy variable is a $(1xT)$ zero vector (where T is the number of observations), which has a 1 in the row corresponding to each specific missing quarter. As a result of the application of (3.19), original values are kept and missing values are created. I then transform the series back into levels in order to estimate productivity parameters.

The data is expressed at constant prices and at quarterly frequency from 1993:Q1 to 2013:Q1. All series used are seasonally adjusted. Net exports is trade balance over output. All series but net exports are taken in logs. All series are Hodrick-Prescott filtered with a smoothing parameter of 1,600.

3.7.2 VAR estimation results

Table 5: VAR estimation results

Variables	y_t	π_t	Δq_t
y_{t-1}	1.45^{***}	-0.20	0.61
	(14.81)	(-1.06)	(1.44)
y_{t-2}	-0.61^{***}	0.10	-0.82^{*}
	(-6.14)	(0.49)	(-1.91)
π_{t-1}	-0.04	1.05^{***}	-0.13
	(-0.62)	(8.90)	(-0.49)
π_{t-2}	0.01	-0.20	0.36
	(0.18)	(-1.64)	(1.39)
Δq_{t-1}	-0.00	0.00	0.72^{***}
	(-0.07)	(0.03)	(6.23)
Δq_{t-2}	-0.00	-0.04	-0.32^{***}
	(-0.04)	(-0.87)	(-2.82)
constant	0.17	1.04^{**}	0.49
	(0.77)	(2.37)	(0.51)
Observations	75	75	75
R-squared	0.89	0.80	0.50

t-statistics in parentheses

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$

Table 6: Granger casualty test (F-statistics)

Variables	y	π	Δq
y	244.18^{***}	1.14	2.02
π	0.41	103.25^{***}	1.82
Δq	0.01	0.54	19.83^{***}

$^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1.$

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