barcelona gse graduate school of economics

Fiscal Policy, Foresight and the Trade Balance in the U.S.

Luca Gambetti

September 2010

Barcelona Economics Working Paper Series Working Paper n° 505

Fiscal Policy, Foresight and the Trade Balance in the U.S.

Luca Gambetti^{*} Universitat Autonoma de Barcelona

September 1, 2010

Abstract

This paper investigates the effects of fiscal policy on the trade balance using a structural factor model. A fiscal policy shock worsens the trade balance and produces an appreciation of the domestic currency but the effects are quantitatively small. The findings match the theoretical predictions of the standard Mundell-Fleming model, although fiscal policy should not be considered one of the main causes of the large US external deficit. My conclusions differ from those reached using VAR models since the fiscal shock, possibly due to fiscal foresight, is nonfundamental for the variables typically used in open economy VARs.

JEL classification: C32, E32, E62.

Keywords: structural factor model, fiscal policy, twin deficits, trade deficit, current account, Mundell-Fleming.

^{*}I am grateful to Mario Forni for helpful discussions. The financial support from the Spanish Ministry of Science and Innovation through grant ECO2009-09847 and the Barcelona Graduate School Research Network is gratefully acknowledged. Contact: Office B3.174, Departament d'Economia i Historia Economica, Edifici B, Universitat Autonoma de Barcelona, Bellaterra 08193, Barcelona, Spain. Tel (+34) 935811289; e-mail: luca.gambetti@uab.cat

1 Introduction

Since the mid 1980s, the U.S. economy has been characterized by a large and growing trade deficit. Around the mid 1980s the deficit was about 3% of GDP while since 2000 has been on average about 5% of GDP. The phenomenon, given its magnitude, has attracted a great deal of attention devoted to assessing the possible causes. Expansionary fiscal policy is in the list. According to the standard textbook Mundell-Fleming model, a fiscal policy expansion worsens the trade balance through the appreciation of the domestic currency following the inflow of foreign capital attracted by a higher interest rate.¹

Quite surprisingly however, little evidence about the effects of fiscal policy shocks on the trade deficit and the exchange rates is available.² Moroever existing empirical analyses based on VAR models yield contrasting results, none of which supporting the predictions of the standard Mundell-Fleming model. Kim and Roubini (2008) finds that an expansionary fiscal shock depreciates the real exchange rate and improves the current account balance. The finding can be rationalized by the presence of crowding out of private investment and Ricardian movements in private savings.³ A similar result is obtained in Corsetti and Muller (2006). Monacelli and Perotti (2007), on the contrary, finds that an increase in government spending depreciates the real exchange rate and worsens the trade balance. This evidence has sparked an important research effort to better understand the mechanisms that propagate fiscal policy actions.

Studying the effects of fiscal shocks using VAR techniques can be problematic though. A few recent works have convincingly argued that, because of the existence of legislative and implementation lags, private agents receive signals about future changes in taxes and government spending before these changes take actually place, the phenomenon called "fiscal foresight" (see e.g. Yang, 2007, Leeper, Walker and Yang, 2008, Mertens and Ravn, 2009).

Leeper, Walker and Yang (2008) (LWY henceforth) shows theoretically that, under fiscal foresight, standard VAR techniques are likely to fail in correctly estimating the fiscal policy shock since a problem of *non-fundamentalness* emerges. Nonfundamentalness typically arises when agents have a larger information set than the econometrician⁴, a situation that can occur when a limited number of variables are con-

¹A partial list of models where a fiscal expansion may generate a worsening of the trade balance includes Dornbusch (1976), Baxter, (1995) and Kollmann, (1998), Erceg, Gust and Guerrieri (2005).

 $^{^{2}}$ On the contrary, a lot of evidence is available on the effects of government spending shocks on domestic variables, see e.g. Blanchard and Perotti (2002) and Ramey and Shapiro (1988).

³An improvement of the current account balance after a permanent increase in government spending can be found in the model of Obstfeld and Rogoff (1995).

⁴see Hansen and Sargent (1980).

sidered like in VAR models⁵. But in presence of fiscal foresight non-fundamentalness becomes a very likely scenario. The intuition is that fiscal variables like taxes or government spending, typically used to identify fiscal policy shocks, are affected only with a delay by fiscal policy actions so that their current and past values do not convey enough information about the current shock.

Forni and Gambetti (2010) provides evidence that government spending shocks are actually *non-fundamental* for the variables usually considered in standard closedeconomy specifications. The finding confirms the result obtained in Ramey (2009) that the fiscal policy shock estimated with a VAR as in Perotti (2007) is Granger-caused by the forecast of government spending from the Survey of Professional Forecasters. Although the specifications considered by the authors do not include open economy variables, the results cast some doubt on the reliability of the findings obtained with structural VARs and motivate the analysis conducted here.

In this paper I depart from the VAR approach and study the effects of fiscal shocks on the trade balance using a large structural factor model. The main motivation is that, as argued in Forni, Giannone, Lippi and Reichlin (2009), in this class of models structural shocks are always fundamental. The factor model uses a large number of variables driven by a much smaller number of economic shocks. Rich information helps *per se* in mitigating the problem of non-fundamentalness since reduces the gap between the information sets of economic agents and the econometrician. But most importantly, having less shocks than variables implies that macroeconomic dynamics are represented by a rectangular, "tall" MA system where, as I shall show, shocks are fundamental.

The model is estimated using US quarterly data for 115 US macroeconomic time series. The shock is identified using sign restrictions. An expansionary fiscal shock is defined as a shock having (i) a positive effect on output (GDP and industrial production), prices (GDP deflator and CPI) and the short term interest rate (the prime rate) at an horizon of three quarters, and (ii) a positive effect on government primary deficit at horizons three to eight quarters.

The main findings are the following. The fiscal shock is non fundamental for the variables typically used in open economy fiscal VAR models, so that its impulse response functions cannot be consistently estimated by means of a VAR. A fiscal policy shock worsens the trade balance and produces an appreciation of the domestic currency but the effects are quantitatively small, the shock accounting for about 14% of the volatility of the trade and current account balance and the exchange rate. The results broadly match the theoretical predictions of the standard Mundell-Fleming model, although fiscal policy cannot be considered the main cause of the large US external deficit.

The remainder of the paper is organized as follows. Section 2 presents the factor

⁵see Lippi and Reichilin (1994).

model; Section 3 discusses the model specification and presents the main results; Section 4 concludes.

2 The structural factor model

In the present section I provide a presentation of the model and estimation procedure. For additional details see Forni, Giannone, Lippi and Reichlin (2009), FGLR from now on.⁶

2.1 Representation

Each macroeconomic variable is the sum of two mutually orthogonal unobservable components, the common component χ_{it} and the idiosyncratic component ξ_{it} :

$$x_{it} = \chi_{it} + \xi_{it}.\tag{1}$$

The idiosyncratic components are poorly correlated in the cross-sectional dimension (see FGLR, Assumption 5 for a precise statement). They arise from shocks or sources of variation which considerably affect only a single variable or a small group of variables. For variables related to particular sectors, like industrial production indexes or production prices, the idiosyncratic component may reflect sector specific variations; for strictly macroeconomic variables, like GDP, investment or consumption, the idiosyncratic component must be interpreted essentially as a measurement error.⁷

The common components are responsible for the main bulk of the co-movements between macroeconomic variables, being linear combinations of a relatively small number r of factors $f_{1t}, f_{2t}, \cdots, f_{rt}$, not depending on i:

$$\chi_{it} = a_{1i}f_{1t} + a_{2i}f_{2t} + \dots + a_{ri}f_{rt} = a_if_t.$$
 (2)

The dynamic relations between the macroeconomic variables arise from the fact that the vector f_t follows the relation

$$f_t = N(L)u_t,\tag{3}$$

⁶FGLR is a special case of the generalized dynamic factor model proposed by Forni, *et al.* (2000, 2004, 2005) and Forni and Lippi (2001, 2010). This model differs from the traditional dynamic factor model of Sargent and Sims (1977) and Geweke (1977) in that the number of cross-sectional variables is infinite and the idiosyncratic components are allowed to be mutually correlated to some extent, along the lines of Chamberlain (1983), Chamberlain and Rothschild (1983) and Connor and Korajczyk (1988). Closely related models have been studied by Forni and Reichlin (1998), Stock and Watson (2002a, 2002b, 2005), Bai and Ng (2002, 2007), Bai (2003) and Bernanke *et al.* (2005).

⁷Altug, (1989), Sargent, (1989), and Ireland (2004) show that the model can be interpreted as the linear solution of a DSGE model with measurement error.

where N(L) is a $r \times q$ matrix of rational functions in the lag operator L and $u_t = (u_{1t} \ u_{2t} \ \cdots \ u_{qt})'$ is a q-dimensional vector of orthonormal white noises, with q < r. Such white noises are the structural macroeconomic shocks.⁸

Since N(L) is tall, as it will be clear from the discussion in subsection 2.4, the rank of N(z) is q for any z, which implies fundamentalness. This ensures that f_t has the finite order VAR representation (Anderson and Deistler, 2008)

$$D(L)f_t = \epsilon_t = Ru_t,\tag{4}$$

where D(L) is a $r \times r$ matrix of polynomials such that $D(L)^{-1}R = N(L)$ and R = N(0).

From equations (??) to (??) it is seen that the model can be written in the dynamic form

$$x_{it} = b_i(L)u_t + \xi_{it},\tag{5}$$

where

$$b_i(L) = a_i N(L) = a_i D(L)^{-1} R.$$
 (6)

The entries of the q-dimensional vector $b_i(L)$ are the impulse response functions.

Observe that, under appropriate regularity conditions on the factor loadings a_i ,⁹ the linear space spanned by the χ 's includes the factors, so that u_t is fundamental for the χ 's. Moreover, since the idiosyncratic components are poorly correlated across sections and the x's are infinite in number, by taking appropriate averages of the x's the idiosyncratic components can be eliminated and the factor without error can be obtained. This can be restated by saying that u_t is fundamental for the x's.

2.2 Identification

Representation (??) is not unique, since the impulse response functions and the related primitive shocks are not identified. In particular, if H is any orthogonal $q \times q$ matrix, then

$$\chi_{it} = c_i(L)v_t$$

where $c_i(L) = b_i(L)H'$ and $v_t = Hu_t$. However, assuming mutually orthogonal structural shocks, post-multiplication by H' is the only admissible transformation, i.e. the impulse response functions are unique up to orthogonal transformations, just like in structural VAR models (FGLR, Proposition 2).

⁸In the large dynamic factor model literature they are sometimes called the "common" or "primitive" shocks or "dynamic factors" (whereas the entries of f_t are the "static factors"). Equations (??) to (??) need further qualification to ensure that all of the factors are loaded, so to speak, by enough variables with large enough loadings (see FGLR, Assumption 4); this "pervasiveness" condition is necessary to have uniqueness of the common and the idiosyncratic components, as well as the number of static factors r and dynamic factors q.

⁹see FGLR, Assumption 4.

As a consequence, structural analysis in factor models can be carried on along lines very similar to those of standard SVAR analysis. Specifically q(q-1)/2 restrictions have to be imposed on the matrix of impulse response functions $B_n(L) = (b_1(L)'b_2(L)'\cdots b_n(L)')'$, where n is the number of variables in the dataset, to pin down all the elements of H.

If the researcher is interested in identifying just a single shock (partial identification), the target is to determine the entries of a single column of the matrix H, say H_1 , which is enough to obtain the first column of $B_n(L)$, say $B_{n1}(L)$.

In the present paper the shock and the impulse response functions are not uniquely identified; rather, following Uhlig (2005), a distribution of shocks and related impulse response functions is identified by imposing a set of sign restrictions on the impulse response functions themselves.¹⁰ The first column H_1 of the matrix H is a point on the unit sphere S^{q-1} . Given the non-structural representation $C_n(L)v_t$, the sign restrictions that are imposed on $B_{n1}(L)$ define an admissible region Θ on the unit sphere, such that for $H_1 \in \Theta$ $B_{n1}(L) = C_n(L)H_1$ satisfies such inequalities. Following Uhlig (2005), a uniform *a priori* probability density in the region Θ is assumed. This in turn implies a density and the associated confidence bounds for each coefficient of the impulse response functions.

2.3 Estimation

Estimation proceeds through the following steps.

- 1. Starting with an estimate \hat{r} , the static factors are estimated by means of the first \hat{r} principal components of the variables in the dataset, and the factor loadings by means of the associated eigenvectors. Precisely, let $\hat{\Gamma}^x$ be the sample variancecovariance matrix of the data: the estimated loading matrix $\hat{A}_n = (\hat{a}'_1 \hat{a}'_2 \cdots \hat{a}'_n)'$ is the $n \times r$ matrix having on the columns the normalized eigenvectors corresponding to the first largest \hat{r} eigenvalues of $\hat{\Gamma}^x$, and the estimated factors are $\hat{f}_t = \hat{A}'_n (x_{1t} x_{2t} \cdots x_{nt})'$. ¹¹
- 2. $\hat{D}(L)$ and $\hat{\epsilon}_t$ are obtained by running a VAR (\hat{p}) with \hat{f}_t where the number of lags \hat{p} is chosen according to some criterion.
- 3. Let $\hat{\Gamma}^{\epsilon}$ be the sample variance-covariance matrix of $\hat{\epsilon}_t$. Having an estimate \hat{q} of the number of dynamic factors, an estimate of a non-structural representation of the common components is obtained by using the spectral decomposition of $\hat{\Gamma}^{\epsilon}$. Precisely, let $\hat{\mu}_j^{\epsilon}$, $j = 1, \ldots, \hat{q}$, be the *j*-th eigenvalue of $\hat{\Gamma}^{\epsilon}$, in decreasing order,

¹⁰The precise set of restrictions imposed is discussed below.

¹¹The factors are identified only up to linear transformations. What is estimated is a basis of the factor space.

 $\hat{\mathcal{M}}$ the $q \times q$ diagonal matrix with $\sqrt{\hat{\mu}_j^{\epsilon}}$ as its (j, j) entry, and \hat{K} the $r \times q$ matrix with the corresponding normalized eigenvectors on the columns. The estimated matrix of non-structural impulse response functions is

$$\hat{C}_n(L) = \hat{A}_n \hat{D}(L)^{-1} \hat{K} \hat{\mathcal{M}}.$$
(7)

To account for estimation uncertainty, the following non-overlapping block bootstrap technique is adopted. Let $X = [x_{it}]$ be the $T \times n$ matrix of data. Such matrix is partitioned into S sub-matrices X_s (blocks), $s = 1, \ldots, S$, of dimension $\tau \times n, \tau$ being the integer part of T/S.¹² An integer h_s between 1 and S is drawn randomly with reintroduction S times to obtain the sequence h_1, \ldots, h_S . A new artificial sample of dimension $\tau S \times n$ is then generated as $X^* = [X'_{h_1}X'_{h_2}\cdots X'_{h_S}]'$ and the corresponding impulse response functions, $\hat{C}_n(L)$, are estimated. A vector H_1 is generated Ntimes by drawing its q entries from a standard normal distribution and normalized by its Euclidean norm. For each of the N vectors the impulse response functions $\hat{B}_{n1}(L) = \hat{C}_n(L)H_1$ are computed. Those satisfying the sign restrictions are kept.¹³ A set of non-structural impulse response functions is obtained by repeating drawing, estimation and identification.

2.4 Discussion

Here I discuss in detail why in the factor model the shocks are fundamental. Let us consider the statistical MA representation

$$\chi_t = B_n(L)u_t,\tag{8}$$

where $\chi_t = (\chi_{1t} \cdots \chi_{nt}) \prime$ is an *n*-vector of weakly stationary variables, $B_n(L)$ is a $(n \times q)$ matrix of rational functions in the lag operator L, with $n \ge q$, and $u_t = (u_{1t} \cdots u_{qt}) \prime$ is a *q*-dimensional white-noise normalized to have identity variance-covariance matrix.

Under what conditions the shocks u_t are fundamental for χ_t , i.e. present and past values of χ_t are sufficient to recover u_t ? Representation (??) is fundamental if and only if the rank of $B_n(z)$ is q for all z such that |z| < 1 (see e.g. Rozanov, 1967, Ch. 1, Section 10, and Ch. 2, p. 76).

In the particular case n = q, such condition reduces to the requirement that the determinant of $B_n(z)$ does not vanish within the unit circle in the complex plane. If this condition holds, then the shock u_t can be found using a VAR for χ_t and the related standard identification techniques. In general, however, there is no guarantee that the q

¹²Note that τ has to be large enough to retain relevant lagged auto- and cross-covariances.

¹³At each step of the bootstrap procedure we collect at most 10 impulse response functions in order to avoid that a single bootstrap provides a disproportionately large number of functions.

variables are sufficient to recover the shocks (see Fernández-Villaverde, Rubio-Ramirez, Sargent and Watson, 2007). In particular, Leeper, Walker and Yang (2008) shows that under fiscal foresight the condition is violated and the shocks are non-fundamental.

Now consider the case n > q. Notice that in this case (??) coincides with the vector of the common components of the factor model. In this situation, $B_n(z)$ is a "tall", rectangular matrix and its rank is less than q for some z, i.e. the shock is non-fundamental, only if all of the $(q \times q)$ sub-matrices of $B_n(z)$ are singular. Clearly this is a very special case since it requires $\binom{n}{q} - 1$ equalities to be satisfied. Therefore, in general, when $n > q \ B(z)$ has rank q for all z and the shocks can be assumed to be fundamental. Intuitively fundamentalness is ensured if the generating processes of χ_{jt} , $j = q + 1, \ldots, n$, have impulse response functions which are sufficiently heterogeneous, with respect to the first q, to prevent the rank reduction.

Finally let us stress again that, as already argued in Section 2, the q-dimensional square submatrices of $N(z) = D(z)^{-1}R$ appearing in equation (??) can be singular for values of z within the unit circle, without hurting consistency of estimation. Similarly, considering a q-dimensional vector of integers I, such that $I_i \leq n, i = 1, ..., q, u_t$ can be non-fundamental for the subvector $(\chi_{I_1t} \cdots \chi_{I_qt})' = B_I(L)u_t = A_IN(L)u_t$ and det $B_I(z)$ can vanish within the unit circle. This is interesting because the smallest root of some selected square subsystems can be estimated and it can be verified whether the corresponding impulse response functions are indeed non-fundamental, implying a problem for VAR estimation.

3 Empirics

We now discuss the model specification and present the main results.

3.1 Data and parameter specification

The data set contains 115 quarterly macroeconomic time series spanning from 1973:I to 2007:IV. It includes fiscal policy variables, GDP and components, industrial production indexes, labor market variables, stock market variables, surveys, leading indicators, price indexes and deflators, money and credit aggregates, long and short term interest rates, and several open economy variables like the trade and current account balance, the real and nominal exchange rate and the terms of trade. The data are transformed to reach stationarity, as required by the model. The full list of variables along with the corresponding transformations is reported in the Appendix. All series are taken from FRED Database, Federal Reserve Bank of St. Louis.

First of all the number of static factor, \hat{r} , the number of shocks, \hat{q} , and the number

of lags, \hat{p} have to be specified. To determine \hat{r} I rely on the IC_{p2} criterion of Bai and Ng (2002), which gives $\hat{r} = 10$. I set $\hat{p} = 3$.

The number of shocks is determined by a few consistent information criteria. Here I use three groups of criteria, proposed by Amengual and Watson (2007), Bai and Ng (2007) and Hallin and Liska (2007). The criterion $\hat{BN}^{ICP}(\hat{y}^A)$ by Amengual and Watson gives 5 primitive factors in the IC_{p1} version and 3 primitive factors in the IC_{p2} version (with $\hat{r} = 10$ and p = 3). The four criteria of Bai and Ng (2007), namely q_1, q_2, q_3 and q_4 , give 6, 5, 5 and 3 shocks respectively (with $\hat{r} = 10$ and p = 3).¹⁴ Finally, the log criterion proposed by Hallin and Liska gives 3 shocks for all of the proposed penalty functions (independently of the initial random permutation). In summary, information criteria do not provide a unique result, the number of shocks being between 3 and 6. Here I conclude in favor of a five-shock specification. Below several robustness checks about the number of factors are made.

Finally the length of the block, τ , is set equal to 16.

3.2 The smallest root of some selected sub-systems

In this subsection I investigate whether the fiscal shock is fundamental for the variables which are typically used in open economy fiscal VARs.

I consider six different variables specifications (listed in Table 1a) corresponding to six different choices of I (see Section 2.4), denoted $I^j j = 1, ..., 6$. The specifications are quite standard, in particular the fifth is the one considered in Kim and Roubini (2008). They all include the real GDP, the fiscal deficit to GDP ratio, the current account deficit to GDP ratio, and the real exchange rate. They differ each other because of the fifth variable included. For each specification the smallest root of the determinant of the corresponding impulse response functions $B_{Ij}(L)$ is computed. If the root is smaller than one in modulus, the shock is non-fundamental for the variables defined in I^j . The roots are computed for all the bootstrap repetitions so that the entire distribution is available.

Table 1b shows the point estimate, the mean, the median, several percentiles of the distribution of the modulus of the smallest root for the six specifications and the associated probability of being smaller than one. The point estimate, the mean, the median and the 68th percentile of the distribution is smaller than one for all the specifications. With probability ranging from 0.74 to 0.89 the shock is non-fundamental for the variables considered in the six specifications. The result implies that standard structural VAR techniques with the variables considered in the six specifications are likely to fail in recovering the fiscal shock correctly.

¹⁴The Bai and Ng criteria have two parameters. I set $\delta = .1$ for all criteria and $m(q_1) = 1.1$, $m(q_2) = 1.9$, $m(q_3) = 1.8$, $m(q_4) = 4$.

3.3 Identifying restrictions

The fiscal policy shock is identified using the structural factor model described above. I prefer not to rely on identification schemes à la Blanchard and Perotti (2002) because they are not fully consistent with fiscal foresight. Instead identification is achieved by means of sign restrictions (Uhlig, 2005) as in Mountford and Uhlig (2009), Pappa (2009) and Forni and Gambetti (2010). Precisely, an expansionary shock is defined as a shock having a positive effect on output (GDP and industrial production), prices (GDP deflator and CPI) and the short term interest rate (the prime rate) at an horizon of three quarters. A positive effect on government primary deficit for horizons from three to eight quarters.

The restrictions on output, prices and the interest rate define the demand nature of the shock. The restriction on fiscal deficit is useful to distinguish the fiscal shock from other demand shocks under the assumption that systematic fiscal policy is countercyclical. Notice that leaving unrestricted the response for the first two quarters means that we allow up to six months of foresight. Restricting the deficit for six quarters reflects the idea that once the policy action is passed and implemented it will exert some significant effect on fiscal policy variables. Below several checks to assess the robustness of the results to various changes in identification scheme are made.

Having defined the relevant sign restrictions, I proceeded as explained at the end of Section 2.3 to get a set of admissible impulse response functions (satisfying the restrictions) and a set of corresponding fiscal shock series. 450 admissible shock series are obtained out of 20,000 draws of the rotation parameters. The simple average of such series is the estimate of the fiscal shock.

Finally to get a distribution for the impulse response functions the bootstrapping procedure described above is used. 300 artificial samples X^* are generated and for each one of them 5,000 rotation vectors H_1 are drawn. Around 1,000 admissible sets of impulse response functions are collected. In the pictures below the average along with the 16th and the 84th percentiles of the related distribution are shown.

3.4 Granger causation

As a diagnostic of the identification procedure, I verify whether the identified shock passes Ramey's Granger-causation test. As already noted, Ramey (2008) shows that the government spending shock obtained with a VAR similar to that of Perotti (2007) is Granger caused by the government spending forecast from the Survey of Professional Forecasters. Here I perform a similar exercise using the estimated shock. Specifically, I regress the fiscal shock on four lags of the shock itself and four lags of the government spending forecast. Table 2 shows the results. None of the parameters is statistically significant. The F-statistic obtained under the null hypothesis that the parameters of the lags of the forecast variable are jointly zero is 0.021, which is very much smaller than the 10% critical value. In conclusion, the fiscal policy shock is not Granger caused by the government spending forecast series.

3.5 The effects of fiscal policy shocks

Figure 1 plots the impulse response functions to an expansionary fiscal policy shock. The shock is normalized to have a 0.2% long run mean effect on the deficit to GDP ratio. The black line is the mean effect while the dotted lines are the 68% confidence bands.

After an initial jump, the fiscal deficit increases very gradually, the response becoming significant only after three quarters, and converges to its new long run level (0.2%) after about 10 quarters.

Both the current account and the trade balance immediately worsen by about 0.12% and 0.07% respectively. The larger effects on the two variables, -0.12% and -0.1% respectively, are observed at an horizon of two quarters. After the second quarter the effects begin to reduce, becoming not significant, and vanish in the long run.

Both the real and nominal exchange rate appreciate instantaneously by about 7% and 10% respectively. Nevertheless the effect is significant only for the latter and on impact. The response of the terms of trade¹⁵ is, as expected, the mirror image of that of the exchange rate, significantly improving on impact by about 4%. In the medium run the response is negative but non significant as for the the exchange rates.

The reaction of GDP, investment and consumption is in line with the results in Forni and Gambetti (2010). GDP immediately and significantly increases by more than 1% and stadily declines from the second quarter, the response vanishing after about two years. Investment significantly increases on impact by about 2% and reduces, although not significantly, in the long run. A similar response is found for private consumption although the effect is never significant.

Conditional on a fiscal policy expansion, fiscal and trade deficits are positively correlated in the short run but roughly uncorrelated in the long run. From a purely accounting perspective, the long run result can be explained by both the crowding out of private investment and the increase in private saving.¹⁶

Table 3 shows the variance decomposition. Columns 2-5 report the percentage of the forecast error variance accounted for by the shock at various horizons. Column 6 (Total)

¹⁵The terms of trade are defined as the ratio of price of imports to the price of exports.

¹⁶Private saving, whose impulse response function is not shown, is defined as the difference between disposable income and private consumption.

reports the percentage of the total variance of the transformed series (i.e. inflation) accounted for by the shock. The shock accounts for about 13% of the variance of the deficit, 14% and 11% of the variance of the current account and the trade balance respectively. As far as the exchange rates are concerned, the shock explains about 11% and 14% of the real and nominal exchange rate respectively. Overall fiscal shocks account for a small, although not negligible, portion of variance of the external deficit and exchange rates.

The findings are in line, at least qualitatively, with those obtained in Erceg, Gust and Guerrieri (2005) which uses a calibrated DSGE model. The authors find that expansionary fiscal shocks have small negative effects on the trade balance. A one percentage point increase in the government spending share of GDP worsens the trade balance to GDP ratio by less than 0.2 percentage points after 2-3 years.

On the contrary our evidence stands in sharp contrast with that obtained with open economy fiscal VARs as in Kim and Roubini (2008), Corsetti and Muller (2006) and Monacelli and Perotti (2007). From the results of subsection 3.2, differences seem to be attributable to the result that the fiscal shock is non-fundamental for the variables used in those models.

Concluding, the findings support the basic predictions of the standard textbook Mundell-Flaming model: a fiscal expansion worsens the trade and current account balance and induces an appreciation of the domestic currency. However the effects on the external deficit and the exchange rate are small, implying that fiscal policy should not be considered one of the main causes of the large trade deficit experienced by the U.S. economy in the last decades.

3.6 Robustness

This subsection studies the robustness of the results to changes in model specification.

First let us compare the results of the benchmark specification (r = 10, q = 5) with five alternative specifications: 1) r = 13 q = 5; 2) r = 16 q = 5; 3) r = 10 q = 4; 4) r = 13 q = 4; 5) r = 16 q = 4. Figure 2 displays the impulse response functions of the trade balance and the real exchange rate in the six different specifications. The first column depicts the responses in the 4 dynamic shock specification, the second column those in the 5 dynamic shock specification. Overall the results are remarkably similar both from a qualitative and from a quantitative point of view.

Second, given that tax and government spending shocks can have different effects, I identified a government spending shock following Forni and Gambetti (2010). An expansionary government spending shock is defined as a shock having a positive effect on government expenditure, output, prices, the prime rate, the government primary deficit and tax receipts (the last inequality is imposed to distinguish the government spending shock from a tax shock). All the restrictions are imposed only on the responses delayed by six months (the third coefficient of the impulse response functions).¹⁷ Figure 3 plots the results. The impulse response functions of external deficit and exchange rates are very similar to those obtained with the other identification scheme. The only minor difference is that the responses are slightly smaller and less significant.

Several other checks, listed below, are made.

- 1. Using trade balance and current account balance deflated by the GDP deflator instead of as a ratio to GDP.
- 2. Leaving unrestricted the interest rate.
- 3. Using two instead of three lags in the VAR for the factors.
- 4. Restricting deficit from period 3 to 6.
- 5. Restricting only period 3.
- 6. Restricting for horizons 3 to 8 the response of government spending to be positive.

The first four checks deliver results which are almost identical to those obtained in the benchmark specification. In the last two experiments some minor differences arise. In the fifth check, as one expects, confidence bands tend to become larger although the sign and the size of the point estimate are unchanged. In the sixth check the response of the exchange rate becomes slightly larger and more significant, and consumption becomes more responsive, the impulse response function being shifted upward at all horizons.

Overall results are very robust to changes in model specification.

4 Conclusions

This paper studied the effects of fiscal policy shocks on the trade balance and the exchange rates using a structural factor model. The main advantage of my approach is that in this model the fiscal shock is always fundamental even in presence of fiscal foresight. The main findings are the following. The fiscal shock is non fundamental for the variables typically used in open economy VARs, implying that VAR techniques are likely to fail in estimating the fiscal shock and the related impulse response functions consistently. A fiscal policy expansion worsens the trade balance and produces an appreciation of the domestic currency but the effects are quantitatively small. The findings match the theoretical predictions of the standard Mundell-Fleming model,

 $^{^{17}}$ I also restricted government spending for five quarters starting from the fourth quarter after the shock and the results are identical.

although fiscal policy shocks cannot be considered the main cause of the large US external deficit.

Appendix: Data

Transformations: 1= levels, 2= first differences of the original series, 5= first differences of logs of the original series, 5= second differences of logs of the original series.

no.series	Transf.	Mnemonic	Long Label		
1	5	GDPC1	Real Gross Domestic Product, 1 Decimal		
2	5	GNPC96	Real Gross National Product		
3	5	NICUR/GDPDEF	National Income/GDPDEF		
4	5	DPIC96	Real Disposable Personal Income		
5	5	OUTNFB	Nonfarm Business Sector: Output		
6	5	FINSLC1	Real Final Sales of Domestic Product, 1 Decimal		
7	5	FPIC1	Real Private Fixed Investment, 1 Decimal		
8	5	PRFIC1	Real Private Residential Fixed Investment, 1 Decimal		
9	5	PNFIC1	Real Private Nonresidential Fixed Investment, 1 Decimal		
10	5	GPDIC1	Real Gross Private Domestic Investment, 1 Decimal		
11	5	PCECC96	Real Personal Consumption Expenditures		
12	5	PCNDGC96	Real Personal Consumption Expenditures: Nondurable Goods		
13	5	PCDGCC96	Real Personal Consumption Expenditures: Durable Goods		
14	5	PCESVC96	Real Personal Consumption Expenditures: Services		
15	5	GPSAVE/GDPDEF	Gross Private Saving/GDP Deflator		
16	5	FGCEC1	Real Federal Consumption Expenditures & Gross Investment, 1 Decimal		
17	5	FGEXPND/GDPDEF	Federal Government: Current Expenditures/ GDP deflator		
18	5	FGRECPT/GDPDEF	Federal Government Current Receipts/ GDP deflator		
19	2	FGDEF	Federal Real Expend-Real Receipts		
20	1	CBIC1	Real Change in Private Inventories, 1 Decimal		
21	5	EXPGSC1	Real Exports of Goods & Services, 1 Decimal		
22	5	IMPGSC1	Real Imports of Goods & Services, 1 Decimal		
23	5	CP/GDPDEF	Corporate Profits After Tax/GDP deflator		
24	5	NFCPATAX/GDPDEF	Nonfinancial Corporate Business: Profits After Tax/GDP deflator		
25	5	CNCF/GDPDEF	Corporate Net Cash Flow/GDP deflator		
26	5	DIVIDEND/GDPDEF	Net Corporate Dividends/GDP deflator		
27	5	HOANBS	Nonfarm Business Sector: Hours of All Persons		
28	5	OPHNFB	Nonfarm Business Sector: Output Per Hour of All Persons		
29	5	UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments		
30	5	ULCNFB	Nonfarm Business Sector: Unit Labor Cost		
31	5	WASCUR/CPI	Compensation of Employees: Wages & Salary Accruals/CPI		
32	6	COMPNFB	Nonfarm Business Sector: Compensation Per Hour		
33	5	COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour		

no.series	Transf.	Mnemonic	Long Label		
34	6	GDPCTPI	Gross Domestic Product: Chain-type Price Index		
35	6	GNPCTPI	Gross National Product: Chain-type Price Index		
36	6	GDPDEF	Gross Domestic Product: Implicit Price Deflator		
37	6	GNPDEF	Gross National Product: Implicit Price Deflator		
38	5	INDPRO	Industrial Production Index		
39	5	IPBUSEQ	Industrial Production: Business Equipment		
40	5	IPCONGD	Industrial Production: Consumer Goods		
41	5	IPDCONGD	Industrial Production: Durable Consumer Goods		
42	5	IPFINAL	Industrial Production: Final Products (Market Group)		
43	5	IPMAT	Industrial Production: Materials		
44	5	IPNCONGD	Industrial Production: Nondurable Consumer Goods		
45	2	AWHMAN	Average Weekly Hours: Manufacturing		
46	2	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing		
47	2	CIVPART	Civilian Participation Rate		
48	5	CLF16OV	Civilian Labor Force		
49	5	CE16OV	Civilian Employment		
50	5	USPRIV	All Employees: Total Private Industries		
51	5	USGOOD	All Employees: Goods-Producing Industries		
52	5	SRVPRD	All Employees: Service-Providing Industries		
53	5	UNEMPLOY	Unemployed		
54	5	UEMPMEAN	Average (Mean) Duration of Unemployment		
55	2	UNRATE	Civilian Unemployment Rate		
56	5	HOUST	Housing Starts: Total: New Privately Owned Housing Units Started		
57	2	FEDFUNDS	Effective Federal Funds Rate		
58	2	TB3MS	3-Month Treasury Bill: Secondary Market Rate		
59	2	GS1	1-Year Treasury Constant Maturity Rate		
60	2	GS10	10-Year Treasury Constant Maturity Rate		
61	2	AAA	Moody's Seasoned Aaa Corporate Bond Yield		
62	2	BAA	Moody's Seasoned Baa Corporate Bond Yield		
63	2	MPRIME	Bank Prime Loan Rate		
64	6	BOGNONBR	Non-Borrowed Reserves of Depository Institutions		
65	6	TRARR	Board of Governors Total Reserves, Adjusted for Changes in Reserve		
66	6	BOGAMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve		
67	6	M1SL	M1 Money Stock		
68	6	M2MSL	M2 Minus		
69	6	M2SL	M2 Money Stock		

no.series	Transf	Mnemonic	Long Label		
70	6	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks		
71	6	CONSUMER	Consumer (Individual) Loans at All Commercial Banks		
72	6	LOANINV	Total Loans and Investments at All Commercial Banks		
73	6	BEALLN	Real Estate Loans at All Commercial Banks		
74	6	TOTALSL	Total Consumer Credit Outstanding		
75	6	CPIALICSI	Concurrent Drice Index For All Listen Concurrence All Items		
76	6	CPILII FSI	Consumer Price Index for All Urban Consumers: All Items Less Food		
70	6	CPILECSI	Consumer Price Index for All Urban Consumers: All Items Less Food		
79	6	CDI FESI	Consumer Price Index for All Urban Consumers: All Items Less Energy		
70	6	CPIENCSI	Consumer Price Index for All Urban Consumers: Energy		
19 80	6	CPILIFDSI	Consumer Price Index for All Urban Consumers: Each		
00 01	6	DDICDE	Consumer Price Index for An Orban Consumers. Food		
01 80	6	PDICPM	Producer Price Index Finished Goods. Capital Equipment		
04 92	6	PDIECC	Producer Price Index. Crude Materials for Further Processing		
00 94	6	PDIECS	Producer Price Index. Finished Consumer Goods		
04	6		Chat Oil Drigg, West Torreg Intermediate		
00 96	5	ULFRICE	Spot On Frice: West Texas Intermediate		
00 97	5	USSERFROF	US Dow Jones Industrials Share Frice Index (EF) NADJ		
01	5	USJOUSIK USI62 F	US Standard & Foor's index in 500 Common Stocks		
00 80	5	USIO2F	US Manufacturara Narri Ordera far Nan Defense Capital Coode (PCI 27)		
09	0 E	USINOIDIN.D	US Manufacturers New Orders for Non Defense Capital Goods (BCI 27)		
90	0 1	USUNORUGD	US INW Orders of Consumer Goods & Materials (BCI 8) CONA		
91	1	USINALIMINO	US Isom Manufacturers Survey. New Orders index SADJ		
92	5	USVACIOIO	US The Conference Board Leading Economic Indicators Index SADI		
95	5	USCILLAD	US Free Conference Board Leading Economic findcators findex SADJ		
94 05	ວ າ	CS10 FEDEUNDS	US Economic Cycle Research institute weekly Leading index		
90 06	2	CS1 FEDEUNDS			
90 07	2	BAA FEDEUNDS			
08	2 5	GEXPND/CDPDEF	Covernment Current Expenditures/ CDP defletor		
90	5	CPECPT/CDPDEE	Government Current Expenditures/ GDT deflator		
99 100	ວ າ	CDFF	Covernment Current Receipts/ GDF denator		
100	5	CCEC1	Real Covernment Consumption Expanditures & Cross Investment, 1 Decimal		
101	5	GOLOI	Real Federal Cons. Expanditures & Cross Investment, 1 Decimal		
102	ວ າ		Federal primary deficit		
103	5		Real Federal Current Tax Revenues		
104	5		Real Covernment Current Tax Revenues		
100	ວ າ		Covernment primary deficit		
100	4	RER1	Real exchange rate Major currencies		
107	4	RER2	Real exchange rate Broad		
100	4	NER	Nominal exchange rate: Major currencies		
110	4	NER(Torms of Trade IMP DEEL /EXP DEEL		
110	4		Covernment primary deficit/CDP		
119	∠ ?	CUB	Current Account/GDP		
112	∠ ົ	TRRAL	Trade Balance/GDP		
110	∠ ?	TUDAL	Covernment primery deficit/CDP		
115	<u>ک</u>		Drivete Serving (Dispersello Income Consumption)		
110	0		i iivate baving (Disponsable income - Consumption)		

References

- Altug, S. (1989). Time-to-Build and Aggregate Fluctuations: Some New Evidence, International Economic Review 30, 889-920.
- [2] Amengual, D. and M.W. Watson (2007). Consistent Estimation of the Number of Dynamic Factors in a Large N and T Panel, Journal of Business and Economic Statistics 25, 91-96.
- [3] Bai, J. (2003). Inferential Theory for Factor Models of Large Dimensions, Econometrica 71, 135-171.
- [4] Bai, J., and S. Ng (2002). Determining the number of factors in approximate factor models, Econometrica 70, 191-221.
- [5] Bai, J., and S. Ng (2007). Determining the Number of Primitive Shocks in Factor Models, Journal of Business and Economic Statistics 25, 52-60.
- [6] Baxter, M. (1995). International trade and business cycles. In: G.M. Grossmann and K. Rogoff, Editors, Handbook of International Economics vol. 3, Amsterdam, North-Holland, pp. 18011864
- [7] Bernanke, B. S., J. Boivin and P. Eliasz (2005). Measuring Monetary Policy: A Factor Augmented Autoregressive (FAVAR) Approach, The Quarterly Journal of Economics 120, 387-422.
- [8] Blanchard, O.J. and R. Perotti (2002). An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output, The Quarterly Journal of Economics: 1329-1368.
- [9] Chamberlain, G. (1983). Funds, factors, and diversification in arbitrage pricing models, Econometrica 51, 1281-1304.
- [10] Chamberlain, G., and M. Rothschild (1983). Arbitrage, factor structure and mean variance analysis in large asset markets, Econometrica 51, 1305-1324.
- [11] Connor, G., Korajczyk, R.A., 1988. Risk and return in an equilibrium APT. Application of a new test methodology. Journal of Financial Economics 21, 255-89.
- [12] Corsetti, G. and G. Mller (2006). Twin deficits: squaring theory, evidence and common sense, Economic Policy 48:597638.
- [13] Dornbusch, R. (1976). Expectations and exchange rates dynamics, Journal of Political Economy 84:11611176.

- [14] Erceg, C.J., L. Guerrieri and C. Gust. Expansionary Fiscal Shocks and the US Trade Deficit, International Finance 8(3):363-397.
- [15] Fernndez-Villaverde J., J.F. Rubio-Ramrez, T.J. Sargent and M.W. Watson (2007). ABCs (and Ds) of Understanding VARs. American Economic Review, American Economic Association, 97(3):1021-1026.
- [16] Forni, M., L. Gambetti (2010) Fiscal Foresight and the Effects of Government Spending. CEPR Discussion Paper No. 7840.
- [17] Forni, M., D. Giannone, M. Lippi and L. Reichlin (2009). Opening the Black Box: Structural Factor Models with Large Cross-Sections, Econometric Theory 25, 1319-1347.
- [18] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2000). The generalized dynamic factor model: identification and estimation, The Review of Economics and Statistics 82, 540-554.
- [19] Forni, M., M. Hallin, M. Lippi and L. Reichlin (2005). The generalized factor model: one-sided estimation and forecasting. Journal of the American Statistical Association 100, 830-840.
- [20] Forni, M. and M. Lippi (2001). The generalized dynamic factor model: representation theory, Econometric Theory 17, 1113-1141.
- [21] Forni, M. and L. Reichlin (1998). Let's get real: a factor analytical approach to disaggregated business cycle dynamics, Review of Economic Studies 65, 453-473.
- [22] Hallin M. and R. Liska (2007). Determining the number of factors in the general dynamic factor model, Journal of the American Statistical Association 102, 603-617.
- [23] Kim, S. and N. Roubini (2008). Twin deficit or twin divergence? Fiscal policy, current account, and real exchange rate in the U.S, Journal of International Economics, 74(2):362-383.
- [24] Kollmann, R. (1998). U.S. trade balance dynamics: the role of fiscal policy and productivity shocks and of financial market linkages, Journal of International Money and Finance 17:637669
- [25] Ireland, P.N. (2004). A method for taking models to the data, Journal of Economic Dynamics and Control 28, 1205-1226.

- [26] Leeper, E.M., Walker, T.B. and S.S. Yang (2008). Fiscal Foresight: Analytics and Econometrics, NBER Working Paper No. 14028.
- [27] Lippi, M. and L. Reichlin (1993). The Dynamic Effects of Aggregate Demand and Supply Disturbances: Comment, American Economic Review 83, 644-652.
- [28] Monacelli, T. and R. Perotti, Fiscal Policy, the Trade Balance and the Real Exchange Rate: Implications for International Risk Sharing. Working Paper, IGIER (2006).
- [29] Mertens, K. and M. Ravn (2010). Measuring the Impact of Fiscal Policy in the Face of Anticipation: a Structural VAR Approach. The Economic Journal, 120:544.
- [30] Mountford, A. and H. Uhlig (2009). What Are the Effects of Fiscal Policy Shocks. Journal of Applied Econometrics 24(6):960-992. CEPR Discussion Paper No. 3380.
- [31] Obstfeld, M. and K. Rogoff (1995). Exchange rate dynamics redux. Journal of Political Economy 103:624660.
- [32] Pappa, E. (2009). The effects of fiscal shock on employment and the real wage, International Economic Review 50:217-244.
- [33] Perotti, R. (2007). In Search of the Transmission Mechanism of Fiscal Policy. NBER Macroeconomics Annual.
- [34] Ramey, V.A. (2009). Identifying Government Spending Shocks: It's All in the Timing, NBER Working Papers no. 15464.
- [35] Ramey, V.A. and M. Shapiro (1998). Costly Capital Reallocation and the Effects of Government Spending. Carnegie Rochester Conference on Public Policy 48, 145-194.
- [36] Sargent, T. J. (1989). Two Models of Measurements and the Investment Accelerator, The Journal of Political Economy 97, 251-287.
- [37] Sargent, T.J. and C.A. Sims (1977). Business cycle modeling without pretending to have too much a priori economic theory. In C.A. Sims, Ed., New Methods in Business Research, Federal Reserve Bank of Minneapolis, Minneapolis.
- [38] Stock, J.H. and M.W. Watson (2002a). Macroeconomic Forecasting Using Diffusion Indexes, Journal of Business and Economic Statistics 20, 147-162.
- [39] Stock, J.H. and M.W. Watson (2002b). Forecasting Using Principal Components from a Large Number of Predictors, Journal of the American Statistical Association 97, 1167-1179.

- [40] Stock, J.H. and M.W. Watson (2005). Implications of Dynamic Factor Models for VAR Analysis, NBER Working Papers no. 11467.
- [41] Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. Journal of Monetary Economics 52, 381-419.

Tables

j	Variables(*)
1	GDP(1), Deficit(111), CUR(112), RER(107), Gov. Cons. & Inv. (101)
2	GDP(1), Deficit(111), CUR(112), RER(107), Cons.(11)
3	GDP(1), Deficit(111), CUR(112), RER(107), Inv. (7)
4	GDP(1), Deficit(111), CUR(112), RER(107), CPI(75)
5	GDP(1), Deficit(111), CUR(112), RER(107), Int. rate(58)
6	GDP(1), $Deficit(111)$, $CUR(112)$, $RER(107)$, $Stock Prices(87)$
	(*) The numbers correspond to those in the Appendix.

Table 1a: Variables

j	Point Est	Mean	Median	68%	84%	90%	95%	prob.
1	0.5891	0.6377	0.6902	0.8438	0.9534	1.0014	1.0388	0.8990
2	0.2529	0.7142	0.7713	0.9207	1.0223	1.0503	1.0782	0.8030
3	0.1345	0.7229	0.7900	0.9089	1.0011	1.0347	1.0630	0.8390
4	0.3219	0.6846	0.7533	0.8917	1.0029	1.0300	1.0540	0.8370
5	0.8705	0.6733	0.7203	0.8959	1.0059	1.0430	1.0693	0.8180
6	0.8563	0.7378	0.8325	0.9653	1.0347	1.0608	1.0838	0.7430

Table 1b: Modulus of the smallest root.

i	\hat{eta}_i	$\hat{\gamma}_i$
1	$0.0199 \ (0.1062)$	0.1317 (0.2707)
2	$0.0209\ (0.1050)$	$0.0318\ (0.2709)$
3	-0.0015(0.1047)	$0.1430\ (0.2761)$
4	-0.0146 (0.1068)	0.0077 (-0.0795)
F-test	$H_0: \gamma_i = 0, i = 1,, 4$	F=0.021

Table 2: Granger causality. The regression is

shock_t = $\alpha + \sum_{i=1}^{4} \beta_i shock_{t-i} + \sum_{i=1}^{4} \gamma_i spf_{t-i} + \varepsilon_t$. Standard errors in parenthesis.

Variables	0	4	8	20	Total
111	13.4831	4.7675	5.3842	7.9807	13.9665
112	17.9564	16.6256	13.5680	11.2501	14.1853
113	12.2453	14.8414	12.6473	10.9221	11.8825
107	11.6440	11.4998	11.3543	11.3894	11.3894
109	16.7146	15.2427	14.9971	14.7958	14.7958
110	7.0172	6.0647	6.0690	6.0358	6.0358
1	16.1968	5.0842	4.0832	4.2564	13.6802
11	6.5370	5.0644	6.8215	9.4937	9.8759
7	9.6978	2.7724	3.1201	4.8522	9.1006

Table 3: Variance decomposition

Figures



Figure 1: Impulse response functions to an expansionary fiscal policy shock.



Figure 2: Robustness: 13 factors (solid line), 10 factors (dotted line), 16 factors (dashed line).



Figure 3: Robustness: impulse response functions to a government spending shock.