Essays on Macroeconometrics

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Abstract

This thesis is a collection of empirical essays, with macroeconomic application. The first two chapters are focused on monetary and fiscal policy. Since the outbreak of the Great Recession, both scholar and policymakers have paid close attention to their optimal mix and their effectiveness as source of economic boost. Our work contributes to the ongoing discussion focusing on some specific features of theses policies, namely the effects of monetary new and of fiscal spillovers. The last essay, is centered around Italy and the role of social capital in its growth profile. Taking advantage of some newly published times series – covering a century and a half of unitary history – we disentangle the effects of technology, human capital and social capital on the long run growth of the country.

In the first chapter, we investigate the effects of anticipated and unanticipated monetary policy shocks. The baseline idea is that markets form expectations on future policy developments that are relevant for investment (and hence production) decisions even before the actual policy change is implemented. We explore theoretically the challenge that this time misalignment implies at the moment of performing estimation, and we discuss alternative solutions to such problem. On an empirical ground, we find that news account for a sizable portion of the overall transmission of monetary policy, accounting in between 25 and 50% of the total policy effect. Out results are comparable to the literature in that we identify both an anticipated and an unanticipated disturbance. Not surprisingly, and consistently with previous works, we observe that that a monetary tightening generates humped-shaped responses of GDP, consumption and investment and a fall in prices. What is interesting and innovative, is that aggregate variables

adjust even before the realization of the announce policy shift. Also, we observe that news have (anticipated) feedback effects in the interest rate, via adjustments of the Taylor rule. To establish robustness of out result we use alternative proxies for market expectations, different Cholesky ordering and alternative identification strategies, relying on sign rather than zero restrictions.

In the second chapter we move the attention to fiscal spillovers in a set of European countries, namely Germany, France Spain and Italy. This work is especially relevant given the near-constant debate on fiscal coordination within the Euro area, that is far from being settled. We use a time varying framework, which is appropriate for the period 1995-2014 that contains both institutional and financial inflection points (e.g. introduction of the common currency or the global recession). We find that the cycles of the four economies are highly correlated, testifying the interwoven faith of these member states. However, we fail to observe evidence of fiscal policy coordination. Notwithstanding this, government spending in a country expand its effects cross-border, affecting other countries' GDP. Broadly speaking, international spillovers are especially strong in the medium run and during the financial crisis, paving the way to the discussion on fiscal coordination across member states. Also, we perform a case by case study, to disentangle the effects of fiscal spillover in each country separately. Our results suggest that responses across countries can be asymmetric and heterogeneous in sign and magnitude.

Finally, the third chapter makes use of time series technique to explore the issue of social capital in Italy and its impact in the growth profile of the country. More specifically, we use a SVAR model to disentangle the relative contributions of technology, human capital and social capital shocks. The definition of social capital is based on trust and ease of economic cooperation, which allows us to design a measurement proxy based on voluntary organizations. Then, taking advantage of long spam times series, we reconstruct a measure of human capital based on year of schooling and computed with the permanent inventory method. The final aim is to estimate a VAR including both social capital and human capital, and differentiate their effects output growth. Empirical results show that an increase in social capital productivity affects output positively. Conversely, it does not have any relevant effect on human capital accumulation. Also, consistently with endogenous growth theory, we find that education is a fundamental factor of GDP growth. Therefore, we establish that social capital has a role in fostering growth, even if its effects are small compared to human capital and TFP.

All remaining errors are my own.

Chapter 1

Monetary News, Surprises and the Macroeconomy.

Abstract

In this work we investigate the effects of anticipated and unanticipated monetary policy shocks. We bring forward empirical evidence that news are a relevant channel of the monetary transmission mechanism accounting in between 25 and 50% of the overall policy effects. Consistently with the theory, a monetary tightening generates humped-shaped responses of GDP, consumption and investment and a fall in prices. Interestingly, aggregate variables adjust even before the announced policy shift actually happens. Accordingly, we testify anticipated feedback effects on the interest rate, via the policy rule. Our results are robust to alternative proxies for market expectations, to different Cholesky ordering and to alternative identification strategies, relying on sign rather than zero restrictions.

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1.1 Introduction.

The effects of monetary policy have long been object of interest in the economic profession. At present day a large amount of studies substantiated its transmission mechanism either using general equilibrium models as experimental laboratories or structural VARs as statistical tools. Christiano et al. (1999) survey the empirical literature, showing that, notwithstanding the variety of identification schemes proposed by different authors, there is a considerable agreement about the qualitative effects of exogenous monetary policy shocks. That is, regardless of the fact that identification relies on the recursiveness assumption (e.g. Sims (1992); Christiano et al. (2005)), on sign restrictions (e.g. Uhlig (2005)) or on narrative methods (e.g. Romer and Romer (2004)), the responses of various economic aggregates is broadly consistent. In a nut shell, after an exogenous monetary tightening, short term interest rates rise, aggregate output, profit and various monetary aggregates fall, and the price level responds sluggishly. Also, there is a widespread consensus that monetary policy shocks account for a modest percentage of the volatility of aggregate output and inflation.

The bulk of the aforementioned literature was focused on exogenous shocks which take the private sector by surprise. There exists some early contributions on the role of monetary anticipation (e.g. Mishkin (1982); Cochrane (1998)) and on the fact that central banks can steer market perceptions signalling through their communicates (Amato et al., 2002). However, it was only recently that the issue captured greater attention. With the zero lower bound impeding further adjustments of the short term rates, monetary authorities were robbed their traditional policy tool and had to resort to unconventional policy instruments, igniting the debate on forward guidance.

The Federal Reserve, through the press releases of the Federal Open Market Committee (FOMC), made extensive use of forward guidance, in order to move long-term yields and stimulate aggregate expenditure. Gürkaynak et al. (2005) and more recently Campbell et al. (2012) present empirical evidence that the central bank effectively telegraphs its intentions, thus affecting market expectations (measured as in Söderström (2001) and Kuttner (2001) with federal funds futures) and consequently asset prices. However, quantitative measures of the effects of such announcements on output and other macroeconomic aggregates are scarce. This is not too surprising, given that the challenge of identifying monetary policy shock is harshened in the case of shocks that are anticipated.

The idea that foresight is a source of sizeable economic fluctuations have been widely explored in fiscal policy (e.g. Yang (2005); Leeper et al. (2013)) and in real business cycle (e.g. Beaudry and Portier (2006); Schmitt-grohe and Uribe (2012); Blanchard et al. (2013); Barsky and Sims (2009); Forni et al. (2014)). Conversely, few are the theoretical contributions in the field of monetary economic (Lorenzoni (2007); Milani and Rajbhandari (2012)) and even fewer the empirical estimates. Our work is aimed at filling this gap in the literature by disentangling the effects of anticipated (news) and unanticipated (surprise) monetary shocks.

We start presenting a small scale new-Keynesian model, introducing the extra feature of monetary foresight. The mechanism of transmission of the policy shocks is standard: due to price rigidities, the central bank has some leverage on real variables and can stimulate the economy by affecting market expectations of the nominal interest rate. The novelty resides in that agents form their beliefs both on the basis of anticipated and unanticipated information, therefore, the central bank has an extra channel to signal its intentions to the private sector.

Intuitively, when future decisions matter, the information contained in present and past data is not sufficient to capture anticipated policy reactions. This translates in the fact that the model is non-invertible and standard structural VARs are unfit to correctly recover the underlying economic shocks. To dodge this problem we propose two alternative approaches. The first, based on dynamic identification, echoes Forni et al. (2013b) and is a useful theoretical exercise to spell out the bias implied by classical VAR techniques. The second resides in closing the informational wedge in between agents and econometrician, by augmenting the VAR with market expectations. Model simulations allow to test the performance of the proposed strategies and, in line with Féve and Jidoud (2012), we find that non-invertibility is especially severe when the roots of the structural MA are close to zero.

Interestingly, while non-fundamentalness impedes the exact identification of both shocks together, it has little to say on the possibility of recovering one shock alone. Indeed, we find that even in the non-invertible representation the effects of unanticipated policy are correctly pinned down in the VAR. That is, disregarding news does not imply any bias in the estimates of the classical surprise shock, which allows for direct comparison with previous literature. However, it does imply neglecting a possibly relevant part of the transmission mechanism with consequent underestimation of the overall policy effects.

The main contribution of this work resides exactly in presenting empirical evidence that this channel is also relevant. Our estimates suggest that anticipation accounts for in between 25 and 50% of the effects of monetary policy on output. Not only news have sizeable effects on the real economy but also they significantly affect prices and market expectations. More in detail, a monetary policy tightening, both anticipated and unanticipated, provokes a contraction in aggregate production and a fall in prices, which is consistent with the theory. Noticeably, agents have foresight on policy actions, thus aggregate variables adjust even before the actual realization of future expected shocks. Lastly, as regards the interest rates, we found impulse responses unprecedented in the literature that testify the indirect feedback of announcements through the Taylor rule. That is, following a news shock, rates fall in the short run, as a reflection of the economic contraction, and raise at longer horizons, when the announced policy shift happens.

In the remainder of the chapter we proceed as follows. Section 1.2 presents the model; Section 1.3 discusses its econometric implications; Section 1.4 proposes two strategies to solve the issue of non-invertibility; Section 1.5 presents the general econometric model; Section 1.6 performs simulation exercises; Section 1.7 presents the empirical evidence; Section 1.8 concludes.

1.2 The Model.

In this section we present a simple model that explores the relevant monetary mechanisms while keeping analytical tractability. We want to capture the idea that policy shocks have an anticipated or news component - which embeds the notion of forward guidance - and an unanticipated or surprise component - reflecting the "classical" exogenous disturbance traditionally analysed in the literature.

1.2.1 A simple model of News and Surprises.

We consider an economy with a plain supply side, where we have no capital and output is completely demand driven $y_t = c_t$. Given the actual level of productivity, labor inputs adjust to match the quantity y_t. As customary in the literature, we summarize the behavior of the central bank with a simple Taylor rule, assuming that monetary authorities fix the short term nominal interest rate according to:

$$i_t = i^* + \phi_\pi \pi_t + \phi_y \tilde{y}_t + v_t \tag{1.1}$$

where $i^* = -log\beta$, the discount factor. ϕ_π and ϕ_y are positive parameters reflecting the strength of the central bank reaction to inflation and output gap respectively, while v_t captures exogenous deviations from the systematic policy rule. To introduce news in the model we use a variant of Campbell et al. (2012) and Milani and Treadwell (2012), assuming that the aforementioned shock is the sum of two components:

$$v_t = \rho(L)\varepsilon_t + \rho(L)\eta_{t-q}. \tag{1.2}$$

where the i.i.d. disturbance ε_t represents an unanticipated change in policy while η_{t-q} corresponds to its anticipated part. In plain words, in every period private agents face a surprise shift in the target rate of ε_t and receive news about future monetary deviations, which will only materialize q periods into the future. As customary, $\rho(L) \equiv \sum_{j=0}^{\infty} \rho^j L^j$ with $\rho < 1$, stands for the persistence of the policy shock. For the sake of parsimony we set $\rho = 0$, which simplifies the above equation to:

$$v_t = \varepsilon_t + \eta_{t-q}. \tag{1.3}$$

The mechanism of transmission of such disturbances is standard: due to nominal rigidities, a change in i_t provokes shifts in current and expected future real rates, at least over some horizons. This gives the central bank the leverage to manipulate aggregate spending and, as a result, aggregate output. More in specific, present deviations of output from its natural level match the discounted sum of expected monetary disturbances, according to:

$$\tilde{y}_t = -\Omega \sum_{k=0}^{\infty} \Omega^k E_t\{v_{t+k}\} \tag{1.4}$$

where $\Omega = \frac{1}{1+\phi_y}$ is a positive parameter smaller than one. Following Blanchard et al. (2013), we show in the appendix that this model can be derived as the limit case of a standard New Keynesian model with Calvo pricing, when θ - the probability of non re-optimizing prices - goes to one (or equivalently the frequency of price adjustment goes to zero).

It could be argued that the above assumptions are over restrictive. However, some lengthy algebra (also in the appendix) shows that it is possible to extend the model, allowing for different calibrations of θ and for positive persistence of monetary policy shocks. The relevant mechanisms are widely unchanged across specifications and thus we privilege the basic setup, which is a cleaner explanatory tool.

Furthermore, in line with Gali (2008), we posit that agents have perfect knowledge of current and past realizations of the shocks, that is, their information set is $I_t = (\varepsilon_{t-j}, \eta_{t-j})_{j=0}^{\infty}$. This assumption slightly differs from Christiano et al. (2005), where agents observe monetary policy up to $t-1$[1]. Either specification could be employed to derive the results presented in this chapter and, although we favour the former for the theoretical section, we will use both of them in the empirical application.

In our setting the expectation of the policy residual is:

$$E_t\{v_{t+j}\} = \begin{cases} \varepsilon_t + \eta_{t-q} & for \;\; j = 0 \\ \eta_{t-q+j} & for \;\; 0 < j \leq q \\ 0 & for \;\; j > q. \end{cases} \tag{1.5}$$

which, plugged into (1.4) simplifies the infinite summation to a finite number of addends:

$$\tilde{y}_t = -\Omega \left(\varepsilon_t + \eta_{t-q} + \Omega \eta_{t-q+1} + \ldots + \Omega^q \eta_t \right). \tag{1.6}$$

Notice that by construction η_t does not affect v_t on impact, and in fact it does not move the policy indicator till $t+q$ periods in the future. However, being that output

[1] Such assumption introduces a one lag delay in the response of the real economy to monetary disturbances and justifies the recursive identification scheme used in their VAR.

adjusts to expected future policy shocks, news on forthcoming realizations of v_t move $\tilde{y}_t$ before the shock is actually realized.

Given q periods of anticipation, equation (1.3) and (1.6) join in the MA representation:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & L^q \\ -\Omega & -\Omega\,\omega_q(L) \end{pmatrix}}_{\mathcal{M}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \tag{1.7}$$

where

$$\omega_q(L) \equiv \sum_{k=0}^{q} \Omega^k L^{q-k} \tag{1.8}$$

is a polynomial in the lag operator gathering all information received up to q periods into the past[2].

Two properties $\omega_q(L)$ are worth mentioning. First, the q complex roots of $\omega_q(L)$ lie inside the open unit disc, more specifically at Ω distance from the origin[3]. Second, some easy algebra shows that:

$$\omega_q(L) = L^q + \Omega\omega_{q-1}(L).$$

This equation has a simple interpretation: at time t the effect of anticipated information on output is given by the old piece of news received at $t-q$ plus a composition of more recent news ($\omega_{q-1}(L)$) discounted by Ω. This formulation features the same characteristic of reverse discounting found by Leeper et al. (2013) regarding fiscal foresight: latest news are discounted more heavily than past one, that is, the effect of η_{t-k} on output is smaller than the one of η_{t-s} for all $k < s$. This stems naturally from the model because recent information affects interest rates further away in the future while past announcements relate to more imminent policy changes.

Hereby, we present the case of $q = 2$, which will be used as a working example

[2] Examples for different anticipation horizons are:

- $\omega_0(L) = 1$.
- $\omega_1(L) = L + \Omega$.
- $\omega_2(L) = L^2 + \Omega L + \Omega^2$.

[3] As an example $\omega_2(L)$ has two roots: $r_1 = \frac{-\Omega(1-\sqrt{3}i)}{2}$ and $r_2 = \frac{-\Omega(1+\sqrt{3}i)}{2}$ with modulus $| r_1 |=| r_2 |= \Omega$.

throughout the discussion:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \begin{pmatrix} 1 & L^2 \\ -\Omega & -\Omega(L^2+\Omega L+\Omega^2) \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{1.9}$$

In this circumstance the effects of η_t on the policy residual materialize in $t+2$. Output gap

$$\tilde{y}_t = -\Omega\left(\varepsilon_t + \eta_{t-2} + \Omega\eta_{t-1} + \Omega^2\eta_t\right)$$

depends on three increasingly discounted elements: the current policy shift $v_t = \varepsilon_t + \eta_{t-2}$, the one expected for next period $\Omega E_t\{v_{t+1}\} = \Omega\eta_{t-1}$ and the one expected for two periods ahead $\Omega^2 E_t\{v_{t+2}\} = \Omega^2\eta_t$. Notice that the exponent on Ω goes in parallel with the expectation horizon, while recent information is more heavily discounted. In short, policy shocks v_t are discounted the usual way, while policy news are discounted in reverse order.

1.3 Failure of Classical SVARs.

1.3.1 Non-Fundamentalness.

Standard SVAR techniques assume that the structural shocks are a linear combination of the reduced form residuals. However, if the system is not fundamental, this assumption fails and the method is no longer valid. Introducing anticipation in the model has severe econometric implications in this sense. Consider the determinant of $M(z)$ in (1.7):

$$\begin{aligned} Det\left(\mathcal{M}(z)\right) &= -\Omega(\omega_q(z) - z^q) \\ &= -\Omega(z^q + \Omega\omega_{q-1}(z) - z^q) \\ &= -\Omega^2\omega_{q-1}(z) \end{aligned} \tag{1.10}$$

where the second equation derives from the aforementioned properties of $\omega_q(z)$. Clearly, the determinant shares the same roots with $\omega_{q-1}(z)$ which, as discussed above, are all inside the unit circle. That is, the system is non-fundamental and non-invertibile[4].

[4]Recall that non-fundamentalness stems whenever the determinant of the MA representation vanishes for values of z within the open unit disc. Non-invertibility arises in that case too, but it also appears for roots equal to unity. Therefore, non-fundamentalness implies

The only notable exception is $q = 1$, for which the determinant is identically equal to 1 and the system admits a VAR representation.

In other words, for anticipation horizons $q \geq 2$, the VAR based on $\tilde{y}_t$ and v_t does not contain enough information to correctly identify the two structural shocks. This does not stem from the difficulty of proxying for v_t and $\tilde{y}_t$ - usually not directly observable in the data. It is rather the consequence of agents' decision making which incorporates in every period a full set of news. Agents keep track of $\eta_t, \ldots, \eta_{t-q+1}$ but since at time t their effect on v_t has not materialized yet, knowledge of the policy indicator cannot be fully revealing of the underlying shocks. As a matter of fact, v_t only contains η_{t-q} and not η_t.

Also, the combination of v_t and $\tilde{y}_t$ is informationally deficient, even if the latter depends on present and past news. The example with $q = 2$ can clarify this point. From (1.9) we have:

$$(L + \Omega)\eta_t = \frac{\tilde{y}_t + \Omega v_t}{-\Omega^2}$$

which contains the non invertible polynomial $(L + \Omega)$. Clearly, it is not possible to derive an expression for η_t in terms of past realization of the data. However, multiplying both sides times $F = L^{-1}$ and rearranging we obtain:

$$\eta_t = F(1 + \Omega F)^{-1} \frac{\tilde{y}_t + \Omega v_t}{-\Omega^2}.$$

That is, the news shock does not reside in the past of the data, but rather in its future. This is why the information set of the econometrician $I_t^e = (\tilde{y}_{t-j}, v_{t-j})_{j=0}^{\infty}$ - who observes data outcomes - is strictly smaller than the one of the agents $I_t = (\varepsilon_{t-j}, \eta_{t-j})_{j=0}^{\infty}$ - who have perfect knowledge of both shocks.

Looking on the bright side, it is important to remark that non-fundamentalness implies VAR inadequacy to recover the two structural shocks at the same time. Nevertheless, it has nothing to say on the possibility of identifying only the unanticipated component. Consider, for instance, the simplified model:

$$v_t = \varepsilon_t + \eta_{t-1}$$

$$z_t = \eta_{t-1}$$

non-invertibility but not all the way round.

where z_t is fully news driven and v_t, as usual, contains news and surprises. Once more, the econometrician faces a VAR failure, being that

$$\begin{pmatrix} v_t \\ z_t \end{pmatrix} = \begin{pmatrix} 1 & L \\ 0 & L \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \tag{1.11}$$

features a root at 0 and thus it is not invertible. As discussed above, this can be imputed to the fact that news $\eta_t = Fz_t$ reside in the future of z_t and cannot be recovered with present and past data. However, ε_t can be easily expressed as a liner combination of the observables: $\varepsilon_t = v_t - z_t$. That is, data up to time t is fully revealing of the surprise shock. Therefore, the variables in (1.11) are informationally deficient for η_t and ε_t together but informationally sufficient for ε_t alone. As we will see in the simulations, and later in the empirical section, this will also be the case for monetary policy. Informational deficiency constrains the econometrician, as far as news are concerned, but it does not alter the effectiveness of VARs in recovering monetary surprises from the data.

1.3.2 What can SVARs do? Blaschke Matrix.

Sims (2012) and Beaudry and Portier (2014) showed that non-invertibility is not to be thought as an "either/or" proposition. Even in a model with foresight and roots in the unit circle, the wedge between VAR innovations and economic shocks might be small and SVAR techniques might still be reliable. Therefore, it is instructive to spell out clearly what the econometrician obtains when trying to estimate our non-fundamental system.

In order to do so, we rely on the use of Blaschke Matrices as presented in Lippi and Reichlin (1994). An $n \times n$ matrix $B(z)$ is a Blaschke matrix (BM henceforth) if it has no poles of modulus smaller or equal to unity and if:

$$B(z)B^*(z^{-1}) = I$$

where $B^*(z)$ denotes the complex conjugate of $B(z)$. A special case of BM can be computed using the Blaschke product as follows: let $r_1, r_2, \dots, r_n$ be a sequence of complex roots smaller than one in modulus[5]. Their Blaschke product[6] is defined by:

$$b_n(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L}. \tag{1.12}$$

where $\bar{r}_j$ is the complex conjugate of r_j. $b_n(L)$ can be used to build the following BM:

$$B(L) = \begin{pmatrix} I & 0 \\ 0 & b_n(L) \end{pmatrix} \tag{1.13}$$

where I denotes the $(n-1)$ dimensional unit matrix.

To understand how to employ BM, we can work out our example for $q = 2$ which will be later generalized. Recall that model (1.9):

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \begin{pmatrix} 1 & L^2 \\ -\Omega & -\Omega(L^2 + \Omega L + \Omega^2) \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}$$

has a root exactly at $L = -\Omega$. The Blaschke factor corresponding to this single roots is:

$$b_1(L) = \frac{L + \Omega}{1 + \Omega L}. \tag{1.14}$$

Next, we can make use of the associated BM to split the system in two blocks:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \begin{pmatrix} 1 & \frac{L^2}{b_1(L)} \\ -\Omega & -\Omega\frac{\omega_2(L)}{b_1(L)} \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ x_t \end{pmatrix} \tag{1.15}$$

$$\begin{pmatrix} \varepsilon_t \\ x_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & b_1(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{1.16}$$

The former is a fundamental representation. Indeed, in (1.15) all the roots smaller than one are eliminated dividing over $b_1(L)$ and the determinant is left with $-\Omega^2(1 + \Omega L)$, which vanishes well outside the unit circle. Therefore, structural VARs apply

[5] In the case of $\omega_{q-1}(L)$ all the roots have modulus Ω, meaning $n = q - 1$. However, for the more general case $\mathcal{M}_{21}(L)$ might have a different number of roots in the unit disc, as well as some roots falling outside.

[6] The Blaschke product delivers an analytical function in the open unit disc constrained to have zeros at a finite (or infinite) sequence of prescribed complex numbers $r_1,\ r_2, \ldots$.

and the first sub-system is what the econometrician can actually estimate. The latter block, in (1.16) relates the fundamental residuals obtained in the first step to the true economic shocks.

A first point to be made - which circles back to the discussion on non-invertibility - is that the RHS of (1.15) contains exactly ε_t. Being that the system is fundamental, the surprise shock (together with x_t) resides in the space spanned by VAR innovations and can be correctly identified from the data. In other words, data is informationally sufficient for ε_t even if the original system (1.9) is overall non-invertible.

Wholly antithetical conclusions apply to η_t. If the naive econometrician were to rely solely on (1.15), she would draw misleading inference on the actual monetary surprise. Indeed, what the VAR delivers is x_t, a linear combination of reduced form residuals. A glimpse at the second sub-system (1.16) shows that

$$x_t = \frac{L+\Omega}{1+\Omega L}\eta_t,$$

i.e., a non-invertible convolution of present and past values of η_t rather than the structural shock itself. Consequently, $\eta_t = b_1(F)x_t$ has its expansion in the future[7] of the fundamental shock x_t which, as previously discussed, is the very reason of data informational deficiency.

It is clear that the first step alone delivers a biased estimate of the effects of monetary news. However, it is not equally evident how severe such bias is and whether, on an empirical ground, the performance of structural VARs is hopelessly compromised. What we can state with confidence is that as Ω decreases:

$$\lim_{\Omega \to 0} x_t = L\eta_t \tag{1.17}$$

the fundamental shock matches a lagged value of the news, and η_t is fully revealed only with one period delay. Conversely, as Ω approaches the unit circle the wedge between the fundamental and the structural shocks disappears:

$$\lim_{\Omega \to 1} x_t = \eta_t. \tag{1.18}$$

[7]Notice that $b(L)^{-1} = b(L^{-1}) = b(F)$.

This makes clear that non-invertibility is not an "eitehr/or" problem. Indeed, how likely it is to reasonably approximate the news shocks depends on the size of the root in the unit circle. The biggest is Ω the more reliable are the estimates from a structural VAR.

To grasp an intuition of why this is the case, let's explicit $\eta_t = b_1(F)x_t$:

$$\eta_t = \Omega x_t + (1 - \Omega^2)(1 + \Omega F)^{-1} F x_t.$$

The above expression conveniently separates x_t in two parts. The coefficient associated to x_t is Ω, while the sum of the coefficients associated its leads[8] is $(1 - \Omega)$. This has a simple interpretation: the news shock is a combination of x_t and its future, weighted by Ω. High values of Ω convey more relevance to the present, thus pushing the news towards the space spanned by the data. Conversely, low Ω give more weight to future values, exacerbating the problem on non-fundamentalness.

1.4 Solving the non-invertibility.

In this section we present two alternatives to circumvent the problem of non-invertibility. In line with Forni et al. (2013b,a), the first is based on Blaschke matrices and designs a dynamic identification scheme. This is an interesting exercise, being that it allows to spell out clearly the bias arising from non-fundamental VARs. Therefore, we will employ it in model simulations, in order to grasp a better insight of the results presented above.

As regards the empirical application we will privilege the second approach, which is based on complementing the VAR with private sector expectations. As we discussed, non-invertibility is essentially a problem of information misalignment. Intuitively, a possible solution is to expand the scope of the VAR with variables that capture agents' expectations about future policy. Also in this case, simulations will allow to test the performance of the proposed strategy.

[8] set $F = 1$

1.4.1 Blaschke Matrix: general model.

In this section we remove the simplifying assumptions of the toy model - $\theta = 1$ and $\rho = 0$ - and we use its extended formulation, which allows for generic parameters calibration and for higher persistence of the policy shock, as in (1.2). Some lengthy algebra (in the appendix) shows that the moving average representation of v_t and $\tilde{y}_t$ in terms of the monetary policy shocks is given by:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} \rho(L) & \rho(L)L^q \\ \boldsymbol{\psi}_1(L) & \gamma(L) \end{pmatrix}}_{\mathcal{D}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \tag{1.19}$$

where $\gamma(L) = \boldsymbol{\phi}_1^{q-1}(L) + \boldsymbol{\psi}_1(L)L^q$. Both $\boldsymbol{\phi}_1^{q-1}(L)$ and $\boldsymbol{\psi}_1(L)$ are polynomials in the lag operator, whose exact definition is available in the appendix. Notice the parallel with the simpler case presented above: the effect of the anticipated shock on output is a composition of the oldest information $\boldsymbol{\psi}_1(L)L^q$ and a collection of $q-1$ more recent news $\boldsymbol{\phi}_1^{q-1}(L)$. Hence, $\boldsymbol{\phi}_1^{q-1}(L)$ is the generalized version of $\Omega_{q-1}(L)$, and similarly to this latter, it is the one generating roots in the unit circle[9]. Therefore, also under a general calibration the model is non-invertible. In fact, the determinant $det(\mathcal{D}(z)) = \boldsymbol{\phi}_1^{q-1}(z)\rho(z)$ shares the same roots with $\boldsymbol{\phi}_1^{q-1}(z)$.

This calls for the use of $b(L)$, that can be built using all the small roots of $\boldsymbol{\phi}_1^{q-1}(L)$. The corresponding matrix $B(L)$ allows to decompose the model in its fundamental and structural couplet:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} \rho(L) & \frac{\rho(L)L^q}{b(L)} \\ \boldsymbol{\psi}_1(L) & \frac{\boldsymbol{\phi}_1^{q-1}(L)+\boldsymbol{\psi}_1(L)L^q}{b(L)} \end{pmatrix}}_{\mathcal{G}(L)} \begin{pmatrix} \varepsilon_t \\ x_t \end{pmatrix} \tag{1.20}$$

and

$$\begin{pmatrix} \varepsilon_t \\ x_t \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & 0 \\ 0 & b(L) \end{pmatrix}}_{B(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{1.21}$$

[9] Figure 3 exemplifies it with a numerical study.

The first block has no roots problems, being that $b(L)$ takes care of twisting inside out all the small roots. Hence it is possible to obtain a consistent estimate ε_t and x_t from the data. Next, with $B(L)$ we can recover the true structural shocks from the first step. This differs from classical techniques in that the shocks are not obtained as a static combination of VARs residuals. On the contrary, they are pinned down by a dynamic convolution of fundamental innovations as in (1.21). As a consequence, a consistent estimate of $B(L)$ is needed to correct for the first step innovations. Thus, the identification procedure follows these steps:

1. Run a VAR on the data and impose the restriction that the x_t does not affect v_t contemporaneously. This arises naturally from the fact that x_t contains a combination of news shocks whose effect on interest is delayed.

2. In order to find the roots falling in the unit circle, exploit the estimates of $\hat{\mathcal{G}}_{11}(L)$ and $\hat{\mathcal{G}}_{12}(L)$:

   (a) Compute:
   $$r(L) = \frac{L^q}{b(L)} = \hat{\mathcal{G}}_{11}(L)^{-1}\hat{\mathcal{G}}_{12}(L).$$
   Notice that $r(L)$ can be expressed as $b(F)F^{-q}$. This means that it shares the same roots of $b(F)$, and as a consequence of $b(L)$.

   (b) Find the the roots $\hat{r}_j$ of $r(L)$, smaller than one in modulus.

   (c) Use $\hat{r}_j$ to build $\hat{b}(L)$ and $\hat{B}(L)$ as in (1.12) and (1.13)

3. The structural representation of the system in terms of the news and surprise shock is given by:
$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \hat{\mathcal{G}}(L)\hat{B}(L)\begin{pmatrix} \eta_t \\ \varepsilon_t \end{pmatrix}.$$

1.4.2 Adding information to the VAR.

As discussed earlier, the non-fundamentalness of the system in (1.19) reflects a mismatch between agents and econometrician's information. When agents anticipate future expected policy developments the naif econometrician can only derive a convolution of the true structural shocks. In this case BMs are a valid tool to identify the underlying shocks dynamically.

Other than BMs, a different way out is to expand the information set of the econometrician by adding agents' expectations on future policy movements. The intuition behind this approach is the following: when market participants act in advance of policy, the econometrician is unable to disentangle which movements in current output are attributable to surprise shocks and which are due to changes in expectation. This opens the wedge between agents and econometrician's information sets and translates into non-invertibility. However, if the econometrician knew markets beliefs about future rates she would have sufficient information to properly disentangle anticipations and surprises.

But what is *sufficient information* in this setting? The answer to this question is intuitive: to solve the informational misalignment the econometrician must have access to market expectations over an horizon that is at least as wide as the central bank announcement. The intuition behind it is simple. Consider the baseline example with $q = 2$ and $\rho = 0$. Notice that $E_t\{v_{t+1}\} = \eta_{t-1}$ only contains past news, while $E_t\{v_{t+2}\} = \eta_t$ contains the current news. In short, agents use η_t to change their projections for $t+q$, thus any forecast below this threshold does not carry the information needed to unveil the structural shock.

Simple algebra can formalize this point in the more general setting. Maintaining the assumption that the policy shock is a compound of news and surprises as in (1.2), we can compute projections over any arbitrary horizon s using Weiner-Kolmogorov formula (see appendix).

$$E_t\{v_{t+s}\} = \left[\frac{\rho(L)\varepsilon_t + \rho(L)L^q\eta_t}{L^s}\right]_+ = \begin{cases} \rho^s\rho(L)\varepsilon_t + \rho(L)L^{q-s}\eta_t & for \;\; s < q \\ \rho^s\rho(L)\varepsilon_t + \rho^{s-q}\rho(L)\eta_t & for \;\; s \geq q \end{cases} \tag{1.22}$$

Therefore, when we condition the VAR on expected policy shocks we need to consider the two cases $s < q$ and $s \geq q$ separately.

$$\begin{pmatrix} v_t \\ E_t\{v_{t+s}\} \end{pmatrix} = \underbrace{\begin{pmatrix} \rho(L) & \rho(L)L^q \\ \rho^s\rho(L) & \rho(L)L^{q-s} \end{pmatrix}}_{\mathcal{R}^{(1)}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix} \qquad (case1)$$

$$\begin{pmatrix} v_t \\ E_t\{v_{t+s}\} \end{pmatrix} = \underbrace{\begin{pmatrix} \rho(L) & \rho(L)L^q \\ \rho^s\rho(L) & \rho^{s-q}\rho(L) \end{pmatrix}}_{\mathcal{R}^{(2)}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \qquad (case2)$$

Notice that when computing the complex zeros of the determinant of the above representations we have:

$$Det(\mathcal{R}^{(1)}(z)) = \rho(z)^2 z^{q-s} - \rho^s\rho(z)^2 z^q$$

which vanishes for $z = 0$ inside the circle. That is, when the market projections available do not match the anticipation horizon ($s < q$), the information set of the econometrician is still too poor to solve the non-invertibility. Conversely:

$$Det(\mathcal{R}^{(2)}(z)) = \rho^{s-q}\rho(z)^2 - \rho^s\rho(z)^2 z^q$$

has roots of modulus $z = \rho^{-1}$, outside the unit circle. In this case the econometrician has access to market beliefs for horizons comparable or exceeding the announcement horizons ($s \geq q$) and thus can confidently use classical SVAR techniques to derive the underlying shocks. Namely, the identification restrictions needed is $\mathcal{R}^{(2)}_{12}(0) = 0$ reflecting that, by construction, news do not move the policy rate up to q periods into the future.

1.5 Multivariate extension.

Let us now consider the extension of the bivariate model developed above, both in the Blaschke and in the additional information setting.

1.5.1 Blaschke Matrix.

Let z_t be a $n-2$ vector of times series, to be included in the analysis. Stacking the vector below $\tilde{y}_t$ and v_t we obtain:

$$
\begin{pmatrix} v_t \\ \tilde{y}_t \\ \hdashline z_t \end{pmatrix} = \underbrace{\left(\begin{array}{cc:c} \rho(L) & \rho(L)L^q & d(L) \\ \boldsymbol{\psi}_1(L) & \gamma(L) & f(L) \\ \hdashline h(L) & j(L) & k(L) \end{array}\right)}_{\mathcal{D}^*(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \\ \hdashline w_t \end{pmatrix}. \tag{1.23}
$$

where $d(L)$, $f(L)$, $h(L)$, $j(L)$, $k(L)$ are conformable matrices and vector of rational functions of L. One restriction in this case is no longer sufficient to completely identify the model, thus we impose full Cholesky triangularization on impact, which is enough to grant that $\mathcal{D}^*_{12}(0)$, that is, the news has delayed effects on the policy indicator.

The structural representation can be derived from the fundamental through BMs as follows:

$$
\begin{pmatrix} v_t \\ \tilde{y}_t \\ \hdashline z_t \end{pmatrix} = \underbrace{\left(\begin{array}{cc:c} \rho(L) & \frac{\rho(L)L^q}{b(L)} & d(L) \\ \boldsymbol{\psi}_1(L) & \frac{\gamma(L)}{b(L)} & f(L) \\ \hdashline h(L) & \frac{j(L)}{b(L)} & k(L) \end{array}\right)}_{\mathcal{F}(L)} \begin{pmatrix} \varepsilon_t \\ x_t \\ \hdashline w_t \end{pmatrix}
$$

and:

$$
\begin{pmatrix} \varepsilon_t \\ x_t \\ \hdashline w_t \end{pmatrix} = \left(\begin{array}{cc:c} 1 & 0 & \mathbf{0}' \\ 0 & b(L) & \mathbf{0}' \\ \hdashline \mathbf{0} & \mathbf{0} & I_{n-2} \end{array}\right) \begin{pmatrix} \varepsilon_t \\ \eta_t \\ \hdashline w_t \end{pmatrix}.
$$

where I_{n-2} is an identity matrix and $\mathbf{0}$ is a $n-2$ dimensional column vector of zeros. In this case the determinant of the first sub-system cannot be derived explicitly, since it depends on a whole set of matrices and vectors in the lag polynomial. Therefore, for empirical applications it would be necessary to test rather than assuming the fundamentalness of the first step, for instance using the procedure of Forni and Gambetti (2014). Once the first sub-system is estimated, identification of the roots needed to build $b(L)$ is achieved using the entries of $\hat{\mathcal{F}}_{11}$ and $\hat{\mathcal{F}}_{12}$ as explained in the bivariate case. Finally, matrix multiplication of the two moving averages above returns the original representation in $\mathcal{D}^*(L)$.

1.5.2 Additional information.

In case additional information (equal or exceeding the foresight horizon q) is introduced in the VAR, we can derive the multivariate extension of the model by stacking the $n-2$ dimensional vector z_t either on the top or on the bottom of the policy instrument. The first option corresponds to the case in which z_t does not react to monetary policy within the same period, and closely relates to Christiano et al. (2005). We will use it as our baseline since it allows clear comparison with previous literature. The latter case brings the model closer the specification of Gali (2008), in which the reaction of the macroeconomy to policy shock is simultaneous. We also present this specification, which will be used as robustness check.

Policy indicator on the bottom.

In the former case the moving average representation reads:

$$\left(\begin{array}{c} z_t \\ \hdashline v_t \\ E_t\{v_{t+s}\} \end{array}\right) = \underbrace{\left(\begin{array}{c:cc} \alpha(L) & \zeta(L) & \vartheta(L) \\ \hdashline \nu(L) & \rho(L) & \rho(L)L^q \\ \xi(L) & \rho^s\rho(L) & \rho^{s-q}\rho(L) \end{array}\right)}_{\underline{\mathcal{H}}(L)} \left(\begin{array}{c} w_t \\ \hdashline \varepsilon_t \\ \eta_t \end{array}\right). \tag{1.24}$$

where $\alpha(L)$, $\zeta(L)$, $\vartheta(L)$, $\nu(L)$, $\xi(L)$ are conformable matrices and vectors in the lag operator. Again, identification requires $\zeta(0)$, $\vartheta(0)$, and the upper triangular part of $\alpha(0)$ to equal zero.

In this setting the second last column of $\underline{\mathcal{H}}(L)$ represents the effects of the classical unanticipated monetary policy shock, in which a recursive scheme is applied: all variables pre-determined for the central bank do not react instantaneously to policy shocks. This is the case both for the anticipated and the unanticipated component which can be distinguished thanks to their effect on market expectations. On the one hand v_t is not moved on impact by news since, by construction, they only affect future policy rates. On the other hand expectations are moved by news instantaneously, given that η_t contains fruitful information to produce policy projections.

Finally, in case the VAR included also non pre-determined variables (e.g. Christiano et al. (2005)), it is possible to split the vector z_t in two blocks: z_{1t} – of length

$k-1$ – with the pre-determined variables and z_{2t} – of length $n-k-1$ – containing the other variables. In this case the ordering of the VAR would be $(z_{1t} \;\; v_t \;\; E_t\{v_{t+s}\} \;\; z_{2t})'$ and, after imposing Cholesky restrictions, the effect of surprise and news shock are to be found in column k and $k+1$ of $\underline{\mathcal{H}}(L)$ respectively.

Policy indicator on top.

If we want to remove the delayed response assumption, it is sufficient to revert the ordering of the variables, stacking the policy block on top or z_t. This is enough to introduce a contemporaneous reaction of real variables to monetary policy shocks. In this case the multivariate representation of the system turns into:

$$\begin{pmatrix} v_t \\ E_t\{v_{t+s}\} \\ \hdashline z_t \end{pmatrix} = \underbrace{\left(\begin{array}{cc:c} \rho(L) & \rho(L)L^q & \nu(L) \\ \rho^s\rho(L) & \rho^{s-q}\rho(L) & \xi(L) \\ \hdashline \zeta(L) & \vartheta(L) & \alpha(L) \end{array}\right)}_{\bar{\mathcal{H}}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \\ \hdashline w_t \end{pmatrix}. \tag{1.25}$$

where $\alpha(L)$, $\zeta(L)$, $\vartheta(L)$, $\nu(L)$, $\xi(L)$ are conformable matrices and vectors in the lag operator. The effects of unanticipated and anticipated monetary policy shocks are now to be found in the first and second column of $\bar{\mathcal{H}}$ respectively. The interesting restriction is $\bar{\mathcal{H}}_{12}(0) = 0$, mirroring the delayed response of the policy indicator to news. The difference with the previous case is that the Cholesky scheme does not restrict $\zeta(L)$ and $\vartheta(L)$ to be zero on impact. Put it differently, in this case the whole set of variables in z_t can react instantaneously both to policy decisions and announcements.

As a robustness check, and to take a more agnostic stance on the timing of the policy effects, we will use both specifications in the empirical section. Notice that, both ordering are legitimate as long as the policy measure proxies for v_t, which is orthogonal to the variables included in the Taylor rule. Conversely, when the policy indicator used is the interest rate, more caution is needed. In fact, letting macro aggregates vary with news within the same quarter implies a prompt adjustment of the short term rate, according to the policy rule. If news have an indirect, though immediate, effect on the policy instrument, the restriction $\bar{\mathcal{H}}_{12}(0) = 0$ is a misspecification. As a consequence, the comparison with previous literature is circumscribed to the case of the the federal funds rate ordered last.

1.6 Simulations.

In this section we run some simulation exercises in order to test the proposed methodology. We draw a sequence of Gaussian white noise errors for η_t and ε_t, and given the MA representations $\mathcal{D}(z)$, as in (1.19), we construct a simulated sample of large size (1000 observations) for v_t and $\tilde{y}_t$. Furthermore, expectations for v_t at different horizons are obtained from $\mathcal{R}^{(1)}(L)$ and $\mathcal{R}^{(2)}(L)$. The model is calibrated to match quarterly data and, in the baseline, parameters are set as in Gali (2008)[10]. Simulations are repeated for 1000 times to obtain 95% confidence bands around the median estimates of the impulse responses.

Figure 4 displays results of the simulation in the bivariate case. The top panel compares the performance of classical structural VAR technique (blue line) against Blashcke-corrected impulse responses (green line). True impulse responses, that is, the d.g.p., are reported in red. As it is clear from the picture, the naive econometrician, who relies only on timing restrictions, would get a poor match of the effects of η_t. On the contrary, the estimates of ε_t are relatively accurate[11]. This supports our claim that data are informationally insufficient for the whole system, but still sufficiently informative for one shock alone. Furthermore, correcting the responses with the BM delivers more precise estimates of η_t, closing the wedge between the non-fundamental model and its empirical counterpart.

The bias of classical VAR is especially severe when the zeros of the theoretical representation are small. As discussed above, when the roots approach the unit circle non-fundamentalness becomes less stringent and the performance of structural VAR more reliable. The bottom panel of Figure 4 provides with an example: higher persistence of the policy shocks implies minimal root closer to unity. As a result, structural VAR techniques and Blaschke-corrected impulse responses behave almost equivalently. As noted by Sims (2012), this testifies that non-fundamentalness can be empirically problematic at quite different extents.

[10] $\theta = 2/3$; $\sigma = 1$; $\psi = 1$; $\beta = 0.99$; $\phi_\pi = 1.5$; $\phi_y = 0.5/4$; $\rho = 0.5$.

[11] Notice that no Blaschke correction applies to the surprise shock, therefore the blue and green line perfectly overlap in the picture and only one of them is visible.

Results for the bivariate case complemented with market expectations are reported in Figure 5. The top panel shows $\mathcal{R}^{(1)}(L)$, the case in which the econometrician has access to expectations falling short of monetary announcements ($s < q$). In this circumstance non-fundamentalness is stringent and the VAR fails to pin down the timing of the anticipated shock. In our specific example, the econometrician would infer that news act with a three periods delay - which corresponds to s - rather than five - which is the actual announcement horizon q.

Notice that, conversely to the Blaschke case, we cannot reduce the empirical bias playing around with parameters calibration. This happens because the smallest root of the MA is at zero anyway, an extreme case for which non-fundamentalness is unsurmountable. Nevertheless, the responses associated to ε_t are spot on, confirming once more that non-invertible systems might still contain enough information to recover one of the two structural shocks.

The bottom panel of figure 5 shows the case corresponding to $\mathcal{R}^{(2)}(L)$. As expected, with $s \geq q$ the informational asymmetry is solved and VAR estimates match closely the true d.g.p. Conversely to the previous case, there is no confusion between s and q. The structural VAR correctly estimates the delayed response of the news shock, thus both η_t and ε_t are recovered with precision. The excellent performance in model simulations coupled with the ease of use in different specifications justifies the choice of the latter approach for the empirical analysis that follows.

1.7 Empirical evidence.

In this section we apply the additional information method to recover and compare the effects of both anticipated and unanticipated policy disturbances. The main result is that monetary news explain a sizeable portion of the forecast error variance of GDP, consumption and inflation. Qualitatively the effects of news and surprise shocks are similar and quantitatively their relative relevance is comparable. This allows us to conclude that news have a salient role in the overall transmission of monetary policy.

1.7.1 Data.

The first step of our empirical analysis is to chose the series to proxy for v_t and $E_t\{v_{t+s}\}$. Recall that the former is the residual from the Taylor rule, that captures both current surprises and past news, while the latter reflects market expectations on future policy developments. For both we propose alternative proxies to perform a series of robustness checks.

To start with market expectations, one option is to use federal funds future contracts on the spirit of Kuttner (2001), Gürkaynak (2005) and Campbell et al. (2012). Federal funds futures (FFF henceforth) are traded by the Chicago Central Board of Trade (CBOT) since late 1988 and are a bet on future interest rates (see Söderström (2001) and Kuttner (2001) for further details). Briefly, the value at expiration of a contract for $m + h$, i.e. at horizon h from the current month m, is $100 - \bar{r}$, where $\bar{r}$ is the average effective federal funds rate over the expiry month. The settlement price at time m is $100 - r_e$ and the seller (buyer) commits to compensate the other party in case the implied rate r_e turns out to exceed (fall behind) $\bar{r}$ at $m + h$. Being that such value is fully disclosed only at the end of the delivery month, r_e reflects market expectations about $\bar{r}$.

To obtain a times series of private sector beliefs the literature suggests to use high frequency identification, looking at the meeting dates of the Federal Open Market Committee (FOMC). More in specific, the strategy is to compute the difference between FFF prices right after the meeting and their quotation the previous day. The underlying assumption is intuitive: the actions and communicates of the FOMC are promptly internalized by the private sector, whose beliefs are directly reflected on FFF prices. Being that in tight windows around the meeting the macroeconomic conditions are fairly stable, any shift in prices can be attributed to the outcomes of the meeting itself. That is, such movements capture market beliefs directly related to policy actions and announcements.

We withdraw the data from Barakchian and Crowe (2010), who report the intraday difference in future rates for each contract from 1 to 6 months ahead, over the time span 1989 I – 2008 II. This provides with six different measures of market expectations related to increasingly longer forecast horizons. Furthermore, through factor analysis, these authors condensate all the individual series into a single summary measure. We will employ this factor measure as our baseline, labelling it Δfff, and include the individual series alone as a robustness check.

Other than Δfff, we will also use alternative indicators of market expectations. One is the 6-months ahead FFF contract in levels, without the intra-day differencing. The others are SPF forecasts of the 3-Month Treasury Bill rate. Once more, we employ each forecast horizon as a different measure and as an extra robustness check.

Also as regards v_t we exploit the data presented in Barakchian and Crowe (2010). Following the same logic as before, we take the intra-day difference of the federal funds rate around FOMC meetings and denote it Δffr. In such a tight window the macro variables considered for systematic policy do not move significantly, thus any change in the funds rates reflects exogenous policy shifts[12]. Notice that we do not discard the cases in which the central bank did not change the target rate being that zero intra-day difference might either mirror no news and surprise or a surprise movement exactly offsetting the effect of past news.

Both the series of v_t and its expectations are passed to quarterly frequency with simple monthly average. The remaining quarterly data, i.e. GDP, consumption, GDP deflator, real investment, wages, productivity, federal fund rates, profits and M2, is obtained from FRED for the period 1989 I – 2014 IV.

1.7.2 VAR analysis.

In this section we present the impulse response functions and variance decomposition of three different VAR specifications. First, we study the bivariate case with the measures of v_t and its expectation, which builds a bridge in between the theoretical simulations and the empirical application. Second, we run the baseline VAR with four variables, namely Δfff, Δffr, GDP and GDP deflator. Lastly, we report the result of a larger scale VAR with 10 variables, using the specification of Christiano et al. (2005). This allows to compare our results with previous literature.

[12]The idea is that the day before of the meeting the interest rate is given by $i_t^{d-1} = f(\Omega_t^{d-1})$, where Ω_t^{d-1} is the information set of the central bank about the state of the macro economy the day prior to the meeting. At meeting dates the bank adjusts the rates according to $i_t^d = f(\Omega_t^d) + v_t$, where v_t contains both the anticipated and unanticipated component. Under the assumption that the information set is fairly stable at high frequencies, $\Delta ffr = i_t^d - i_t^{d-1} = v_t$, is a proxy for the monetary policy stance.

Toy VAR.

The bivariate case is the simpler parallel of the simulation exercises, where Δffr and Δfff stand for the policy residual and its expectation. We include four lags in the analysis and we identify the system with a zero Cholesky restriction. Figure 6 displays the corresponding impulse response functions. The baseline case is reported in black and refers to the factor measure of market expectations. In green we have the responses obtained replacing Δfff with the individual series of each future contract separately.

Δffr represents the exogenous policy shift, and contains both anticipated and unanticipated shocks. Notice how, regardless of the measure of expectations used, the policy indicator shows a delayed response to news, whose higher effect materializes after four quarters. Conversely, its response to a surprise shock peaks on impact and goes to zero approximately after a year.

Recall that in our setting the intra-day difference in FFFs mirrors updates in expectations and it can be affected both by the current surprise and the last news received. Indeed, the bottom right panel of Figure 6 follows closely η_t, with unitary and significant response only on impact. This is in line with Barakchian and Crowe (2010) with the caveat that they consider such measure as being pure news, neglecting the possible effects of monetary surprises contained in it. It is true that the contribution of the surprise shock to Δfff is limited when compared to news. However, expectations react significantly also to ε_t, at least within the first year. Our approach has therefore the advantage of providing with a refinement of the news shock series, cleaning it out from the effects of unanticipated monetary disturbances.

Lastly, it is interesting to underline the similarity between the simulations in Figure 5 and the 2-VAR presented here. This not only builds a bridge in between the theory and the empirical application but also reassures us in the proxy choice. Then, starting from this building block, we can expand the analysis to a VAR with a larger set of variables.

Baseline VAR.

The variables included in the baseline specification are GDP, GDP deflator, Δffr and Δfff. We include four lags in the estimation and rely on the assumption that the macroeconomy does not move with monetary policy within the same quarter. As a robustness check we will later remove this assumption. Also, we keep the theoretical restriction that news have a delayed effect on the policy indicator. This implies that the two shocks can be recovered as the last two Cholesky shocks with GDP and inflation ordered first. The relevant impulse response functions are displayed in Figure 7. As in the bivariate case, we report in black the factor measure of Δfff and in green all the measures from each individual future contract. Furthermore, the red line is the impulse response obtained removing Δfff and identifying the unanticipated shock alone as the last Cholesky shock of the tri-variate system (with the policy instrument ordered last).

Consistent with the theory, a monetary policy contraction implies negative responses of output and prices. Noticeably, GDP reacts in a humped-shaped fashion to both shocks, with higher effect at around 4-5 quarters. On the contrary, movements in inflation are more sluggish and prices fall on longer horizons. As regard interest rates and expectations, the picture is similar to the bivariate case presented above, with the policy indicator responding with a delay to monetary news.

A first point to be made is that the effects of the surprise shock are consistent across all the specifications of Δfff. That is, notwithstanding the specific choice of the future contract, the responses of GDP and inflation to ε_t are widely unchanged. On the contrary, the effects of news are qualitatively similar but display more heterogeneity. This supports two of our main theoretical findings. The first one is that expectations on a wider horizon are a more reliable tool to solve the non-invertibility. In fact, FFF with longer maturity are richer in news and have increasingly higher effects on GDP. Analogous conclusions apply to inflation: notice how news produce an initial price puzzle which is absent for the surprise shock. However, as long as the foresight horizon of the FFF increases, the price puzzle disappears and the effects of both ε_t and η_t became comparable both in shape and magnitude. The second finding relates to data sufficiency. In the theory we argued that a subset of the structural shocks might be correctly recovered even if the whole system is flawed by non-fundamentalness. Indeed, under all specifications (with and without market expectations) the VAR performs equivalently in identifying ε_t. This means that the extra information contained in Δfff, which is vital to pin down the news shock, is redundant to recover the surprise shock alone.

This latter result implies that previous empirical literature, focused only on unanticipated monetary policy shock, should not face large bias in recovering ε_t, as long as the identification scheme is correct. However, Figure 7 makes it clear that both surprises and news have sizeable repercussions on GDP and prices. Therefore, not accounting for news leads to neglecting a significant portion of the overall monetary transmission mechanism. In order to quantify the relative relevance of both shocks Figure 8 reports their forecast error variance decomposition.

As noted by previous literature, monetary policy has a secondary role in explaining fluctuations of aggregate macroeconomic variables. However, if we consider news and surprises together, they account for 15% of the total output variance over a 25-periods horizon, equally split among the two disturbances. That is, news account for half of the overall transmission mechanism on the real economy, which moderates the claim of limited scope of monetary policy. Similar conclusions apply to inflation. Both shocks have comparable effects, even if on a 25 periods span they account only for 10% of the total variance of prices.

A different picture emerges as regards financial markets. A high portion of the interest rate variance is explained by surprises especially at short horizons. This can be read as the cautious behaviour of monetary authorities, who prefer to adjust the short term rate according to specific contingencies rather than announcing an explicit path for the policy rate. This latter option, described by Campbell et al. (2012) as *odyssean forward guidance*, could be a powerful tool for steering market expectation. However, it has the drawback of limiting the future range of actions of central banks, exacerbating the trade-off between present commitment and subsequent credibility. Notwithstanding the fact that forward guidance is not completely explicit, monetary news explain a 10% of the interest rates movements in the medium run, which is still a sizeable portion. That is, announcements are a significant instrument in the monetary policy tool kit.

As regards expectations, the picture is completely reversed. Not surprisingly, the bulk of their fluctuations is attributable to news, which account for 80% of the total variance in the short run. Also at longer horizons this percentage does not fall below 60%, revealing that the private sector is much attentive to announcements that might contain information on future policy developments. This seems to corroborate the view of Gürkaynak et al. (2005) that the central bank communicates effectively his intentions, thus affecting private sector expectations.

Extended VAR.

In this section we extend our methodology to the specification of Christiano et al. (2005), which represents a popular benchmark in the literature. To do so, we use the same set of variables, namely: GDP, consumption, GDP deflator, real investment, wages, productivity, federal funds rate, profits and M2. On top of that we add a measure of expectations, which is fundamental to capture news effects. Notice that in this case the policy indicator is the interest rate itself instead of the Taylor residual. Therefore, to proxy for market expectations we will use the 6-months ahead federal funds future in levels (FF6), that corresponds more closely to the policy instrument at hand.

Echoing Christiano et al. (2005), identification relies on the assumption that the variables in the central bank information set are not affected by monetary policy within the same quarter. Furthermore, our theory suggests that news do not move the policy rate contemporaneously. Therefore the structural shocks can be retrieved with Cholesky restrictions ordering the federal funds rate and the FF6 after the predetermined variables (namely in the seventh and eighth position).

Figure 9 shows the impulse response functions of both shocks. Results are similar to the previous case: after a contractionary policy shock GDP, consumption, productivity and investment fall in a humped shaped manner. Inflation falls too, showing some initial price puzzle only for the surprise component. What stands out in this specification is the behaviour of the interest rate. We can appreciate how in response to a news shock the interest rate falls, at least initially, and later reverts its trend, switching sing in the medium run. The economic intuition behind this fact is as follows. The effects of news on the policy rate are delayed, and likely more than one period. However, the private sector anticipates future contractions, which explains why real variables and prices begin to fall from the beginning. This happens before the actual materialization of the anticipated shock and feeds back into the Taylor rule, pushing the rates down in the short run. Finally, when the period of inaction of monetary news is over, the positive shock materializes, generating upwards pressure on the policy rate and provoking its sign reversal.

Other than establishing evidence of feedbacks in the policy rate, we can exploit the larger VAR to test for informational sufficiency in the data. To this end, we remove the federal funds future and we re-estimate the effects of the unanticipated component alone. For ease of comparison the corresponding impulse responses are added in red in Figure 9. Once more, results are almost identical across specifications, supporting the hypothesis that data is informationally sufficient to properly recover the surprise shock.

Lastly, Figure 10 reports the variance decomposition of the two shocks. Noticeably, surprises explain a larger share of the fluctuations of GDP, consumption and investment. However, news are responsible for a sizeable portion of the real movements, accounting in between 25 and 30% of the overall policy effects. The same holds true for inflation, whose variance explained by η_t adjusts to a third of the one attributable to ε_t. Finally, as in the previous section, the bulk of the movements in the interest rate are due to surprises while news have a more prominent role in explaining expectations, especially in the short run.

To sum up, also in the extended setting we find that news and surprises have similar effects and that anticipation offers a significant contribution to the overall monetary transmission mechanism.

1.7.3 Robustness analysis.

A part from the seven measures of federal funds futures, which are already a preliminary robustness check, in this section we report three additional specifications. First, we remove the assumption of delayed response of the real economy, by reverting the order of the variables as in (1.25). Then, we propose a different identification strategy, based on sign rather than zero restrictions. Finally, we replace the measure of market expectations with SPF data.

Policy indicator ordered first.

As discussed in the theoretical section, removing the assumption of delayed response of the macro economy is as simple as reverting the order of the variables and looking at the first two Cholesky shocks. On the one hand, Figure 11 displays the resulting impulse responses, both for the factor and the individual measures of Δfff. To facilitate the comparison, the baseline VAR (with the policy indicator ordered last) is also reported in the graph, using red lines. On the other hand, Figure 14 contains the corresponding variance decomposition.

As in the baseline case, the specific choice of the federal funds future is irrelevant to pin down the surprise shock while it provokes higher dispersion in the responses of the anticipated component. As previously discussed, this phenomenon relates to the informational content of the data. The exercise we are performing in this section consists merely in rearranging the variables and, by its own nature, it cannot alter the relevant information carried by the VAR. Thus, it comes as no surprise that we find once more informational sufficiency for the surprise component alone.

Furthermore, from the graph it is evident how impulse responses are consistent regardless of the variable ordering, especially in what concerns the news shock. The most compelling difference with the baseline case resides in the stronger response of the macroeconomy to the surprise component. Output jumps significantly on impact, while maintaining its humped-shape pattern. Also inflation is pushed down with more intensity. However, the contemporaneous movements in prices and the impact response of GDP to news are not significant, showing that the zero restrictions imposed in the baseline are not too unreasonable after all.

As a consequence of the higher responses of output and inflation to the surprise shock, their variance decomposition associates more weight to ε_t. However, this does not subtract relevance to news which maintain the same percentages as in the baseline, and still account for a 25% of the overall policy effects. Moreover, also in this alternative specification, news keep their primacy as explanatory factor of expectations, accounting for more that 60% of their variance.

Sign restrictions.

In this section we propose a different approach based on a mix of sing and zero restrictions, that is, a partial identification strategy. Accordingly, we only recover the effects of the news shocks and compare the results with the Cholesky scheme employed so far (always reported in red in the pictures). We repeat this exercise for two different specifications: one with Δffr and the other using the federal funds rate.

As regards the former case we use a mixed strategy. Our theory suggests that news have delayed effects on Δffr which points at a zero contemporaneous restriction. Also, we posit a positive response of the policy indicator and a negative response of output after five horizons. In this fashion we leave the contemporaneous reaction of GDP unconstrained, while we impose the sign restriction only in a later moment, when the news shock is more likely to have materialized.

Figure 13 and Figure 14 show the corresponding impulse responses and variance decomposition. Following a news shock, the policy indicator takes four quarters to peak, while output, which is not constrained on impact, falls immediately. At first glance it is cleat that the responses obtained with sign restrictions mimic closely the ones of the the baseline model (in red). Indeed, the red lines are always well inside the 68% confidence bands. As regards variance decomposition, this methodology attributes high relevance to news in explaining GDP, inflation and market expectations. Again we find that anticipation plays role in monetary policy that should not be neglected.

Regarding the second example, with the federal funds rate as the policy instrument, we need to modify the identification restrictions. In fact, if output and inflation react to news on impact, any significant change in those variables would automatically translate into a change in the interest rates, according to the policy rule. That is, a zero contemporaneous restriction does not apply to the federal funds rate. Therefore, we use only sign restrictions to identify news, imposing negative effects on both output and inflation after five periods, and positive effects on expectations at short horizons. This allows us to take an agnostic stance on the reaction of the interest rate, which we leave unrestricted.

Results are presented in Figure 15 and Figure 16. The impulse responses of GDP, inflation and FF6 are in line with the theory and the variance decomposition is sensibly comparable to the baseline case. What really catches the eye is the response of the policy instrument. After an initial significant drop, the interest rate reverts its path and switches sign from negative to positive. The same behaviour shows up in the Cholesky case (red line in the graph) and it was already found in the extended VAR. This stands as an extra evidence that, through the policy rule, news shocks might feedback on the interest rate, even before their actual materialization.

SFP data.

As a last exercise we use a different measure of market expectations, namely SFP forecasts of the 3-Month Treasury Bill rate. Being that we cannot compute intra-day differences of SPF data we keep it in levels. We choose the one and two quarters ahead projections, which relate more closely to the foresight horizons of the federal funds future at hand. Moreover, for comparison, we report the results obtained with the levels of the FF6.

SPF forecast is a rougher indicator of monetary news, being that it might be affected by other types of information and macro movements within the quarter. However, Figure 17 shows that it delivers impulse responses widely in line with those obtained with the FF6 in level. That is, both measures carry a similar informational content, with the difference that the latter is available at higher frequency and allows to better isolate the effects of policy announcements around meeting dates.

As regards financial variables, the relevant features are maintained: expectations are highly responsive to news especially on impact, while the policy indicator reacts with a certain delay. Results are slightly less satisfactory for the macro variables, given the initial price puzzle associated to news and the scarce reaction of output to surprises. However, the rest of the responses are in line with the theory and broadly consistent across specifications. Once more, the variance decomposition reported in figure Figure 18 attributes to monetary news a sizeable role both for the macroeconomic and the financial variables.

1.8 Conclusions.

In this chapter we disentangled and compared the effects of monetary news and surprises on the macroeconomy. We have presented a small scale new Keynesian model with monetary foresight and we have showed that in this framework the structural MA representation of the economic variables is non-fundamental. This is in turn implies a failure of classical structural VARs.

We proposed two alternative solutions to the issue. The former, based on Blaschke matrix, is more a theoretical exercise that allows us to spell out clearly the bias implied by standard techniques. The latter resides in expanding the information set of the econometrician with market expectations on future policy developments. Through simulations we tested the performance of the proposed strategies and we concluded that non-invertibility is especially detrimental when the minimal root of the structural MA is close to zero. Also, we found that non-fundamentalness does not restrict the possibility of correctly recovering the unanticipated component alone, meaning that data is informationally sufficient for one of the two disturbances.

In the empirical section we have estimated a VAR complemented with market expectations and identified with Cholesky restrictions. This adds to previous literature in the sense that impulse responses and forecast error variance decomposition are estimated from the data rather than obtained form DGSE simulations. Also, we showed that previous studies correctly identified the surprise component while neglecting foresight as a transmission channel of monetary policy. Therefore, the main contribution of the chapter resides in presenting evidence that this channel is also relevant, and accounts in between 25 and 50% of the overall policy effects. Indeed we found that news have sizeable effects on the real economy, prices and market expectations.

The impulse responses obtained are broadly consistent with the theory and in line with previous literature. Distinctly, we found a peculiar response of the short rate to news, testifying the indirect effect of announcement through the Taylor rule. Finally, we drew the conclusion that news are the main factor explaining market expectations, which is exactly the channel trough which anticipation operates. Our results are robust to alternative proxies for market expectations, to different Cholesky ordering and to alternative identification strategies, relying on sign rather than zero restrictions.

This work establishes the empirical relevance of news in monetary policy and proposes solutions to the issue of non-invertibility, which is usually the main excuse to favour DSGE models over VARs. It goes without saying that it paves the way to a number of possible extensions. An example could be applying dynamic identification strategy, as in the Blaschke matrix case, to recover the structural disturbances. Furthermore, we have seen how news act through the expectation channel. It might be interesting to introduce a noise component and understand how miscommunication can affect market beliefs and cause aggregate effects, even when no underlying policy movement is implied. Another, interesting question is whether the role of news has changed over time and became more relevant in recent years with binding zero lower bound. Threshold VARs and consequent non linearities could be an adequate approach to this problem. These questions and related issues, which are interesting to grasp a deeper understanding on the role of monetary news, are left for future research.

Appendix.

.1 Derivation of the model from new Keynesian theory.

Consider a standard New Keynesian model, as in Gali (2008). Preferences are given by:

$$E\sum_{t=0}^{\infty}\beta^t\left(logC_t - \frac{1}{1+\varphi}N_t^{1+\varphi}\right)$$

where N_t represents labor and $C_t = \left(\int_0^1 C_t(i)^{\frac{\epsilon-1}{\epsilon}}di\right)^{\frac{\epsilon}{\epsilon-1}}$ is an aggregate consumption good. Each component $C_t(i)$ is offered by a monopolistic firm which faces prices à la Calvo. In each period, the probability of keeping prices unchanged is θ. Output is demand driven, $Y_t(i) = C_t(i)$, and firms hire labor at the flexible market wage W_t to produce with the linear technology:

$$Y_t(i) = A_t N_t(i).$$

The period budget constraint for the agents takes the form:

$$\int_0^1 P_t(i)C_t(i)di + Q_t B_t = B_{t+1} + W_t N_T + T_t$$

where B_t are nominal one-period bonds purchased at price Q_t, $P_t(i)$ is the price of good $C(i)$ and T_t is a lump sum transfer that includes dividends from the firms.

Standard steps for the consumers and firm maximization problem and log-linearization around the zero inflation steady state lead to the New Keynesian Phillips curve and to the dynamic IS:

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \kappa\tilde{y}_t \tag{26}$$

$$\tilde{y}_t = -(i_t - E_t\{\pi_{t+1}\} - r_t^n) + E_t\{\tilde{y}_{t+1}\} \tag{27}$$

where $\kappa = (1+\varphi)(1-\theta)(1-\beta\theta)/\theta$. Output gap $\tilde{y}_t \equiv y_t - y_t^n$ is defined as the deviation of output from its natural counterpart and r_t^n is the natural interest rate which we assume is unaffected by monetary shocks and is given by $r_t^n = -log\beta = i^*$.

We also assume that central bank sets the nominal interest rate $i_t = -logQ_t$ according to the policy rule:

$$i_t = i^* + \phi_\pi \pi_t + \phi_y \tilde{y}_t + v_t \tag{28}$$

where $\phi_\pi > 1$, $\phi_y > 0$ and v_t is the exogenous disturbance that represents monetary policy shocks.

From (26),(27) and (28) it is possible to get to the following system of differential equations:

$$\begin{pmatrix} \tilde{y}_t \\ \pi_t \end{pmatrix} = A \begin{pmatrix} E_t\{\tilde{y}_{t+1}\} \\ E_t\{\pi_{t+1}\} \end{pmatrix} - Bv_t \tag{29}$$

where:

$$A \equiv \Omega \begin{pmatrix} 1 & 1-\beta\phi_\pi \\ \kappa & \kappa + \beta(1+\phi_y) \end{pmatrix}$$

$$B \equiv \Omega \begin{pmatrix} 1 \\ \kappa \end{pmatrix}$$

$$\Omega = \frac{1}{1+\phi_y + \kappa\phi_\pi}$$

The system has a unique solution as long as the eigenvalue of the matrix A lie inside the unit circle [13]. Forwards substitutions of (29) yield:

$$\begin{pmatrix} \tilde{y}_t \\ \pi_t \end{pmatrix} = -\sum_{k=0}^{\infty} A^k B E_t\{v_{t+k}\}. \tag{30}$$

Now on the spirit of Blanchard et al. (2013) we take a limit case of the model with $\kappa \to 0$. In such case $B = (\Omega \;\; 0)'$ and the matrix A is upper triangular. Its k^{th} power

[13]It can be shown that a necessary and sufficient condition for uniqueness is given by $\kappa(\phi_\pi - 1) + (1-\beta)\phi_y > 0$.

is again a upper triangular matrix of the form:

$$A^k = \begin{pmatrix} a_{11}^k & a_{11}^{(k-1)}a_{12} + a_{12}^{(k-1)}a_{22} \\ 0 & a_{22}^k \end{pmatrix}$$

where $a_{ij}^{(k)} = [A^k]_{i,j}$. Notice that the product $A^k B$ always delivers.

$$A^k B = \begin{pmatrix} \Omega^{k+1} \\ 0 \end{pmatrix}$$

which substituted into (30) implies:

$$\tilde{y}_t = -\Omega \sum_{k=0}^{\infty} \Omega^k E_t\{v_{t+k}\}. \tag{31}$$

Given that $\kappa \to 0$ as $\theta \to 1$ this completes the argument.

.2 Properties of $\omega_q(L)$.

The identity:

$$\omega_q(L) = L^q + \Omega\omega_{q-1}(L)$$

is easily proved.

$$\begin{aligned} \omega_q(L) &\equiv \textstyle\sum_{k=0}^{q} \Omega^k L^{q-k} \\ &= L^q + \textstyle\sum_{k=1}^{q} \Omega^k L^{q-k} \\ &= L^q + \textstyle\sum_{k=0}^{q-1} \Omega^{k+1} L^{q-1-k} \\ &= L^q + \Omega \textstyle\sum_{k=0}^{q-1} \Omega^k L^{q-1-k} \\ &= L^q + \Omega\omega_{q-1}(L). \end{aligned}$$

Moreover, notice that at $q = 1$ the only root is $r_1 = -\Omega$. For $q = 2$ we find two roots $r_{1,2} = \frac{-\Omega \pm \sqrt{3}\Omega i}{2}$ which both have modulus $|r_1| = |r_2| = \Omega$. For $q = 3$ we find three roots, $r_1 = -\Omega$, $r_{2,3} = \pm\Omega i$ whose modulus is again equal to Ω.

Even if we do not provide a formal proof of it, the following picture exemplifies how this pattern is repeated for higher order of anticipation: the q complex roots of

$\omega_q(L)$ always fall within the open unit disc[14], and they all lie on the circle of radius Ω.

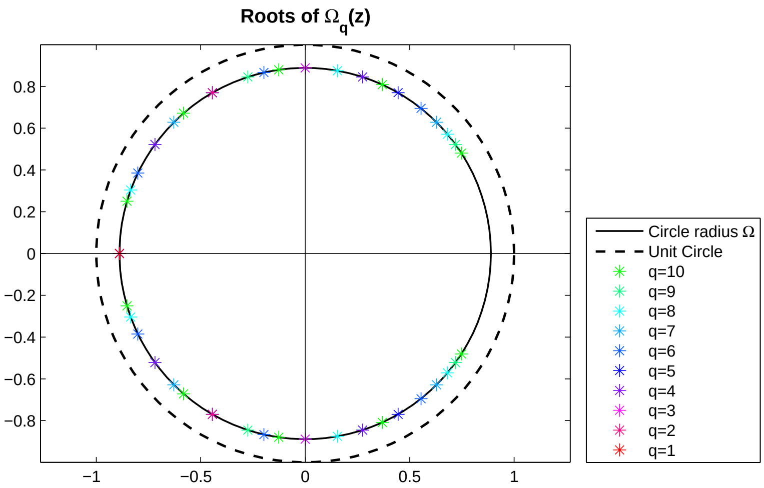


Figure 1: Roots of $\omega_q(L)$ for different anticipation periods.

[14]Whenever $\phi_y > 0$ or $\kappa > 0$ we have $\Omega < 0$ thus the roots always fall in the open unit disc. Only in the degenerate case of both $\phi_y = 0$ and $\kappa = 0$, $\Omega = 1$ and the roots of $\omega_q(L)$ are pushed on the unit circle.

.3 Comparison with the literature.

Given that foresight is closely related to non-fundamentalness in VARs, previous literature privileged alternative methods to study the effects of monetary news shocks, namely, DSGE models (Laséen and Svensson, 2011; Milani and Treadwell, 2012; Del Negro et al., 2012) or univariate regressions (Gürkaynak et al., 2005; Campbell et al., 2012). For the sake of comparison, we can show how their models translate to our framework and understand the implied VAR failures.

These authors assume that in every period the central bank delivers a vector of information

$$\overrightarrow{\eta_t} = (\eta_{t,0}\ ,\ \eta_{t,1}\ ,\ \dots\ ,\ \eta_{t,q})'$$

where each element $\eta_{t,s}$ represent news delivered at time t and affecting the interest rate at $t+s$. Equation (1.3) becomes:

$$v_t = \sum_{s=0}^{q} \eta_{t-s,s} \tag{32}$$

where $\eta_{t,0}$ is the monetary surprise ε_t. In addition there are q different shocks affecting the economy at horizons $1, 2, \dots, q$, respectively.

The expectation at time t of v_{t+j} is given by a summation of past news with different impact horizons[15] :

$$E_t\{v_{t+j}\} = \begin{cases} \sum_{s=0}^{q-j} \eta_{t-s,s+j} & for \;\; 0 < j \leq q \\ 0 & for \;\; j > q. \end{cases} \tag{33}$$

Now we can plug (33) in (1.4) to obtain:

$$\begin{aligned} \tilde{y}_t &= -\Omega \left(\sum_{s=0}^{q} \eta_{t-s,s} + \Omega \sum_{s=0}^{q-1} \eta_{t-s,s+1} + \ldots + \Omega^q \sum_{s=0}^{0} \eta_{t-s,s+q} \right) \\ &= -\Omega \left(\eta_{t,0} + \sum_{s=0}^{1} \Omega^s \eta_{t-1+s,1} + \ldots + \sum_{s=0}^{q} \Omega^s \eta_{t-q+s,q} \right) \\ &= -\Omega \left(\varepsilon_t + \omega_1(L)\eta_{t,1} + \ldots + \omega_q(L)\eta_{t,q} \right). \end{aligned} \tag{34}$$

where the first equivalence is obtained expanding the summations and grouping anticipated shocks with the same horizon of impact. The last equation is given by the definition of $\omega_q(L)$ in (1.8) and by the fact that $\eta_{t,0}$ is ε_t in our setting.

It is now possible to rewrite (32) and (34) in matrix notation as:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \begin{pmatrix} 1 & L & \cdots & L^q \\ -\Omega & -\Omega\omega_1(L) & \cdots & -\Omega\omega_q(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_{t,1} \\ \vdots \\ \eta_{t,q} \end{pmatrix} \tag{35}$$

[15] To better understand the formulation in (33) consider the values of $j = 0$ and $j = q$. On the one hand, time t expectation of v_t reads:

$$E_t\{v_t\} = \eta_{t,0} + \eta_{t-1,1} + \ldots + \eta_{t-q,q}.$$

This equation states that today's changes in the policy rate are given by a summation of all the available information: the contemporaneous $\eta_{t,0}$; the news delivered one period before and acting one period later; ...; and so on down to the oldest new $\eta_{t-q,q}$ received q period before and materializing with q periods of delay.

On the other the expected value at time $t+q$:

$$E_t\{v_{t+q}\} = \eta_{t,q}$$

can only be based on information received today for q periods into the future. This is because all other shocks affecting v_{t+q} will be revealed in the future and their present expectation equals zero.

All intermediary cases for $0 < j < q$ follow the same logic: only available past information, whose impact horizon is $t+j$, can be used to generate the expectation. Notice that the further in time we project v_{t+s} the less news available we have. This explains the decreasing number of addends in $\sum_{s=0}^{q-j} \eta_{t-s,s}$.

where the rectangular matrix in (35) is $2 \times (q+1)$ and the vector of shocks contains $q+1$ fundamental innovations.

Once more, we rely on a simple example to clarify the general formulation. With $q = 2$, the policy residual is given by:

$$v_t = \varepsilon_t + \eta_{t-1,1} + \eta_{t-2,2}. \tag{36}$$

and the implied MA representation is:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \begin{pmatrix} 1 & L & L^2 \\ -\Omega & -\Omega\omega_1(L) & -\Omega\omega_2(L) \end{pmatrix} \begin{pmatrix} \varepsilon_t \\ \eta_{t,1} \\ \eta_{t,2} \end{pmatrix}. \tag{37}$$

Clearly (37) contains a rectangular matrix with more than two columns. VARs techniques are not viable in this setting because the number of shocks exceeds the number of dynamically independent time series. Therefore, to map the system into our framework it is necessary to simplify it to two structural shocks. This can be done assuming either:

$$v_t = \varepsilon_t + \eta_{t-1} \tag{v1}$$

$$v_t = \varepsilon_t + \eta_{t-2} \tag{v2}$$

$$v_t = \eta_{t-1} + \eta_{t-2} \tag{v3}$$

$$v_t = \varepsilon_t + \eta_{t-1} + \eta_{t-2} \tag{v4}$$

The cases (v1) and (v2) correspond to the baseline model with $q = 1$ and $q = 2$, which have already been discussed. Assuming (v3) - i.e., no monetary surprises - is equivalent to removing the first column from the MA matrix in (37). In this case the system would feature a root for $L = 0$, showing that a purely news-based model is also non fundamental. This evidence seems to support the claim of Milani and Treadwell (2012) that SVAR techniques are doomed to fail when news shocks are involved.

However, (v4) provides with an example that foresight does not necessarily imply non fundamentalness. In this latter case, the two news shocks acting at one and two horizons have been summarized in one single shock with a double delayed effect (possibly the closest mapping between $\overrightarrow{\eta_t}$ and η_t). Under this specification the expectations of v_t is:

$$E_t\{v_{t+j}\} = \begin{cases} \varepsilon_t + \eta_{t-1} + \eta_{t-2} & for \;\; j = 0 \\ \eta_t + \eta_{t-1} & for \;\; j = 1 \\ \eta_t & for \;\; j = 2 \\ 0 & for \;\; j \geq 3. \end{cases} \tag{38}$$

and the equation for $\tilde{y}_t$ turns into:

$$\tilde{y}_t = -\Omega(\varepsilon_t + \Omega(1+\Omega)\eta_t + (1+\Omega)\eta_{t-1} + \eta_{t-2}) \tag{39}$$

leading to a MA representation of the kind:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & L + L^2 \\ -\Omega & -\Omega^2(1+\Omega) - \Omega(1+\Omega)L - \Omega L^2 \end{pmatrix}}_{\mathcal{M}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{40}$$

The determinant of the system vanishes for $L = -(1+\Omega)$ which is outside the unit circle. Contrary to general wisdom, no problem of fundamentalness is found in this case. This apparently surprising result can be explained looking at the impulse responses of $\tilde{y}_t$. As noted by Beaudry and Portier (2014), news rich processes whose effects are delayed but not monotonically increasing up to q might have an invertible representation. Indeed, as exemplified in Figure 2, under (v4) the highest effect of the news shock is delayed only once, even if there are two periods of foresight. Conversely, assuming (v2) the impulse response of output peaks exactly after 2 horizons and generates a non-invertible representation.

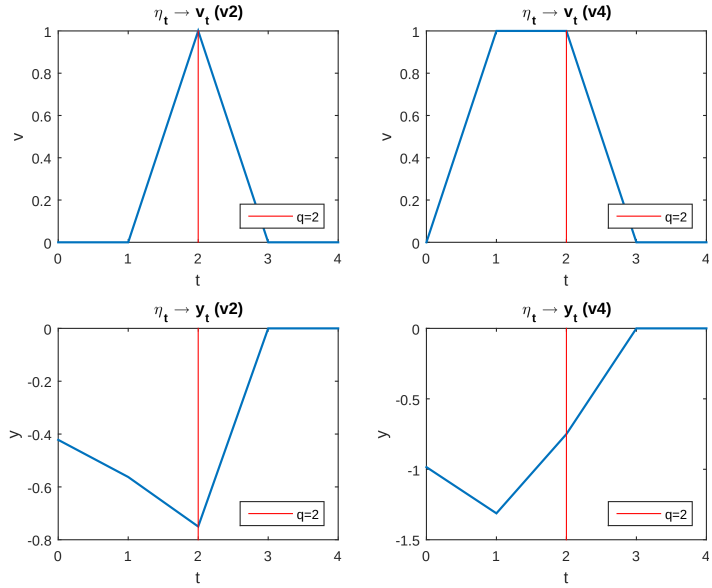


Figure 2: Comparison of the the response of v_t and $\tilde{y}_t$ to the news shock. Left hand columns refer to (v2) and right hand columns refers to (v4).

.4 The general model.

Results are presented in the paper under specific parameter values and the assumption of i.i.d. policy shocks. In order to extend the model we start from a general calibration of (30) and we allow for richer dynamics of the policy shock, as in (1.2):

$$v_t = \underbrace{\rho(L)\eta_{t-q}}_{v_t^a} + \underbrace{\rho(L)\varepsilon_t}_{v_t^u}.$$

where v_t^a and v_t^u are the anticipated and unanticipated component respectively. As customary, $\rho(L) = \sum_{k=0}^{\infty} \rho^k L^k$ with $\rho < 1$ and L is the lag operator.

Expectations at t of v_t^a and v_t^u are obtained with linear projections using the Weiner-Kolmogorov formula. Exploiting the properties of the annihilator operator $[\cdot]_+$, which sets to zero all negative exponents of the lag polynomial, we easily obtain projections for the unanticipated component:

$$E_t\{v_{t+s}^u \mid I_t\} = \left[\frac{\rho(L)}{L^s}\right]_+ \varepsilon_t = \left[\sum_{i=0}^{\infty} \rho^{i+s} L^i\right]_+ \varepsilon_t = \rho^s \rho(L)\varepsilon_t \qquad (41)$$

As regards the anticipated component we need to be more cautious, since relevant information is received q periods beforehand:

$$E_t\{v^a_{t+s} \mid I_t\} = \left[\frac{\rho(L)}{L^s}\right]_+ \eta_{t-q} = \left[\sum_{i=0}^{\infty} \rho^i L^{i+q-s}\right]_+ \eta_t$$

and we need to consider horizons preceding and exceeding q separately:

$$E_t\{v^a_{t+s} \mid I_t\} = \begin{cases} \left[\sum_{i=0}^{\infty} \rho^i L^{i+\overbrace{q-s}^{\geq 0}}\right]_+ \eta_t = \rho(L)L^{q-s}\eta_t \quad for \;\; s \leq q \\ \left[\sum_{i=0}^{\infty} \rho^i L^{i+\overbrace{q-s}^{<0}}\right]_+ \eta_t = \rho^{s-q}\rho(L)\eta_t \quad for \;\; s > q. \end{cases} \tag{42}$$

Equations (41) and (42) imply:

$$E_t\{v_{t+s}\} = \begin{cases} \rho(L)L^{q-s}\eta_t + \rho^s\rho(L)\varepsilon_t \quad for \;\; s \leq q \\ \rho^{s-q}\rho(L)\eta_t + \rho^s\rho(L)\varepsilon_t \quad for \;\; s > q \end{cases} \tag{43}$$

which, as expected, features no contemporaneous effect of η_t.

Substituting (43) in (30):

$$\begin{aligned} \begin{pmatrix} \tilde{y}_t \\ \pi_t \end{pmatrix} &= -\sum_{s=0}^{\infty} A^s B E_t\{v_{t+s}\} \\ &= -\sum_{s=0}^{q-1} A^s B\left[\rho(L)L^{q-s}\eta_t + \rho^s\rho(L)\varepsilon_t\right] - \sum_{s=q}^{\infty} A^s B\left[\rho^{s-q}\rho(L)\eta_t + \rho^s\rho(L)\varepsilon_t\right] \\ &= \underbrace{-\sum_{s=0}^{\infty} A^s B\left[\rho^s\rho(L)\varepsilon_t\right]}_{(a)} \underbrace{-\sum_{s=0}^{q} A^s B\left[\rho(L)L^{q-s}\eta_t\right]}_{(b_1)} \underbrace{-\sum_{s=q+1}^{\infty} A^s B\left[\rho^{s-q}\rho(L)\eta_t\right]}_{(b_2)}. \end{aligned} \tag{44}$$

yields convolute infinite summations. In order to simplify this expression we proceed by sections as follows:

(a): Given that by assumption the matrix A has its eigenvalues inside the unit circle and that $\rho < 1$, the infinite summation in (a) converges to:

$$\begin{aligned} -\sum_{s=0}^{\infty} A^s B\left[\rho^s\rho(L)\varepsilon_t\right] &= -(I - A\rho)^{-1}B\rho(L)\varepsilon_t \\ &= \boldsymbol{\psi}(L)\varepsilon_t. \end{aligned} \tag{a}$$

where:

$$\boldsymbol{\psi}(L) = \begin{pmatrix} \boldsymbol{\psi}_1(L) \\ \boldsymbol{\psi}_2(L) \end{pmatrix} \equiv -(I - A\rho)^{-1} B \sum_{s=0}^{\infty} \rho^s L^s \tag{45}$$

is a 2×1 vector in the lag operator.

($\mathbf{b_1}$): This part of the summation contains q MA processes:

$$\sum_{s=0}^{q} A^s B \left[\rho(L) L^{q-s} \eta_t\right] = A^q B\rho(L)\eta_t + A^{q-1} B\rho(L)\eta_{t-1} + \cdots + A^0 B\rho(L)\eta_{t-q}.$$

Expanding all its addends we find one η_t, two η_{t-1}, and so on till η_{t-q} which appears $q+1$ times. All elements lagged more than q will also appear $q+1$ times. Grouping together coefficients relative to the same lag we can rearrange the equation as:

$$\sum_{s=0}^{q} A^s B \left[\rho(L) L^{q-s} \eta_t\right] = \sum_{s=0}^{q-1} D_s B L^s \eta_t + \sum_{s=q}^{\infty} \rho^{s-q} D_q B L^s \eta_t. \tag{b_1}$$

where:

$$D_s \equiv \sum_{m=0}^{s} A^{q-m} \rho^{s-m}. \tag{46}$$

Notice that this matrix of coefficient varies with s within the first $q-1$ lags, while from q onward (b_1) always features:

$$D_q = \sum_{m=0}^{q} A^m \rho^m$$

multiplied by increasing powers of ρ. This fact allows us to divide the infinite summation at $q-1$ (instead of q), which mirrors the misalignment between anticipation and surprise and will be useful in further steps.

($\mathbf{b_2}$): We proceed as in (a). Rearranging the counter of the summation and solving the (convergent) sum we have:

$$\begin{aligned} \textstyle\sum_{s=q+1}^{\infty} A^s B \left[\rho^{s-q} \rho(L) \eta_t\right] &= A^{q+1} \rho \textstyle\sum_{s=0}^{\infty} (A\rho)^s B \rho(L) \eta_t \\ &= A^{q+1} \rho (I - A\rho)^{-1} B \rho(L) \eta_t \\ &= C_q B \rho(L) \eta_t. \end{aligned} \tag{b_2}$$

where:

$$C_q \equiv A^{q+1}\rho(I - A\rho)^{-1} \tag{47}$$

is a matrix of coefficients decreasing in the foresight horizon[16]. Adding (b_2) and (b_1) yields:

$$\begin{aligned}
-[(b_2)+(b_1)] &= \overbrace{-\sum_{s=0}^{\infty} C_q B\rho^s L^s \eta_t}^{(b_2)} \overbrace{-\sum_{s=0}^{q-1} D_s B L^s \eta_t - \sum_{s=q}^{\infty} \rho^{s-q} D_q B L^s \eta_t}^{(b_1)} \\
&= -\textstyle\sum_{s=0}^{q-1}(C_q\rho^s + D_s)BL^s\eta_t - \sum_{s=q}^{\infty}(C_q\rho^s + \rho^{s-q}D_q)BL^s\eta_t \\
&= \boldsymbol{\phi}^{q-1}(L)\eta_t - \textstyle\sum_{s=q}^{\infty}(I - A\rho)^{-1}\rho^{s-q}BL^s\eta_t \\
&= \boldsymbol{\phi}^{q-1}(L)\eta_t - \textstyle\sum_{s=0}^{\infty}(I - A\rho)^{-1}\rho^{s}BL^sL^q\eta_t \\
&= \boldsymbol{\phi}^{q-1}(L)\eta_t + \boldsymbol{\psi}(L)L^q\eta_t.
\end{aligned} \tag{b}$$

where:

$$\boldsymbol{\phi}^{q-1}(L) = \begin{pmatrix} \boldsymbol{\phi}_1^{q-1}(L) \\ \boldsymbol{\phi}_2^{q-1}(L) \end{pmatrix} \equiv -\sum_{s=0}^{q-1}(C_q\rho^s + D_s)BL^s \tag{48}$$

---

[16] Both (a) and (b_2) deliver a re-scaling of the MA coefficients of $\rho(L)$. Few words on the intuition behind such result are in order. Notice that – as in (41) – linear projections for $t+s$ of an AR(1) process contain the s^{th} power of ρ. This implies that further away projections are more heavily discounted by ρ. In the multivariate case the powers of A, which approach zero as the expectation horizon increases, act in a similar fashion. Therefore there are two sources of discounting: ρ – coming from the AR nature of the policy shocks – and A – coming from the recursive substitutions of the forward looking system (30).

For the unanticipated shock agents can only create expectations though linear forecast at time t, therefore the discounting due to forward substitutions and due to linear projections go in parallel (notice that we always have $A^s\rho^s$). Conversely, regarding η_t, agents have (anticipated) information for the first q periods, out of which they can generate their expectations. After that horizon, that is the (b_2) part of the summation, they are again constrained to use linear projections with the same philosophy employed for (a). This is enough to introduce a misalignment in discounting: since projections only begin in period $q+1$, results of (b_2) are comparable to (a) but are additionally discounted by A^{q+1} (which makes the difference between C_q and $(I - A\rho)^{-1}$). Thus both (a) and (b_2) are a re-scaling of different magnitude of the same process, and what is more relevant to understand the difference between η_t and ε_t are the first q periods – captured by the (b_1) part of the summation.

is a 2×1 vector in the lag operator and the third equality of (b) makes use of:

$$
\begin{aligned}
C_q \rho^s + \rho^{s-q} D_q &= A^{q+1}\rho(I - A\rho)^{-1}\rho^s + \rho^{s-q}\textstyle\sum_{m=0}^{q} A^m \rho^m \\
&= A^{q+1}\rho^{s+1}\textstyle\sum_{k=0}^{\infty} A^k \rho^k + \rho^{s-q}\sum_{m=0}^{q} A^m \rho^m \\
&= \rho^{s-q}\left(A^{q+1}\rho^{q+1}\textstyle\sum_{k=0}^{\infty} A^k \rho^k + \sum_{m=0}^{q} A^m \rho^m\right) \\
&= \rho^{s-q}\left(\textstyle\sum_{k=q+1}^{\infty} A^k \rho^k + \sum_{m=0}^{q} A^m \rho^m\right) \\
&= (I - A\rho)^{-1}\rho^{s-q}.
\end{aligned}
$$

Plugging (a) and (b) in (44) allows us to rewrite the system (30) as a MA representation in output gap and inflation as follows:

$$
\begin{pmatrix} \tilde{y}_t \\ \pi_t \end{pmatrix} = \underbrace{\begin{pmatrix} \boldsymbol{\psi}_1(L) & \boldsymbol{\phi}_1^{q-1}(L) + \boldsymbol{\psi}_1(L)L^q \\ \boldsymbol{\psi}_2(L) & \boldsymbol{\phi}_2^{q-1}(L) + \boldsymbol{\psi}_2(L)L^q \end{pmatrix}}_{\mathcal{C}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{49}
$$

When we condition the VAR on monetary policy instead of inflation, we obtain:

$$
\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} \rho(L) & \rho(L)L^q \\ \boldsymbol{\psi}_1(L) & \gamma(L) \end{pmatrix}}_{\mathcal{D}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}. \tag{50}
$$

where $\boldsymbol{\psi}_1(L)$ and $\boldsymbol{\phi}_1^{q-1}(L)$ are the upper elements of the vectors $\boldsymbol{\psi}(L)$ and $\boldsymbol{\phi}^{q-1}(L)$ and $\gamma(L)$ simplifies the notation:

$$
\gamma(L) \equiv \boldsymbol{\phi}_1^{q-1}(L) + \boldsymbol{\psi}_1(L)L^q.
$$

.4.1 Roots of the MA determinant.

The study of the determinant $\mathcal{D}(z)$ is analytically non trivial, and calls for numerical methods. We proceed as follows: we first calibrate the parameters[17]. Then we build the relevant matrices to obtain the coefficients of $\boldsymbol{\psi}(L)$ and $\boldsymbol{\phi}(L)$. In this case we need to deal with a MA(∞), which for ease of computation we approximate with a MA

[17]The Baseline calibration is as in Gali (2008) p.52: $\theta = 2/3$; $\sigma = 1$; $\psi = 1$; $\beta = 0.99$; $\phi_\pi = 1.5$; $\phi_y = 0.5/4; \rho = 0.5$.

of finite (but substantially high) order[18]. Finally we compute $Det(D(z))$ and verify whether the characteristic polynomial has roots falling within the unit circle.

Results for $\mathcal{D}(z)$ are shown in Figure 3 and are broadly in line with the findings of the limit-case model. Under the baseline calibration the systems features roots in the open unit disc at all values of q. Therefore, classical VARs need to be corrected either with Blaschke matrix or with additional information.

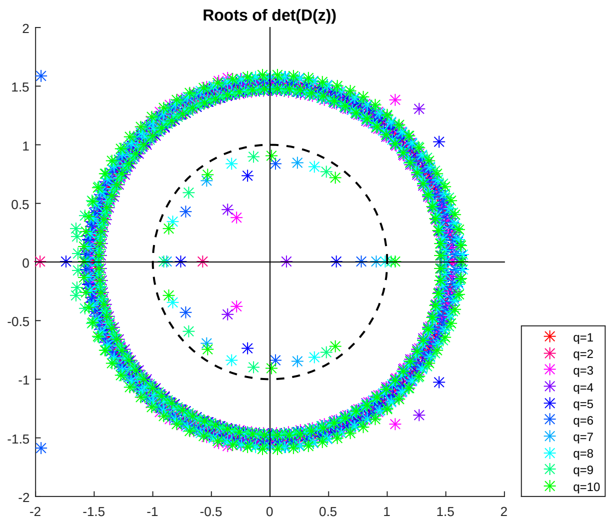


Figure 3: Roots of the determinat of the MA representation with $\tilde{y}$ and v. The MA matrix is truncated at 100 elements. Specification for different foresight horizons q are reported together in the same graph. The dashed line represent the unit circle in the complex plane.

.4.2 Deriving the toy model from the general case.

From the general setting, it is simple to derive the model in its limit-case calibration, with $\theta = 1$ and $\rho = 0$. Trivially:

$$v_t = \varepsilon_t + L^q \eta_t$$

and

$$\psi_1(L) = -\Omega(1 - \Omega\rho)\rho(L) = -\Omega.$$

[18]Namely we used a MA(100), whose last coefficients are already sufficiently close to zero to be negligible.

The operator $\boldsymbol{\phi}_1^{q-1}(L)$ turns to:

$$\begin{aligned}
\boldsymbol{\phi}_1^{q-1}(L) &= -\textstyle\sum_{s=0}^{q-1}\sum_{m=0}^{s}\Omega^{q+1-m}\rho^{s-m}L^s \\
&= -\textstyle\sum_{s=0}^{q-1}\Omega^{q+1-s}L^s \\
&= -\Omega^2\textstyle\sum_{s=0}^{q-1}\Omega^{q-1-s}L^s \\
&= -\Omega^2\textstyle\sum_{s=0}^{q-1}\Omega^{s}L^{q-1-s} \\
&= -\Omega^2\omega_{q-1}(L).
\end{aligned}$$

which plugged into $\gamma(L)$ simplifies it to:

$$\begin{aligned}
\gamma(L) &= -\Omega L^q - \Omega^2\omega_{q-1}(L) \\
&= -\Omega(L^q + \Omega\omega_{q-1}(L)) \\
&= -\Omega\omega_q(L).
\end{aligned}$$

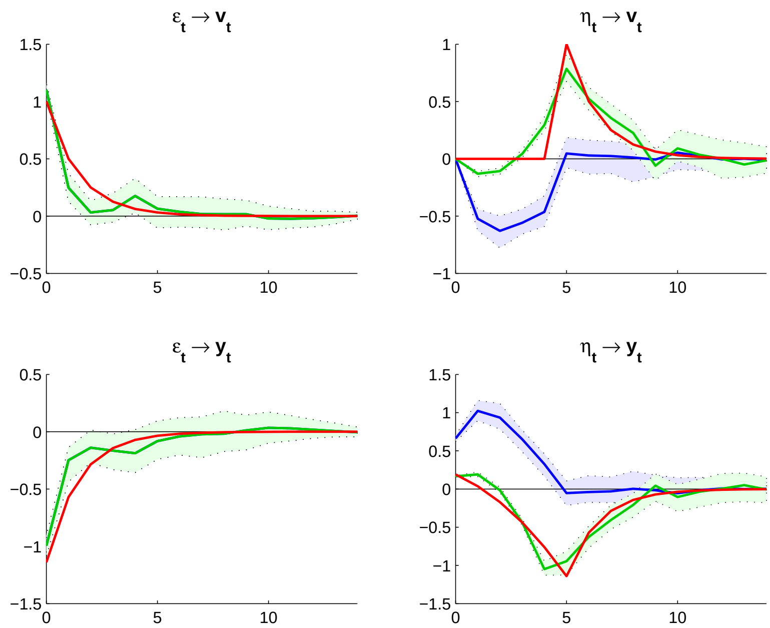
Now, replacing the above expressions in (50), we obtain:

$$\begin{pmatrix} v_t \\ \tilde{y}_t \end{pmatrix} = \underbrace{\begin{pmatrix} 1 & L^q \\ -\Omega & -\Omega\,\omega_q(L) \end{pmatrix}}_{\mathcal{M}(L)} \begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}$$

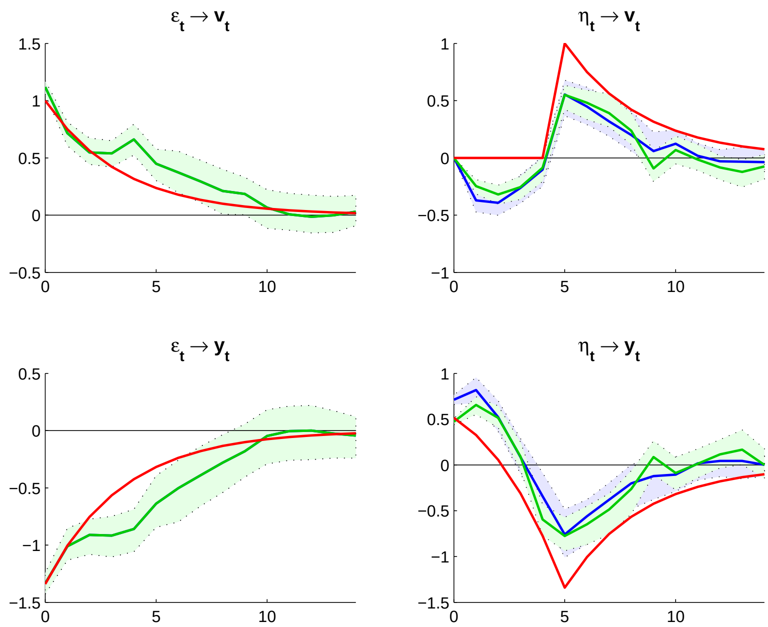
which should make clear the parallel with the toy model discussed in the paper.

.5 Figures.

.5.1 Simulations.

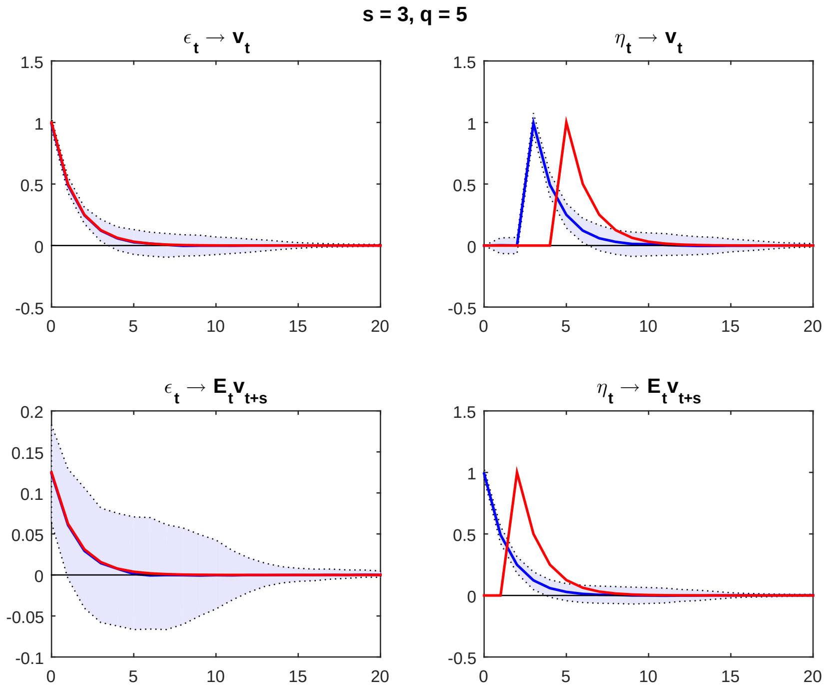


(a) $\rho = 0.5$: minimal root modulus 0.56.

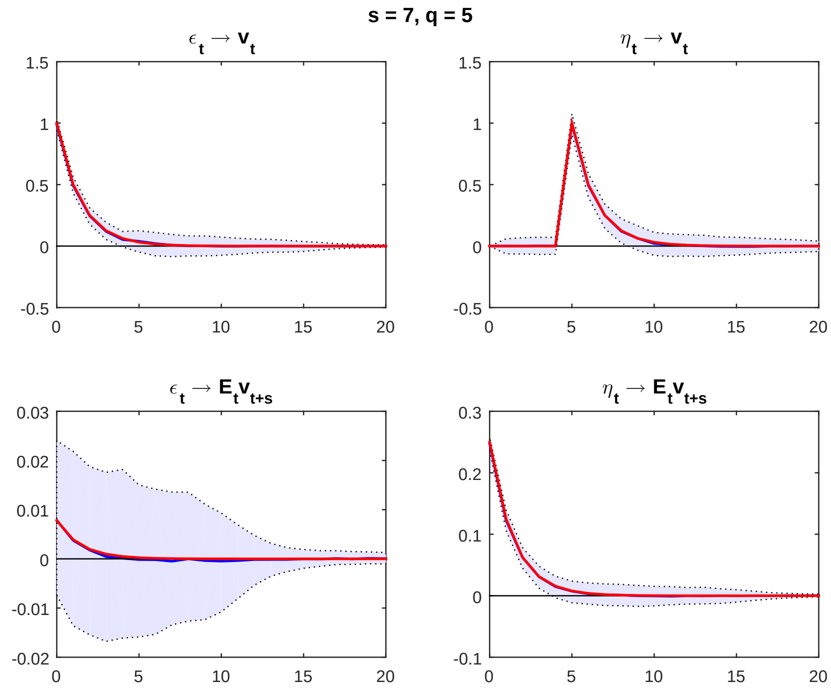


(b) $\rho = 0.75$: minimal root modulus 0.89.

Figure 4: VAR and Blaschke methods compared. Red line is d.g.p, the blue line is the result of a standard SVAR, the green line is the correction of the SVAR by a Blaschke matrix. Top panel obtained with baseline calibration as in Gali, while the bottom panel features higher persitstence of the policy shocks. Confidence bands are obtained with 1000 simulations from the d.g.p.



(a) $s < q$.



(b) $s \geq q$.

Figure 5: Adding expectation in the VAR. The red line is the d.g.p., $\mathcal{R}^{(1)}(L)$ in the top panel and $\mathcal{R}^{(2)}(L)$ in the bottom panel. The blue line is the result of standard SVAR. Confidence bands are obtained with 1000 simulations from the d.g.p.

.5.2 VAR analysis.

Toy VAR.

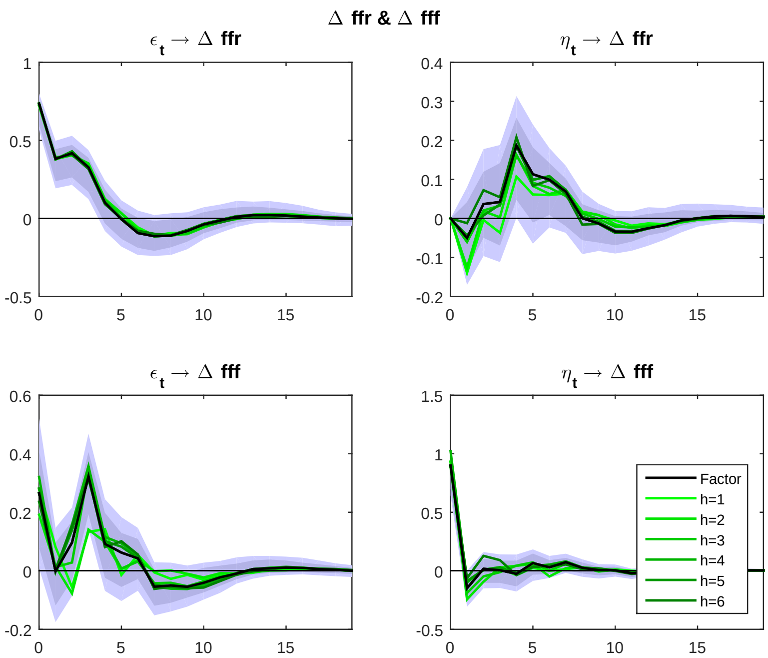


Figure 6: Toy VAR with Δffr and Δfff from Barakchian and Crowe (2010). Sample from 89Q1 to 08Q2. Individual measures for h-ahead contracts are reported in green. The factor measure that summarizes all of them is black.

Baseline VAR.

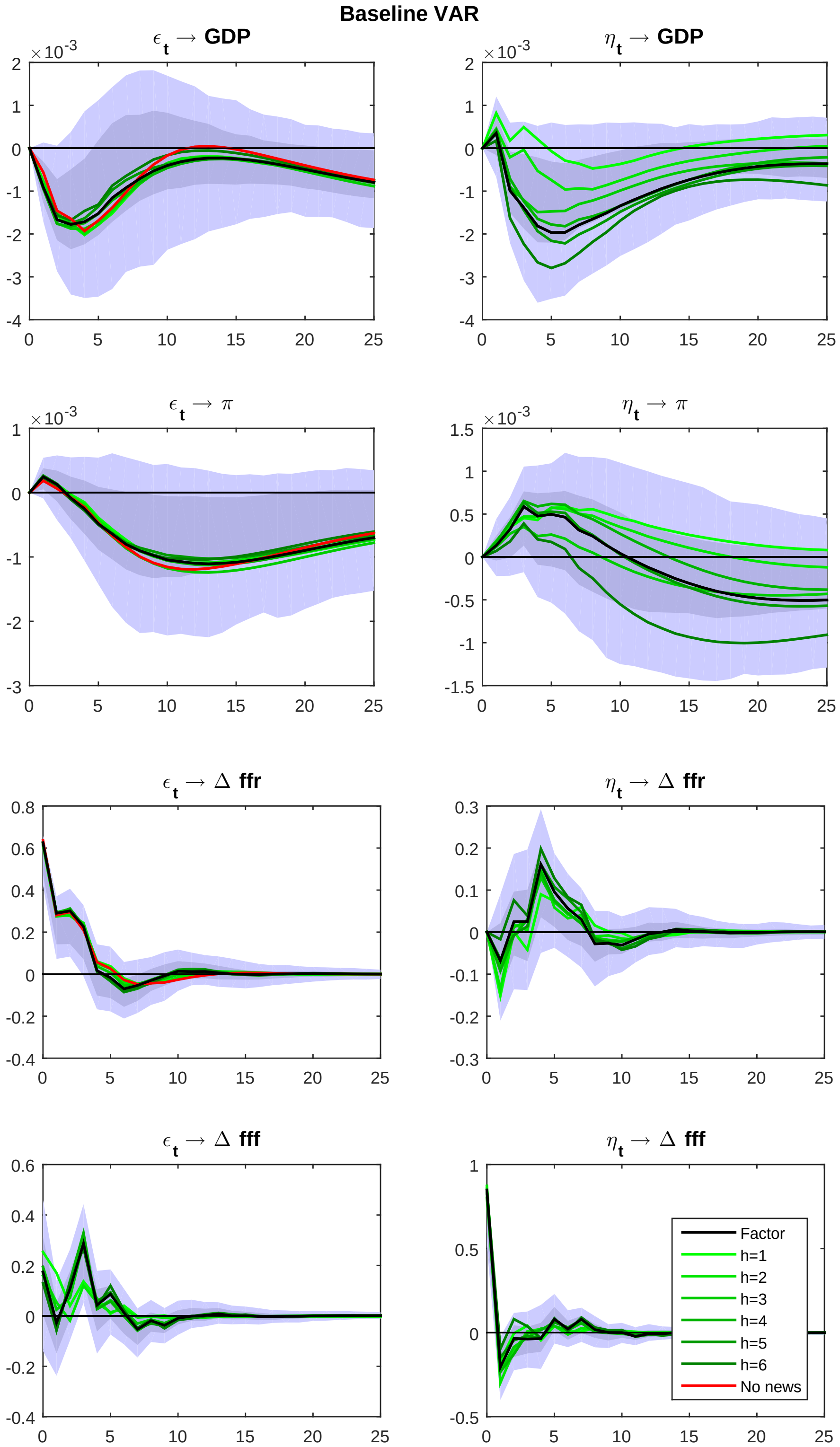


Figure 7: Baseline VAR with GDP, GDPDEF, Δffr and Δfff. Sample from 89Q1 to 08Q2 on Barakchian and Crowe (2010) data. Green lines are the measure derived from h-ahead future contract for $h = 1, \ldots, 6$. Black line is the factor measures summarizing all the individual contracts. 95% and 68% bands computed with bootstrap methods refer to the latter.

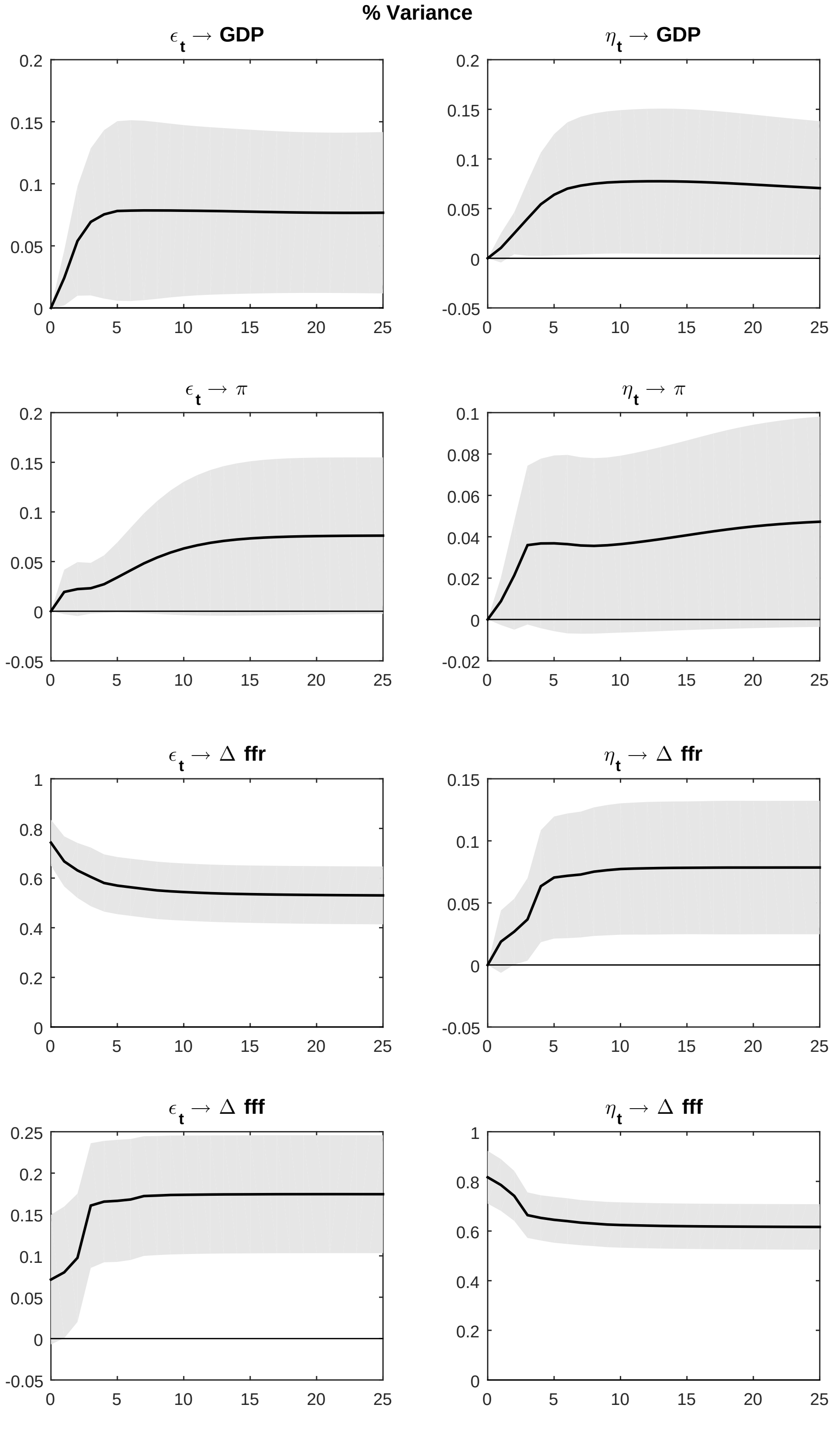


Figure 8: Variance decomposition of baseline VAR with GDP, GDPDEF, Δffr and Δfff (factor measure for the market expectations). One standard deviation bands in gray.

Extended VAR.

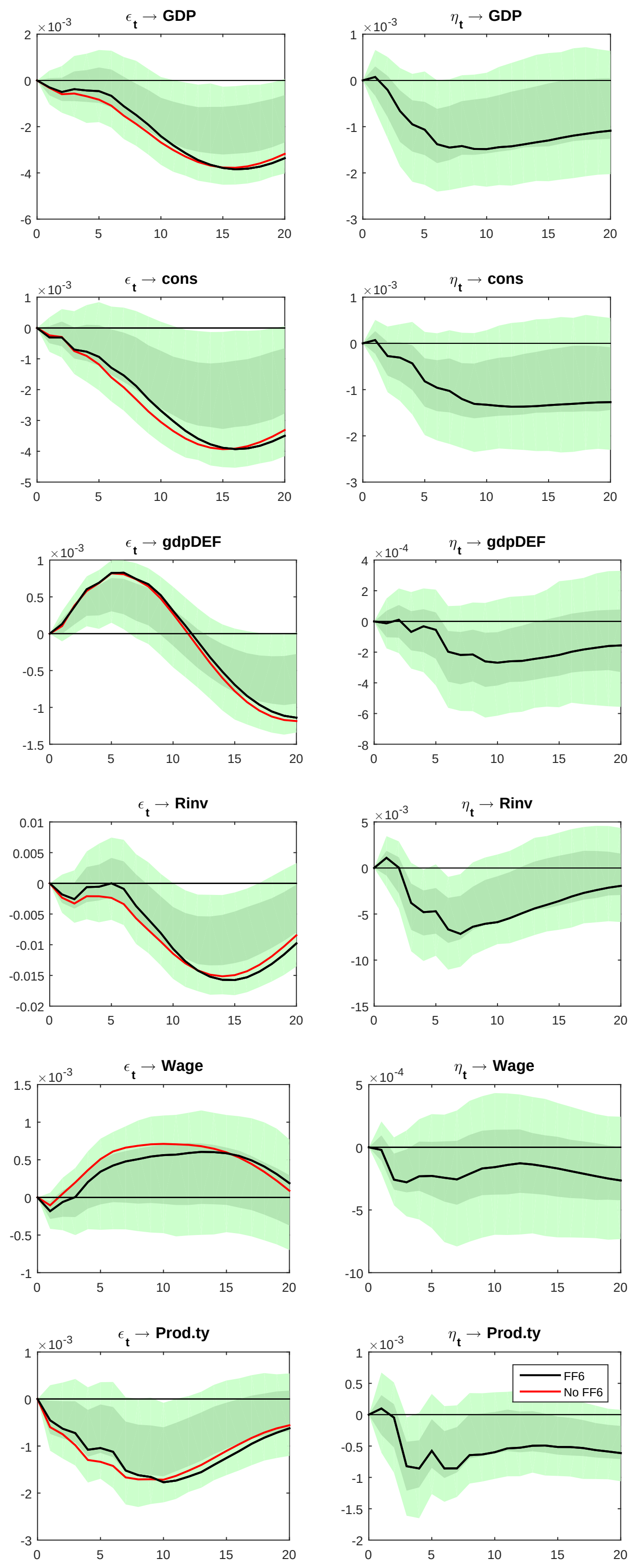


Figure 9

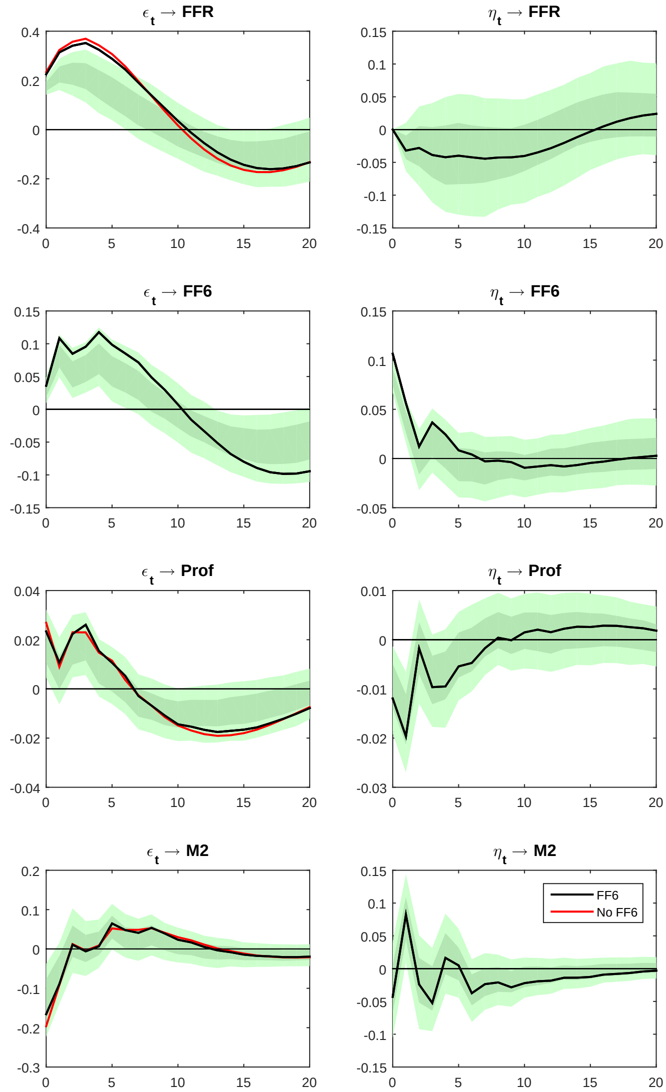
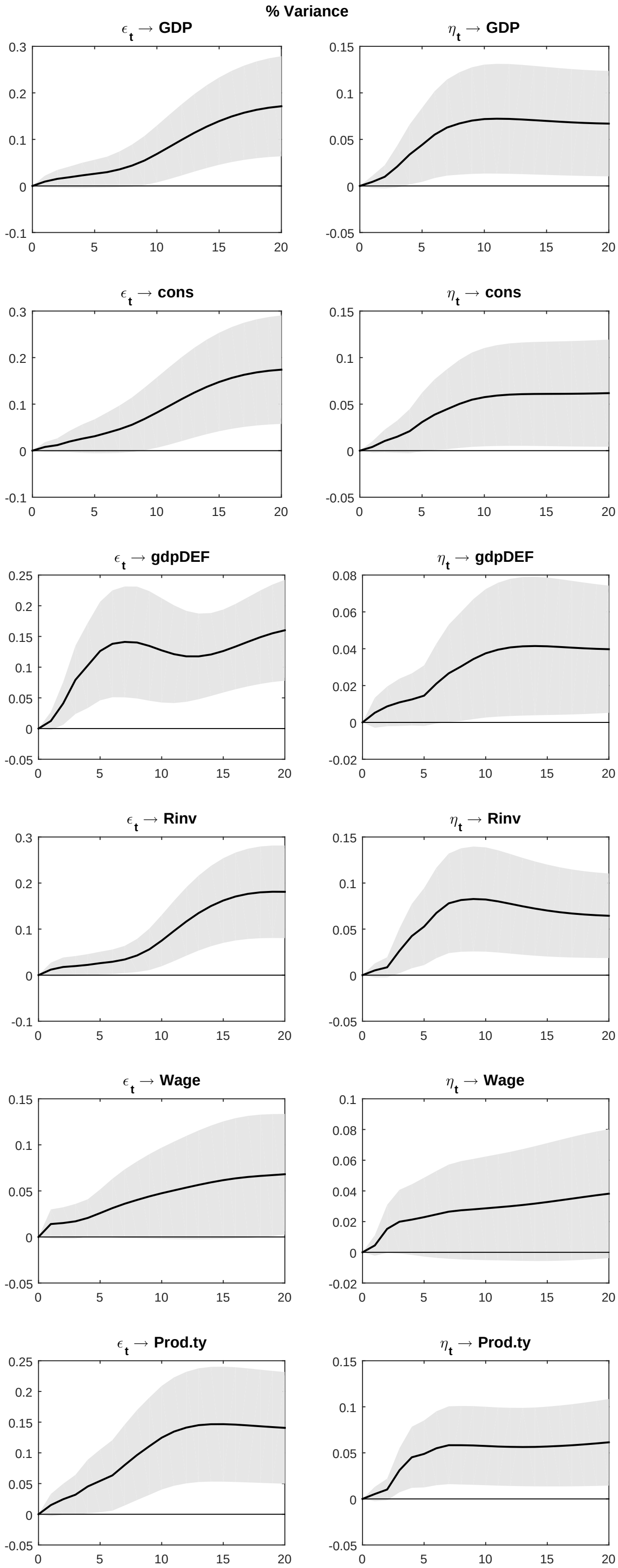


Figure 9: Christiano et al. (2005) VAR with timing restriction. The variables (in order) are GDP, CONS, GDPDEF, Real Investment, Wages, Productivity, FFR, log(FF6), Profits and M2 on the sample 89Q1-14Q4. All variables are in log levels, but M2 which is in growth rates. 95% and 68% bands computed with bootstrap methods. The red line compares the results obtained from the baseline case with no news specification.



% Variance
ϵt → GDP
ηt → GDP
ϵt → cons
ηt → cons
ϵt → gdpDEF
ηt → gdpDEF
ϵt → Rinv
ηt → Rinv
ϵt → Wage
ηt → Wage
ϵt → Prod.ty
ηt → Prod.ty

Figure 10

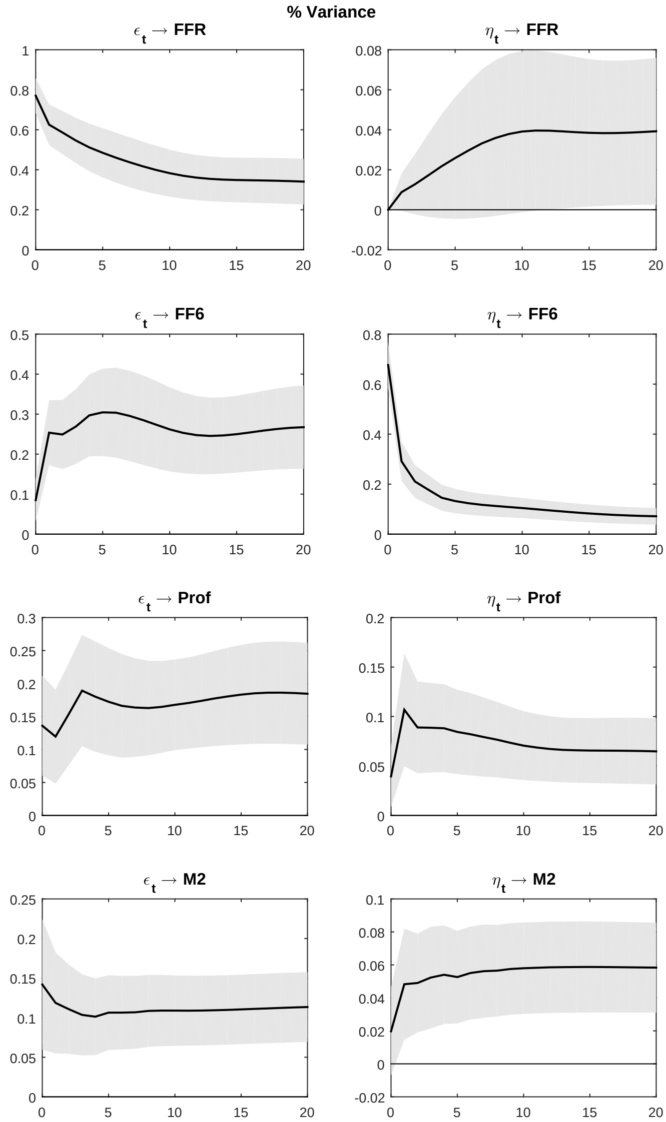


Figure 10: Variance decomposition of Christiano et al. (2005) VAR with timing restriction. The variables (in order) are GDP, CONS, GDPDEF, Real Investment, Wages, Productivity, FFR, log(FF6), Profits and M2 on the sample 89Q1-14Q4. All variables are in log levels, but M2 which is in growth rates. One standard deviation bands in gray.

.5.3 Robustness analysis.

Policy indicator ordered first.

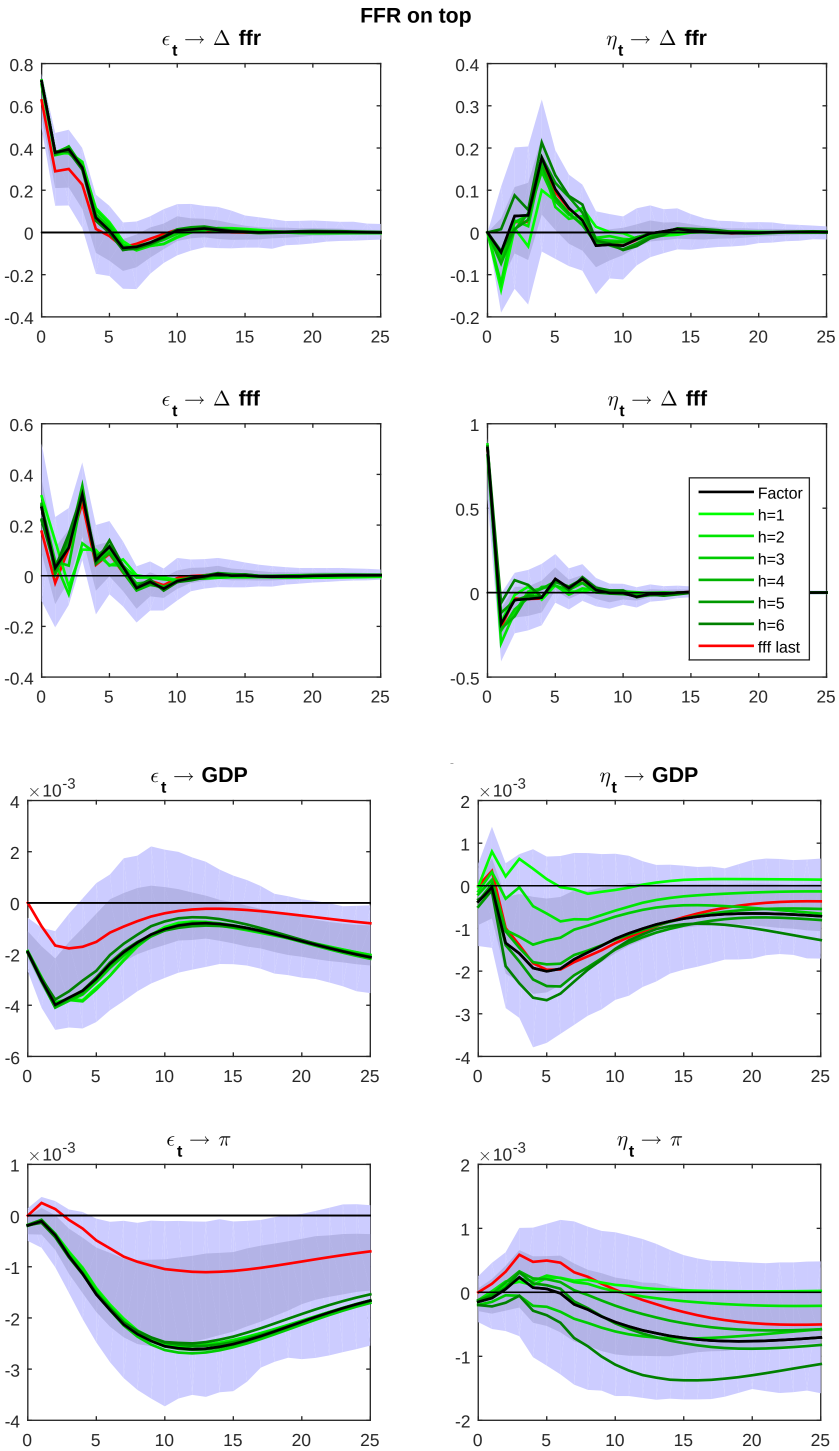


Figure 11: VAR with $\Delta fff r$, Δfff, ordered first. Sample from 89Q1 to 08Q2. Green lines are the measure derived from h-ahead future contract for $h = 1, \ldots, 6$. Black line is the factor measures summarizing all the individual contracts. 95% and 68% bands computed with bootstrap methods refer to the latter. The red line is the baseline case of Figure 7 with the reversed variable ordering.

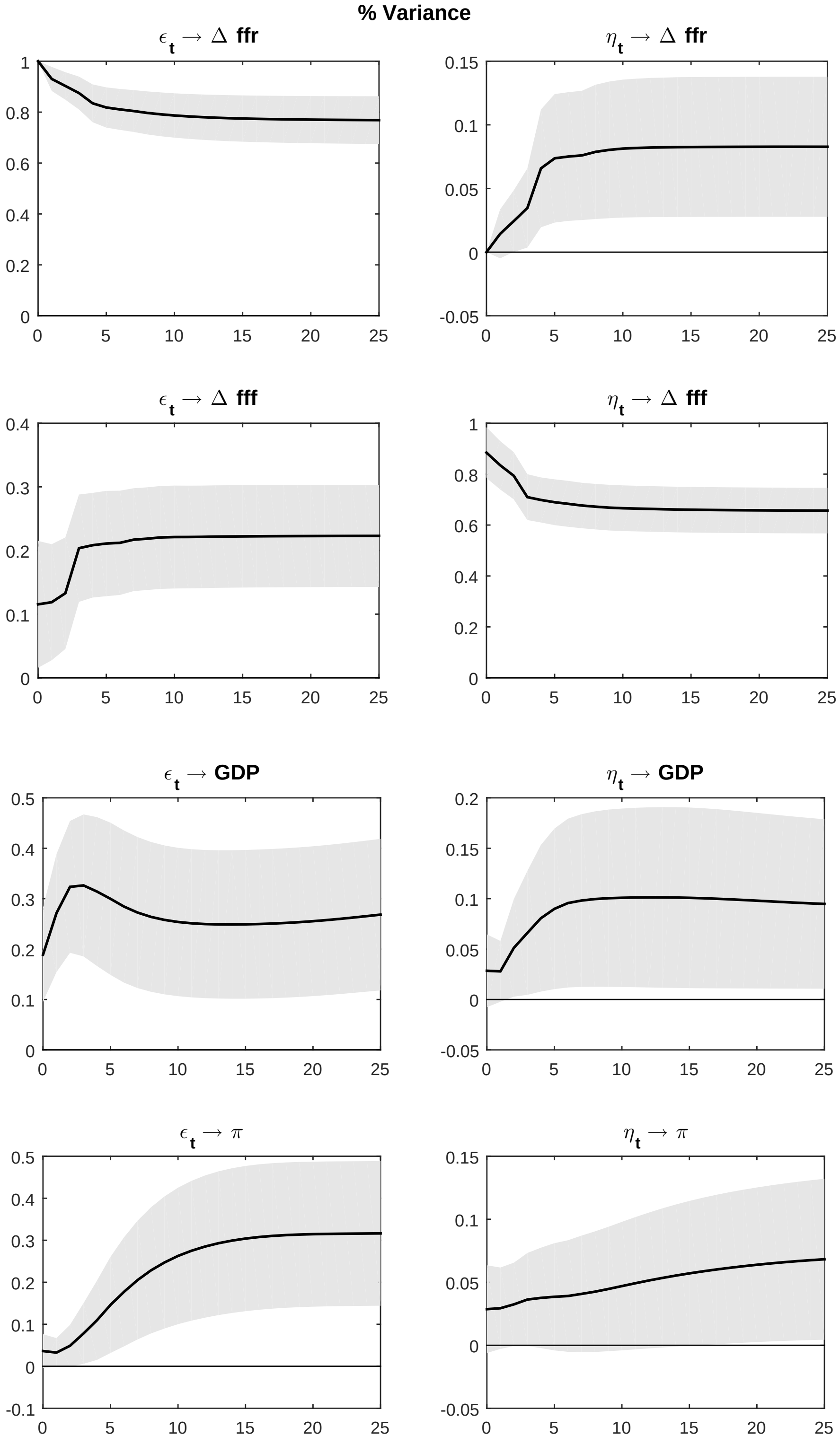


Figure 12: Variance decomposition of VAR with Δffr, Δfff, GDP, GDPDEF. One standard deviation bands in gray.

Sign restrictions.

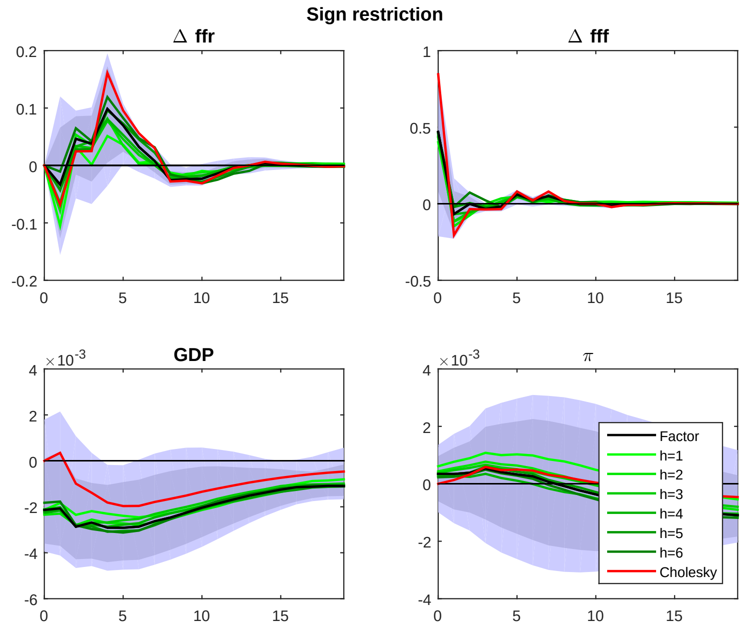


Figure 13: Baseline VAR with Δffr, Δfff, GDP, GDPDEF. News shock identified zero and sign restrictions. Results are compared to the Cholesky scheme. Restrictions on the news shock effects: (-) for GDP at h=5 and (+) for Δffr at h=5 and zero at h=0.

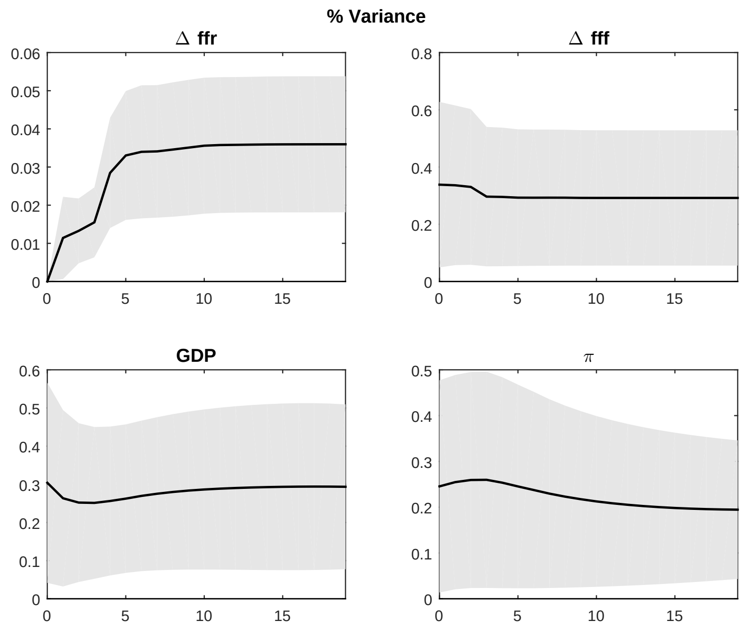


Figure 14: Variance decomposition of baseline VAR with Δffr, Δfff, GDP, GDPDEF identified with sign restrictions. One standard deviation bands in gray.

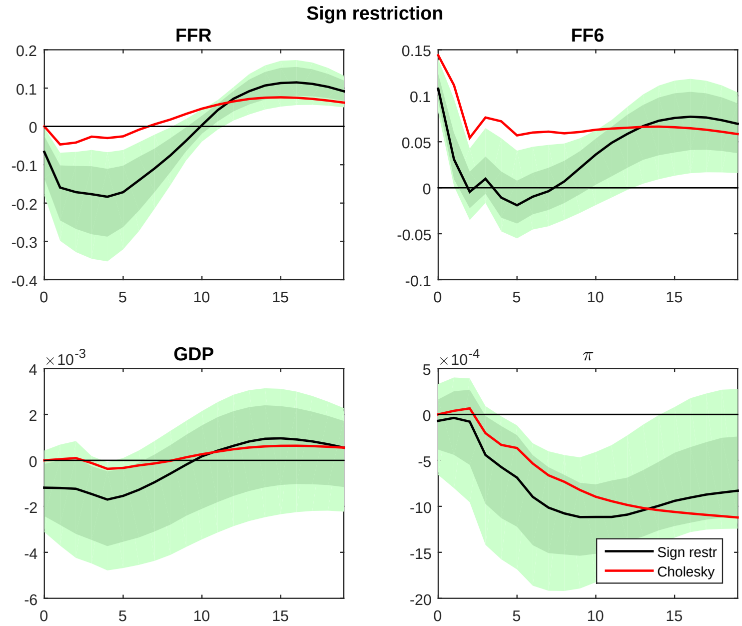


Figure 15: Baseline VAR with FFR, FF6 GDP, GDPDEF, identified with zero and Sign restrictions. News shock identified with sign restrictions. Results are compared to the Cholesky scheme. Restrictions set are on the news shock effects: (-) for GDP at h=5; (-) for inflation at h=5; (+) for FF6 at h=2.

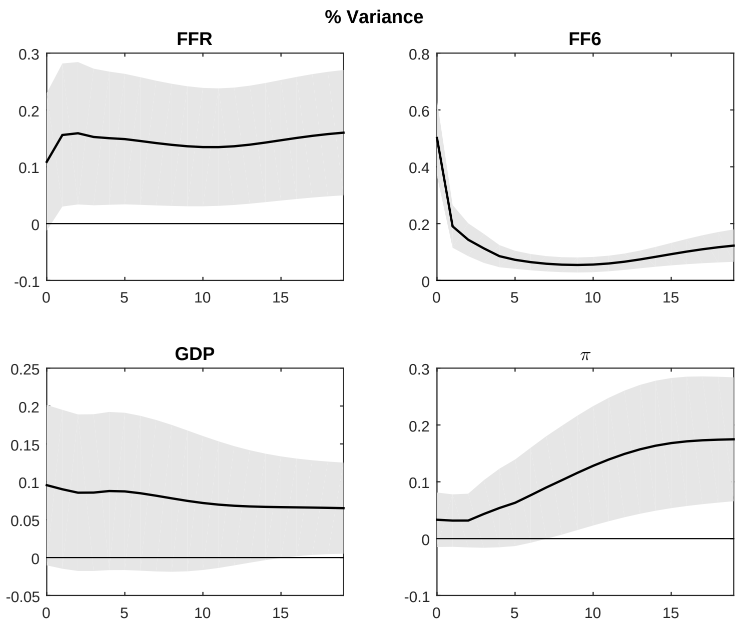


Figure 16: Variance decomposition of baseline VAR with FFR, FF6, GDP, GDPDEF, identified with zero and Sign restrictions. One standard deviation bands in gray.

SPF data.

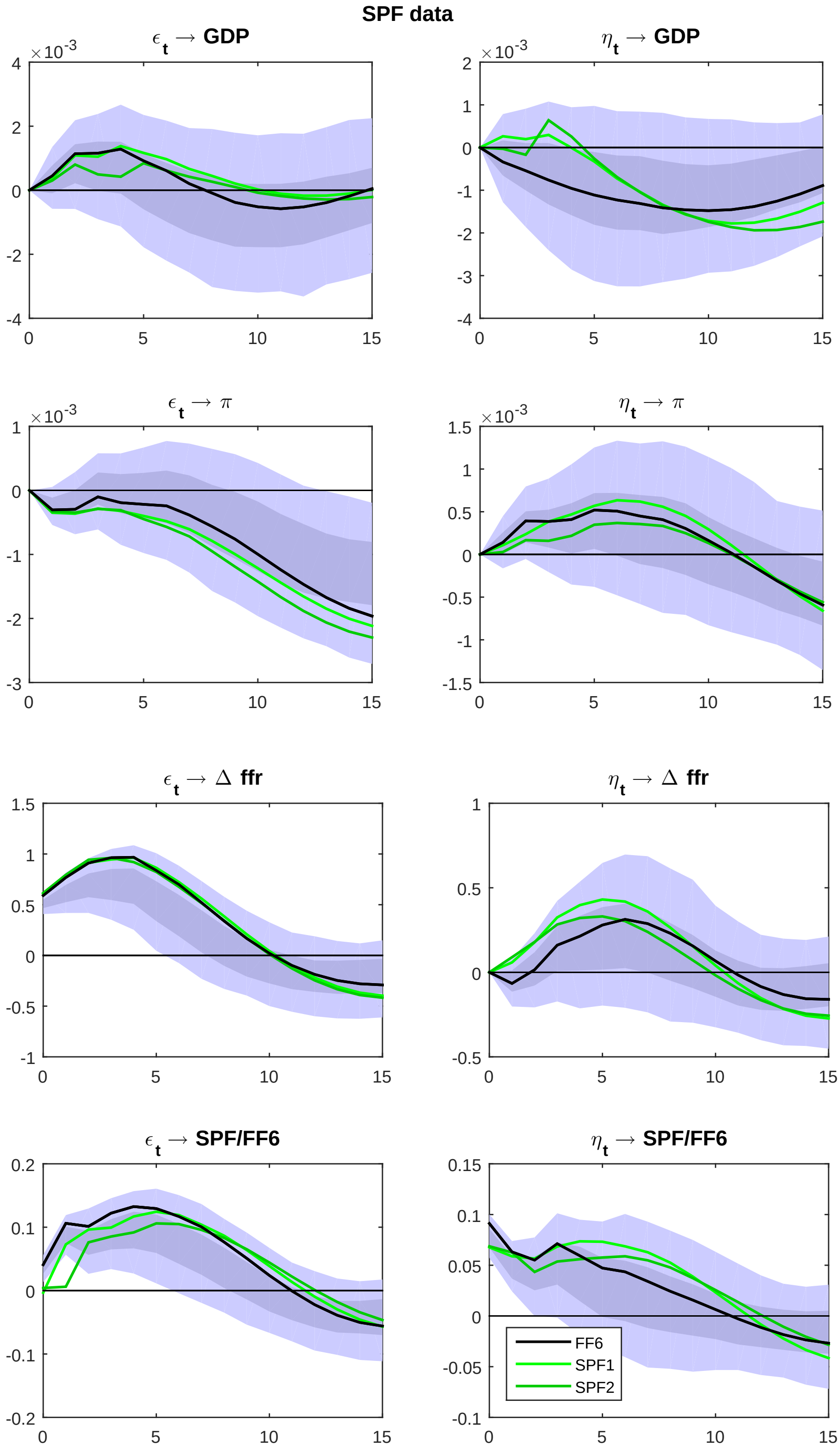


Figure 17: Baseline VAR with GDP, GDPDEF, Δffr and FF6 (black line) or 1 and 2 quarters ahead SPF forecast of T-bill (green lines). The policy shock has been cumulated to obtain an I(1) series. 95% and 68% bands computed with bootstrap methods refer to the FF6 case.

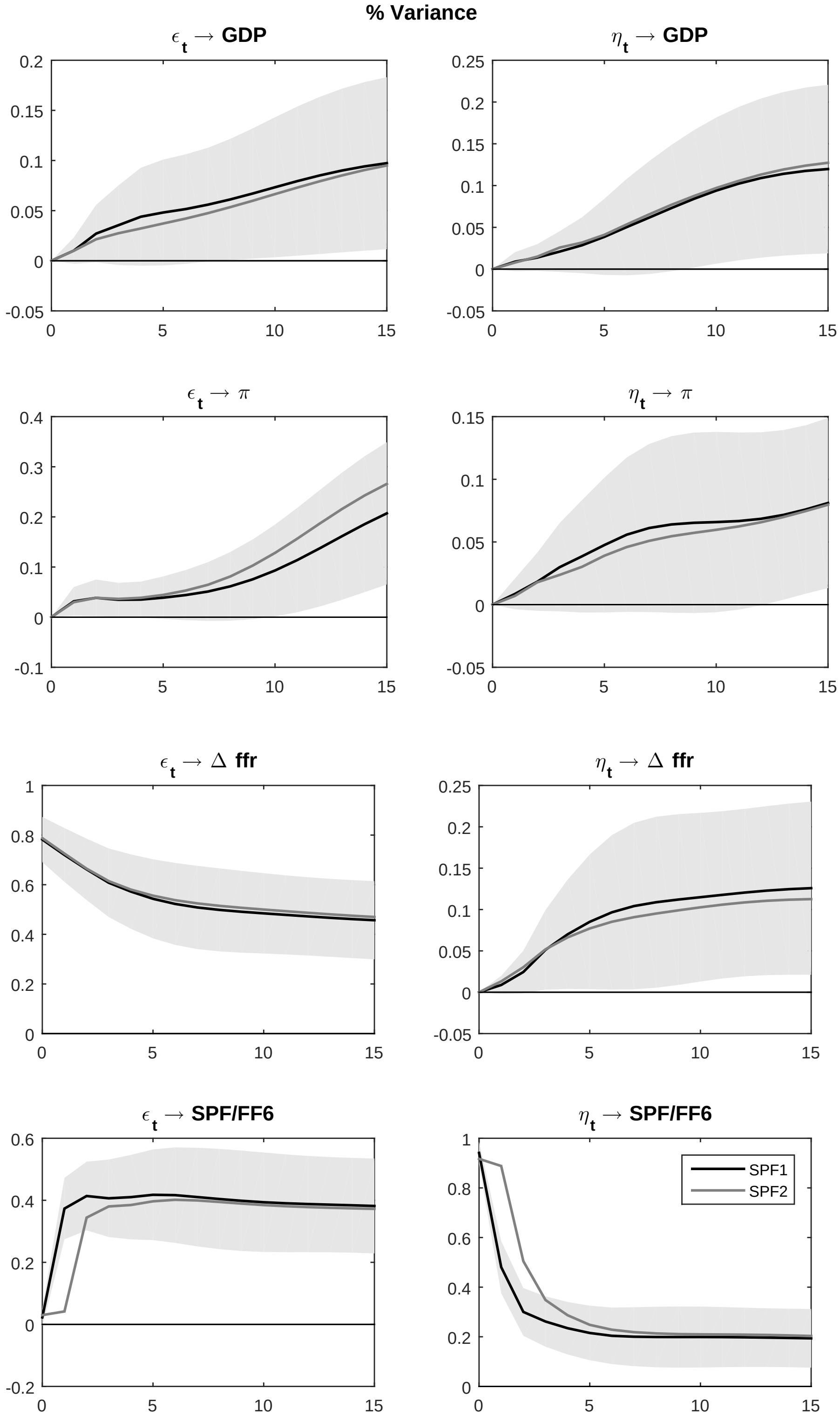


Figure 18: Variance decomposition of baseline VAR with GDP, GDPDEF, Δffr and 1 and 2 quarters ahead SPF forecast of T-bill. One standard deviation bands in gray refer to SPF1.

Chapter 2

Measuring Fiscal Policy Spillovers in the Euro Area.

(joint with Luca Gambetti)

Abstract

We study fiscal policy coordination and fiscal policy spillovers in Germany, France Spain and Italy using a Time-Varying Coefficients VAR model for the period 1995-2014. While the four country-specific cycles share large commonalities, fiscal policy coordination across countries, measured as the time-varying correlation between government spending growth, is very low. Country-specific government spending shocks generate significant effects on the remaining countries. International spillovers are especially strong in the medium run and during the financial crisis. Also, we find heterogeneous and asymmetric response to spending across countries.

JEL classification: C32, E32, E62.

Keywords: fiscal spillovers, government spending shock, time-varying coefficients VAR, Euro Area.

2.1 Introduction.

The rencent global crisis has revived the interest for fiscal policy and it role as a tool of economic boost (e.g. Blanchard and Leigh (2013), Mertens and Ravn (2014) and Auerbach and Gorodnichenko (2012)). In a time financial distress, the debate among advocates of fiscal austerity and fiscal stimulus has been quite prolific, generating a vast amount of academic prodcution. We refer the reader to Ramey (2011) for a recent survey of the literature.

Theoretical models have shown that monetary policy can hinder in the transmission of fiscal policy and ultimately offset its effects. Indeed, Fernández-Villaverde et al. (2015), Eggertsson (2011) Woodford (2011) and Christiano et al. (2011) agree on the fact that fiscal multipliers are higher when interest rates are constrained by the zero lower bound. On the same line, Hall (2009) shows that in a liquidity trap, multipliers can be larger if employment is responsive to demand. This conjecture, however, has not gone unchallenged. As an example, Ramey and Zubairy (2014) fail to find significant evidence of multipliers above average during the Great Recession. This gives a taste of how the debate is still fervent and far from being settled.

Other theoretical conditions that can amplify the effectiveness of government actions are summarized by Canova and Pappa (2011): high pricing frictions, strongly countercyclical markups and fiscal speding coming with provisions of future spending cuts. Similarly, Corsetti et al. (2010) support the notion that short term stimulus policies are most effective when coupled with medium term spending reversals.

On an empirical ground, scholars have been much concerned about estimating the size of fiscal multiplier . However, this is no easy task. The main challenges come come from the endogeneity of government spending and the formation of expectations about future tax policies (Leeper et al. (2013)). To circumvent these problem, some studies has resorted to structural VARs (Mertens and Ravn (2014), Mountford and Uhlig (2009) Blanchard and Perotti (2002)), also in time varying frameworks (Kirchner et al. (2010); Pereira and Silva Lopes (2014)). Other empirical strategies rely on instrumenting fiscal spending with military expenditure (inter alia, Barro and Redlick (2009)).

Furthermore, the crisis has shown how interconnected the world is and how quickly downturns in a country can spread their contagion internationally. Not withstanding this, little work is done on the cross-country effects of fiscal policy. Our work addressed this gap in the literature and it is aimed at shading some light on spillovers effects in the euro area.

This is especially interesting taken into consideration that EU monetary policy is common, markets are highly integrated, countries are institutionally bond but fiscal policy is not quite unified. Since the outbreak of the crisis, the idea of increasing fiscal coordination beyond the European Stability Mechanism has been a near-constant subject of political discussion. This is why it is important to testify the existence and quantify the amount of fiscal spillovers, in order to provide policymakers with robust evidence to drive the process of European integration.

However, as it is the case of fiscal multipliers, the current literature on fiscal spillover has not quite reached a consensus. Gros and Hobza (2001) do a review of result from different macro models and report how cross-country spillovers are are indeed uncertain, both in sign and magnitude. For instance, Cwik and Wieland (2011) present five DSGE new Keyenesian models calibrated to the euro area, finding that spillovers between countries are negligible or even negative.

There are though theoretical reasons lending support to the existence of fiscal spillover. Policy shocks can propagate via the demand channel, when domestic demand affects foreign demand too. This can happen due to inflationary pressure in a country shifting trade balances across EU states. Also, spillovers can act through financial markets, when the excessive borrowing in the source country increases the risk premium of foreign economies. Even if there is no explicit bail out rule, markets might expect members states to be somehow liable for their neighbors sovereign debt, thus associating higher risk premium to higher risk of financial of contagion.

Our work thus contributes to the ongoing discussion, presenting empirical evidence of the cross border effects of fiscal policy across four countries in the Euro zone, namely Italy, France, Germany and Spain. Using a Time-Varying Coefficients VAR model we find that economic cycles are correlated, underlining the interdependence across member states. Furthermore, even in absence of explicit fiscal coordination, e find that shifts in government spending cause international spillovers, with heterogeneous signs and magnitudes across countries.

We include time variation in the analysis, given that Auerbach and Gorodnichenko (2013) suggest that spillovers vary across the business cycle, showing stronger effects in recessions. On the contrary, Faccini et al. (2016) find limited state dependence in the international transmission of fiscal policy. However, our sample spanning from 1995 to 2014, includes institutional as well a financial beaks and naturally calls for a time varying setting. Indeed, we found that spillovers are especially sizable in the medium run and during the financial crisis. Our empirical approach relies on estimating the effects of shocks in one source country on all the other country's output. This has the the twofold advantage of providing with a transparent and straightforward interpretation while allowing for heterogeneity in the transmission across member states.

The remainder of the chapter is organized as follow, section 2.2 presents the model, the, the identification strategy and the estimation approach, of time-varying impulse responses and second moments. Then, section 2.3 reports the empirical evidence on cross-border spillovers across the countries at hand. Finally, section 3.6 summarizes and concludes.

2.2 Econometric Approach.

2.2.1 The Model.

We perform the analysis using a structural time-varying VAR model with stochastic volatility (see Primiceri (2005)). With the model we compute time-varying second moments to measure fiscal policy coordination and identify a government spending shock using zero restrictions. Let y_t be a n- dimensional vector of macroeconomic variables. We assume that

$$y_t = A_{0,t} + A_{1,t} y_{t-1} + ... + A_{p,t} y_{t-p} + \varepsilon_t \tag{2.1}$$

where ε_t is a $n \times 1$ Gaussian white noise vector with time-varying covariance matrix Σ_t, $A_{0,t}$ is a $n \times 1$ vector of time-varying coefficients and $A_{i,t}$ are $n \times n$ matrices of time-varying coefficients, $i = 1, ..., p$. Let us define $A_t = [A_{1,t}, A_{2,t} ..., A_{p,t}]$, and $\theta_t = vec([A_{0,t}\ A_t]')$, where $vec(\cdot)$ is the stacking column operator. We assume that the VAR coefficients evolve as

$$\theta_t = \theta_{t-1} + \omega_t \tag{2.2}$$

where ω_t is a Gaussian white noise vector with covariance Ω.

Let us now consider the following decomposition of the innovation covariance: $\Sigma_t = F_t D_t F_t'$, where F_t is a lower triangular matrix with ones on the main diagonal and D_t a diagonal matrix. Let σ_t be a column vector containing the diagonal elements of $D_t^{1/2}$ and let $\phi_{i,t}$, $i = 1, ..., 4$, be a column vector containing the first i elements of the $(i+1)$-th row of F_t^{-1}. In addition we assume that the states evolve according to

$$\begin{aligned} \log \sigma_t &= \log \sigma_{t-1} + \xi_t & (2.3) \\ \phi_{i,t} &= \phi_{i,t-1} + \psi_{i,t} & (2.4) \end{aligned}$$

where ξ_t and $\psi_{i,t}$ are Gaussian white noise vectors with zero mean and variance Ξ and Ψ_i respectively. Let $\phi_t = [\phi_{1,t}', \ldots, \phi_{n-1,t}']$, $\psi_t = [\psi_{1,t}', \ldots, \psi_{n-1,t}']$ and let Ψ be the covariance matrix of ψ_t. We assume that $\psi_{i,t}$ and $\psi_{j,t}$ are uncorrelated for $j \neq i$ and that ξ_t, ψ_t, ω_t, ε_t are mutually uncorrelated.

2.2.2 Time-varying second moments.

The time-varying second moments of y_t, in particular correlations, can be studied using the "approximate" MA representation

$$y_t = \mu_t + C_t(L)\varepsilon_{t-k} \tag{2.5}$$

where $C_t(L) = \sum_{k=0}^{\infty} C_{k,t}L^k$, $C_{0,t} = I$, $C_{k,t} = \mathcal{S}_{n,n}(\mathbf{A}_t^k)$, $\mathbf{A}_t = \left(\begin{smallmatrix} & A_t \\ I_{n(p-1)} & 0_{n(p-1),n} \end{smallmatrix}\right)$, $A_t = [A_{1t}...A_{pt}]$, and $\mathcal{S}_{n,n}(X)$ is a function selecting the first n rows and n columns of the matrix X. The time-varying covariance matrix of y_{it} is given by

$$V_t = \sum_{k=0}^{\infty} C_{k,t}\Sigma_t C'_{k,t}.$$

The time-varying correlation between variable j and i is simply given by

$$\rho_t^{i,j} = \frac{V_{t,ji}}{\sqrt{V_{t,jj}V_{t,ii}}} \tag{2.6}$$

where $V_{t,ji}$ denotes the element j, i of V_t.

2.2.3 Identification.

One of the main focus of the chapter is the investigation of the existence of fiscal policy spillovers across the four countries. Let $y_t = [g_{jt}\ g_{it}\ x_{jt}\ x_{it}]'$ where g_{jt} and g_{it} is government spending in country j and i and x_{jt} and y_{it} are GDP growth in country j and i. We consider six different models with all possible combinations of countries. A government spending shock in country i is identified following Blanchard and Perotti (2002). The shock is the only shock orthogonal to government spending in country j which has a non-zero contemporaneous effect on government spending in country i. Orthogonality to foreign spending is important to "control" for fiscal policy in other countries. Identification is implemented as follows. Let S_t be the Cholesky factor of Σ_t ($S_tS_t' = \Sigma_t$). Postmultiply the reduced form impulse response functions $B_t(L) = C_t(L)S_t$. The government spending shock so that the second column of $B_t(L)$ represents the effects of the government spending. The shock is the second shock in the vector $e_t = S_t^{-1}\varepsilon_t$.

2.2.4 Specification and estimation.

Estimation is standard and is done along the lines of Galí and Gambetti (2015)[1] . Below we discuss some aspects of the prior densities calibration. We use one lag. As it is standard in the literature, we assume that Ω, Ξ Ψ θ_0, ϕ_0 and $\log\sigma_0$, are all independent. Let $W(S, d)$ denote a Wishart distribution with scale matrix S and degrees of freedom d, we assume:

$$
\begin{aligned}
\theta_0 &\sim N(\hat{\theta}, \hat{V}_\theta) \\
\log\sigma_0 &\sim N(\log\hat{\sigma}_0, I_n) \\
\phi_{i0} &\sim N(\hat{\phi}_i, \hat{V}_{\phi_i}) \\
\Omega^{-1} &\sim W(\underline{\Omega}^{-1}, \underline{\rho}_1) \\
\Xi^{-1} &\sim W(\underline{\Xi}^{-1}, \underline{\rho}_2) \\
\Psi_i^{-1} &\sim W(\underline{\Psi}_i^{-1}, \underline{\rho}_{3i})
\end{aligned}
$$

Scale matrices are parametrized as follows: $\underline{\Omega} = \underline{\rho}_1(\lambda_1\hat{V}_\theta)$, $\underline{\Xi} = \underline{\rho}_2(\lambda_2 I_n)$ and $\underline{\Psi}_i = \underline{\rho}_{3i}(\lambda_3\hat{V}_{\phi_i})$. The degrees of freedom $\underline{\rho}_1$ and $\underline{\rho}_2$ are equal to the number of rows $\underline{\Omega}^{-1}$ and I_n plus one respectively and $\underline{\rho}_{3i}$ is $i+1$ for $i = 1, ..., n-1$. The parameters $\hat{\phi}_i, \hat{V}_{\phi_i}, \log\hat{\sigma}_0, \hat{\theta}, \hat{V}_\theta$ are imposed equal to the OLS estimates of obtained from a time invariant VAR estimated for the full sample. Finally we assume $\lambda_1 = 0.0005$, $\lambda_2 = 0.01$ and $\lambda_3 = 0.01$. The choice of the λ's is relatively conservative especially for λ_1 and is motivated by the fact that we want time variations not to be inflated by our priors. The posterior distribution of the parameters is obtained with the Gibbs sampler. See the online appendix of Galí and Gambetti (2015) for the details of the of the seven steps involved in the algorithm.

[1]For details about the estimation we refer the reader to the online appendix of of Galí and Gambetti (2015).

2.3 Evidence.

Here we present and discuss the main results of the chapter, divided in two main groups. First, we discuss evidence about fiscal policy and coordination and business cycle synchronization. Second we present results about fiscal policy spillovers.

2.3.1 Cycles and Fiscal policy coordination.

To study fiscal policy coordination we use model (2.1) where y_t is a vector including the series of real government spending for the four countries. We estimate the model and compute the time varying correlations (2.6). The use of time varying techniques allows to investigate the evolution of the model parameters, which is especially interesting in a sample featuring financial distress and regime switching. Thus we assess the time evolution of real GDP and governments spending growth, both in terms of cross-country correlations and of variances. We find evidence of strong correlation of the business cycles. Conversely, we observe no cross-country synchronization in fiscal spending. Also, we find heterogeneity in terms of variance, with similar patterns in France and Germany but distinctive behaviors in Spain and Italy.

Figure 2.1 reports the time varying correlations for the GDP growth of the four countries. The solid lines depicts the median draw from the posterior distribution while the grey areas represent the 68% confidence bands. As emerges from the picture, cross-country correlations in GDP growth is high and roughly stable throughout the sample period. This implies that business cycle fluctuations are very much synchronized across countries.

Also, notice how correlations increase during the global financial crisis, peaking around 2009. This mirrors how the economic slowdown hit all the countries pervasively, provoking parallel recessions. Only Spain and Italy maintained a stable time varying correlation, showing that their GPD performance has similar faith both in good and in bad times. Indeed, especially in the cross comparison with France and Germany, we observe similar pattern of convergence during the recession period followed by a drastic reduction in correlations after 2010. This latter drop might be explained by a different pace of recovery between the peripheral and core countries of the sample.

Figure 2.2 plots the time varying variance of GDP growth. The series differ in magnitude, with higher values in Italy and Germany. However, they follow identical dynamics. On the one hand, we observe a first spike around 1999, which coincides with the introduction of the monetary union and the common currency. This advocates in favor of our choice of a time varying model, that spots and controls for regime switches. On the other hand, the maximal peak is to be found a decade later in correspondence of the global recession. The financial turmoil spread uncertainty across borders, provoking a steep increase in the variance of GDP growth. Such trend is reverted at the end of the sample, where the progressive economic recovery shrunk the variances back to their pre-crisis levels.

If on the one hand, output growth is highly synchronized across countries (also in terms of uncertainty), on the other hand we do not observe any co-movements in fiscal policy. Figure 2.3 displays the time-varying correlations of government spending across member states. Clearly, correlations are largely non significant, mirroring the absence of coordinated fiscal spending across states. The only exception the Italian-Spanish case, whose estimates are positive, even if very low. Once more we find higher affinity within the peripheral states and larger heterogeneity with the core countries.

Notice for instance the case of France, whose point estimates suggest opposite reactions to spending in other countries. Especially when coupled with Germany, we observe persistently negative correlations, significant at least in the initial part of the sample. If anything, it seems that there is a counter reaction rather than a coordination of spending among the two countries. This suggest that French aversion for German fiscal management may date older that the 2012 elections, in which the winning party vowed to break the austerity measures sweeping

Europe. In fact, we do not observe much discontinuity in the correlations before and after the Socialist party came in office.

Notwithstanding the lack of coordination, France and Germany show quite similar features regarding second moments. Figure 2.4 plots the time-varying variance of government spending growth. We can see that both France and Germany present a decreasing trend, with confidence bands shrinking towards the recent part of the sample. This drop in variance could be attributable to a reduction of the the discretionary part of fiscal policy, which translates into a limit to governments' actions and to smaller swings in spending. Also, the time-varying variance has spikes in 1999 and in 2009, suggesting that regime changes and periods of economical distress take their tall on fiscal spending too.

Moreover, Italy and Spain display a completely *sui generis* behavior in terms of variance. Italy presents relatively constant estimates, inflating in 2000-2004 but stabilizing at a roughly fixed value. Spain on his side, shows an overall upwards trend, especially from 2011 when the popular party come to power. If is not coincidental, the recent increase in volatility can be read as the government need to resort to larger spending swings to achieve its program of cutting deficit, recapitalizing banks and promoting labor market reforms.

2.3.2 Fiscal spillovers in EU countries.

We identify a government spending shock in each country via timing restrictions. On impact, a policy shock in country i is constrained to be orthogonal to spending in country j. In this fashion, structural disturbances are cleaned out of contemporaneous policy co-movements and represent purely non-coordinated domestic shocks. Notice that we do not impose restriction on output growth. In fact, a policy shift can redirect consumers towards national or foreign produced goods, with consequent adjustment of the trade balance, and direct effect on output growth.

The mechanism of transmission is posited in business-cycle models, as in Chari et al. (2002) and Corsetti et al. (2010) among others, even if the magnitude and sign of spillovers greatly depend on calibration and the debate on overall policy effect is far from being settled. In a nut shell, an exogenous increase of government spending can affect other countries via the trade channel. In fact, a fiscal stimulus can ease market frictions and benefit foreign output via increased demand for imports. However, there are also forces counteracting positive spillovers effects. Higher demand puts pressure on output gap and inflation. This translates into an increase in the long rate, which in turns dampens consumption. Such effect is amplified especially when spending is debt-financed and the country has already an high burden of public debt.

Furthermore, Corsetti et al. (2010) show that spillovers effect depend on whether fiscal policy is financed only with taxes or it is coupled with a credible medium-term consolidation plan. Their results point out that coordinated spending reversal reduce fluctuations in the long rates, thus easing the trade off between demand for output and crowding out of consumption and investment.

Our work contributes to the ongoing discussion by presenting empirical insights on international spillovers effects in a sample of European countries. Given the mixed evidence inherited from theory, it comes as no surprise that we obtain heterogeneous results, both in term of signs and magnitudes.

A summary of the estimated spillover effects is presented in Table 2.1. It reports the average of cumulative percentage effect on GDP re-scaled by the average of cumulative percentage effect on government spending of the country where the shock takes place. In simple words, we compute, over 4 and 12 horizons, how much variation in GDP relative to spending is implied by an exogenous fiscal shock. Therefore these ratios can be interpreted as mean spillover effects across countries.

A first result is that, with few exception, spillovers are larger in the medium run. That is, wide swings in domestic spending are associated to moderate reactions of foreign output within the first year. Conversely, when we expand the analysis to 12 quarters, we observe spillover ratios that are as high as twice their short run value. We can read this result in light of the lack of coordination of fiscal policy. Without synchronization, there is few simultaneous contagious between neighbor countries and spillovers take the form of delayed demand and trade adjustments.

Once we have established that spillovers peak in the medium run, it is interesting to assess which historical moment features the stronger cross-country contagion. Table 2.2 contains the results of this exercise, reporting the dates of maximal spillovers, measured in terms of effects on GDP within the first three years after the shock. The interesting results is that higher spillovers are concentrated in the 2008-2010 period. This points to the fact that global distress amplifies cross-border effects, making countries more sensitive to their partners domestic policies. Therefore, especially in harsh times, there might be space for fruitful fiscal coordination, which is not observed in the data so far.

Next, to detail the consequences of spillovers of each country, Figure 2.6 to Figure 2.9 present a battery of time varying impulse responses. The panels gather the effects of a spending shock in a specific country after zero, four and eight quarters. Each subplot displays the time evolution of such effects. Put it differently, for each t in the sample range, we plot the (median posterior) impulse response at a fixed horizon k. The shaded area represent conventional 68% confidence bands. Broadly speaking, we observe that domestic effects of government spending are positive, even if non significant for France and Spain - questioning the overall effectiveness of their fiscal strategy. As regards spillovers, we have heterogeneous results, both in terms of significance and magnitude. Therefore, we review each case individually.

Starting with Figure 2.6, we observe how a spending shock in France has positive and significant effects of the GDP of Germany and Spain (while it falls short in affecting Italy). This result stands out, being France the only observation whose spending is negatively correlated with the remaining countries. In a sense France in the least "coordinated" and at the same time it is the one with stronger cross-border spillovers. Observe, for instance the positive effects on Spanish GDP, which - as discussed above - have higher and more significant effects in the medium run. Furthermore the median estimates peak in 2008, confirming the interwoven fate of France and its southern neighbor in the crisis periods. As regards the French-German spillovers, we observe an interesting change in timing. Up to 2004, there was virtually no effect on impact, while in the medium run we had stable and significant estimates. From 2004 the situation is reversed with sizable effects happening only contemporaneously.

Figure 2.7 reports results for Germany. Clearly, fiscal shocks have positive effects domestically for all the displayed horizons. However, starting from the financial crisis, an increased variance of the estimates made it harder to read these results. Similar conclusions apply to spillovers on Italy, which are positive and stable, but non strongly significant after 2006. What is more surprising is the null effects over France, which brings forward the empirical fact that spillovers are non necessarily symmetrical across borders. Somehow less surprising is the lack of German-Spanish effects. Indeed, we saw that Spain and Germany are the two countries with weakest correlations both in terms of cycles and in terms of spending, and it comes as no surprise that spillovers only have a limited scope.

As regards Spain, responses are displayed in Figure 2.8. The majority of the international effects of Spanish spending are non significant on other countries, with exception of Germany. Curiously, an expansionary policy shock has persistently negative effects on German output. This singularity in the data might be the reflection of a consumption crowding out which more than compensates the positive demand spilled over. Once more, we observe asymmetric effects across countries.

Finally, Italy is reported in Figure 2.9, and has small but generally non-zero effects on the other countries. The difference is that spillovers on France and Germany are mostly significant at intermediate horizons, while the bulk of the transmission with Spain happens on impact, especially from the financial crisis onward. Furthermore, Italy displays positive domestic response to fiscal spending, peaking during the crisis period. This replicates closely the behavior observed in Germany, and shade some optimistic light on the positive scope of fiscal policy as a mean of economic stimulus.

2.4 Conclusions.

In this chapter we present empirical evidence on fiscal spillovers for a set of European countries - namely France, Spain, Germany and Italy - over the last two decades.

To attack the issue we setup a time varying VAR for GPD and government spending growth. This has a twofold advantage. On the one hand it is especially fit in periods with regime switching and global instability. On the other hand, it allows to explore the time change of the parameters and better understand the evolution of structural dynamics among the countries.

Identification is reached via Cholesky restrictions. More in detail, we impose that a fiscal shock in one country is uncorrelated on impact with foreign spending. This is enough to ensure that we are extracting purely domestic fiscal disturbances. Also, we leave the response of GDP growth unrestricted, since they channel spillovers via the trading balance.

The main results of the empirical analysis are grouped in two blocks. First, we present time varying correlations and variances of both the GDP and the spending growth rates. Then, we explore the role of fiscal spillovers, using impulse responses from the identified shocks.

A first result in the data is that the four countries have very much synchronized business cycles, whose variance peaks in moments of regime switch (introduction of the euro) or of economic distress (global financial crisis). Conversely, we observe a complete lack of fiscal coordination, both in terms of co-movements and of second moments. Only Spain and Italy display some positive, but very small, spending correlation.

As regards spillovers, we exploit the impulse responses to compute multipliers as the ratio of (cumulative) variation in GDP relative to spending. We find that spillovers have higher strength in the medium run, reaching up to twice the impact effects after 12 quarters. Also, we show that spillovers are maximal during the crisis period. This paves the way of the debate on gains of fiscal coordination, especially in averse times, which we leave for future research.

Finally, we present evidence of heterogeneous responses to fiscal shocks across countries. We observe mixed evidence in term of sign, magnitudes and significance, with France and Italy affecting nearly all the others countries and Spain displaying even negative effects on Germany. This leads us to the conclusion that with uncoordinated fiscal spending spillovers do not act symmetrically and are not always significant nor benign.

This work want to contribute to the ongoing discussion on the role and benefits of fiscal stimulus, especially in periods of global turmoil. It might be interesting to expand the analysis to include a wider range of macroeconomic indicators, for instance interest rates or consumption growth. This might help disentangling details of the transmission mechanism, such as crowding out of consumption or inflationary pressure. This, and other correlated issues are left to future research.

Tables.

	Shock France		Shock Germany		Shock Spain		Shock Italy	
	1 year	3 years	1 year	3 years	1 year	3 years	1 year	3 years
France	−−	−−	0.0369	0.0606	0.0100	0.0266	0.1168	0.1684
Germany	0.3117	0.3941	−−	−−	-0.1825	-0.1901	0.0995	0.1888
Spain	0.3203	0.6466	-0.0080	-0.0374	−−	−−	0.0884	0.1507
Italy	-0.0172	0.1332	0.1975	0.2313	-0.0028	0.0529	−−	−−

Table 2.1: Spillover effects. The numbers represent the average (over draws and over time) cumulated percentage effect on GDP in the four countries in the first 4 quarters and 12 quarters, rescaled by the average (over draws and over time) cumulated percentage effect on the government spending variable of the country where the shock takes place.

	Shock France	Shock Germany	Shock Spain	Shock Italy
France	−−	2001:Q2	1996:Q2	2008:Q3
Germany	2009:Q2	−−	2011:Q4	2008:Q3
Spain	2008:Q3	2000:Q2	−−	2009:Q3
Italy	2008:Q2	2008:Q4	2011:Q4	−−

Table 2.2: Dates of maximal spillover effects considering the effects on GDP within the first three years after the shock. The cumulated effects of GDP are divided by the cumulated effects on the government spending variable of the country where the effects take place.

Figures.

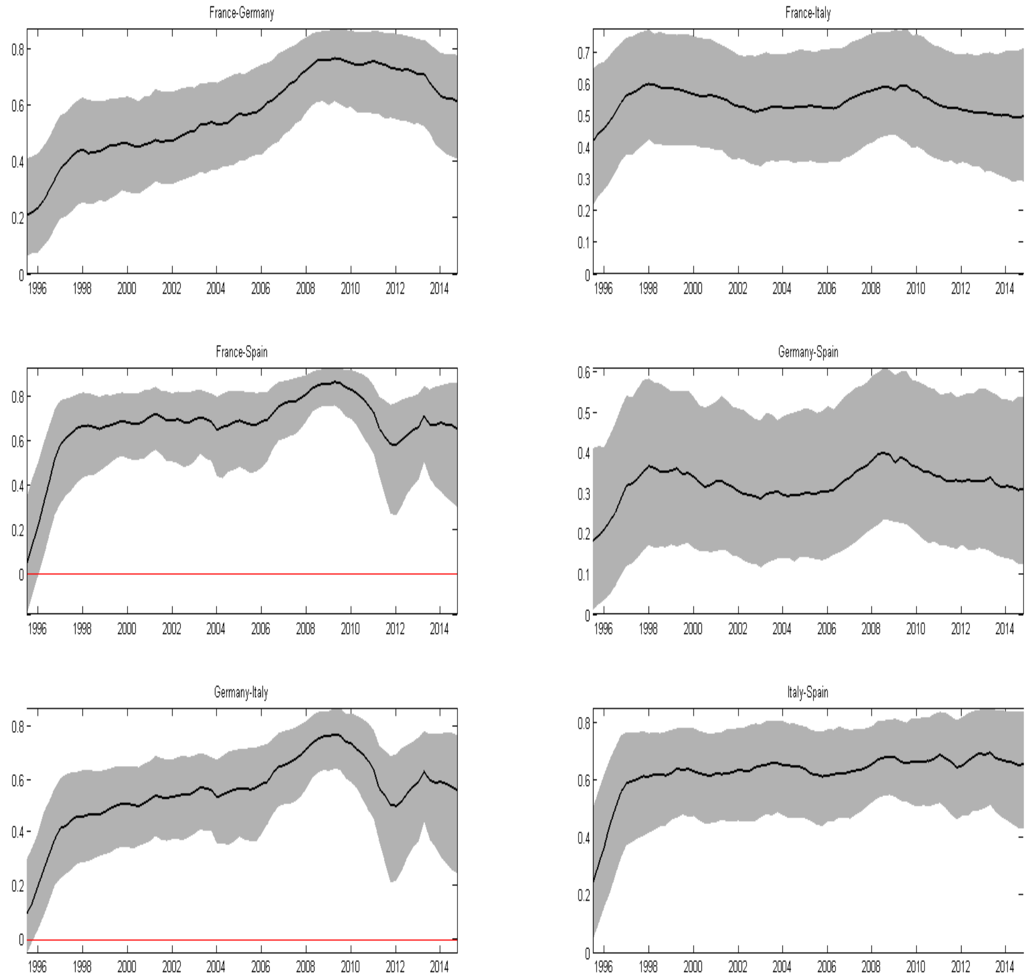


Figure 2.1: time-varying correlations of GDP growth across countries. Solid line posterior median, grey area 68% confidence bands.

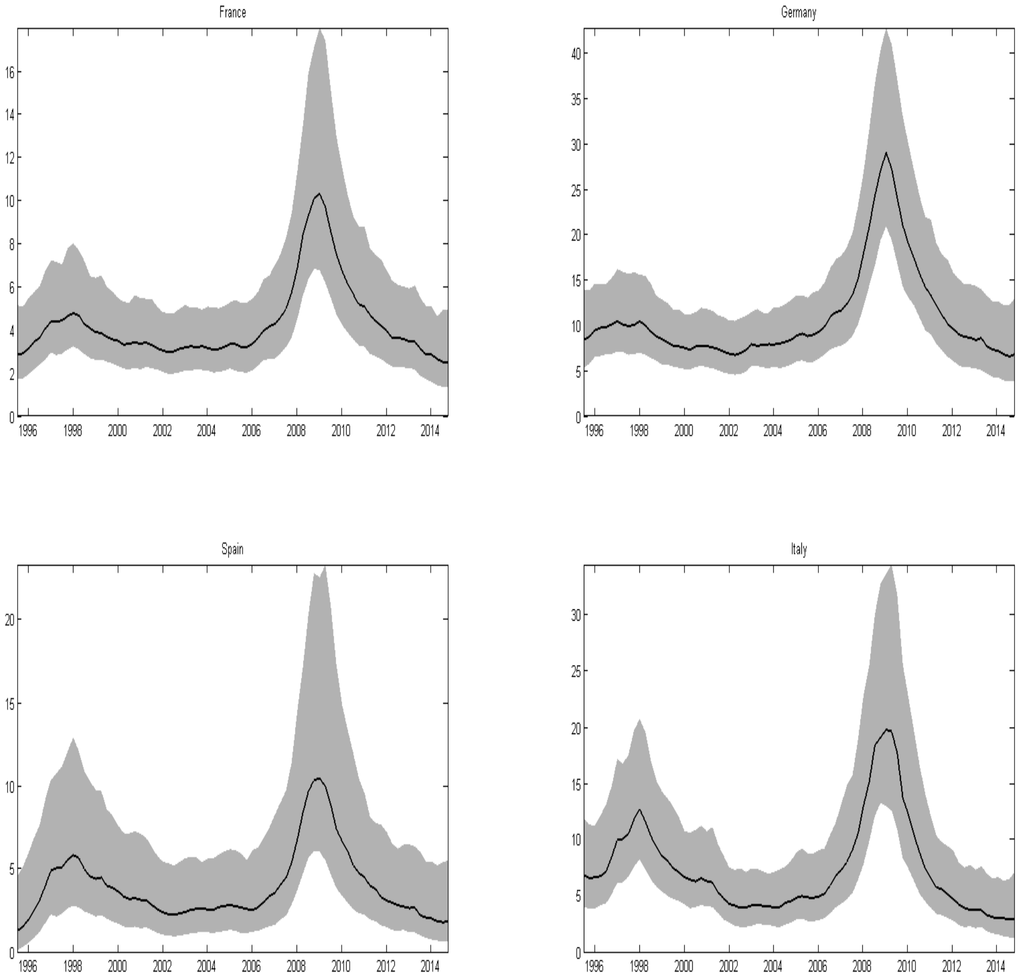


Figure 2.2: time-varying variance GDP. Solid line posterior median, grey area 68% confidence bands.

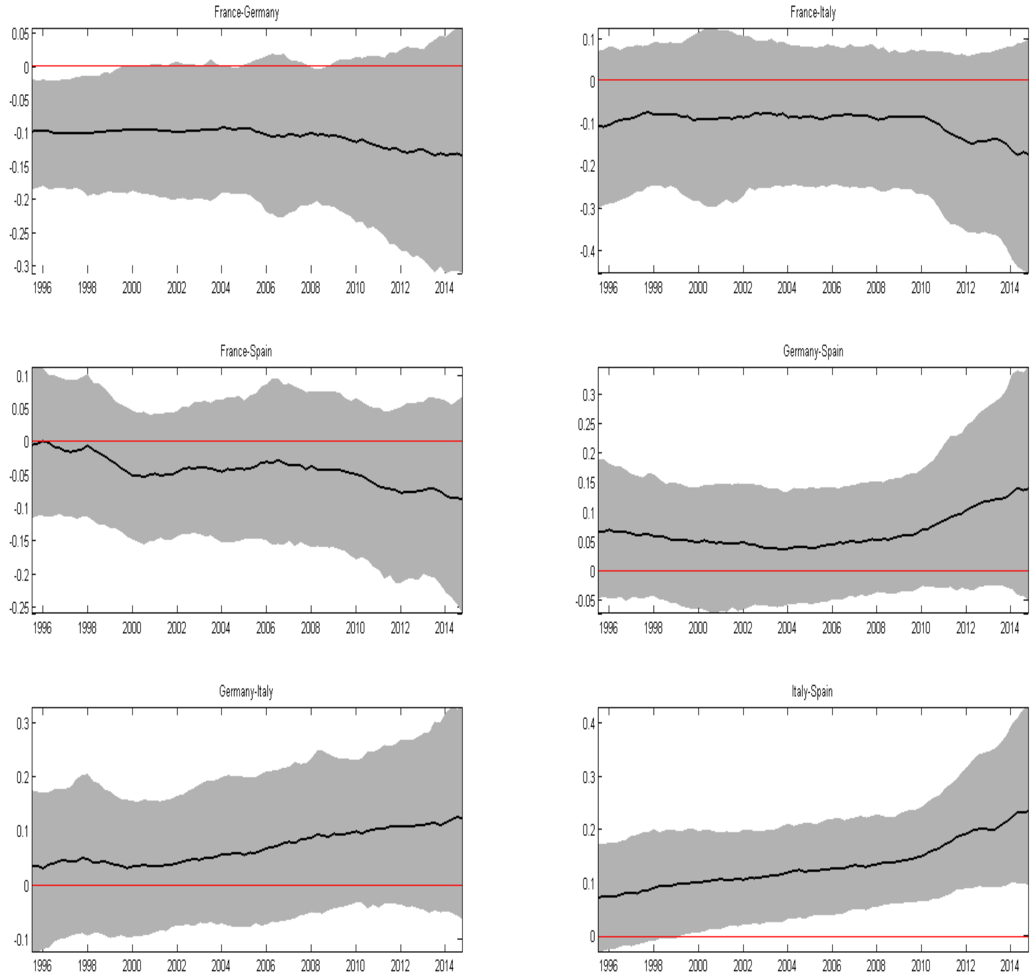


Figure 2.3: time-varying correlations of government spending growth across countries. Solid line posterior median, grey area 68% confidence bands.

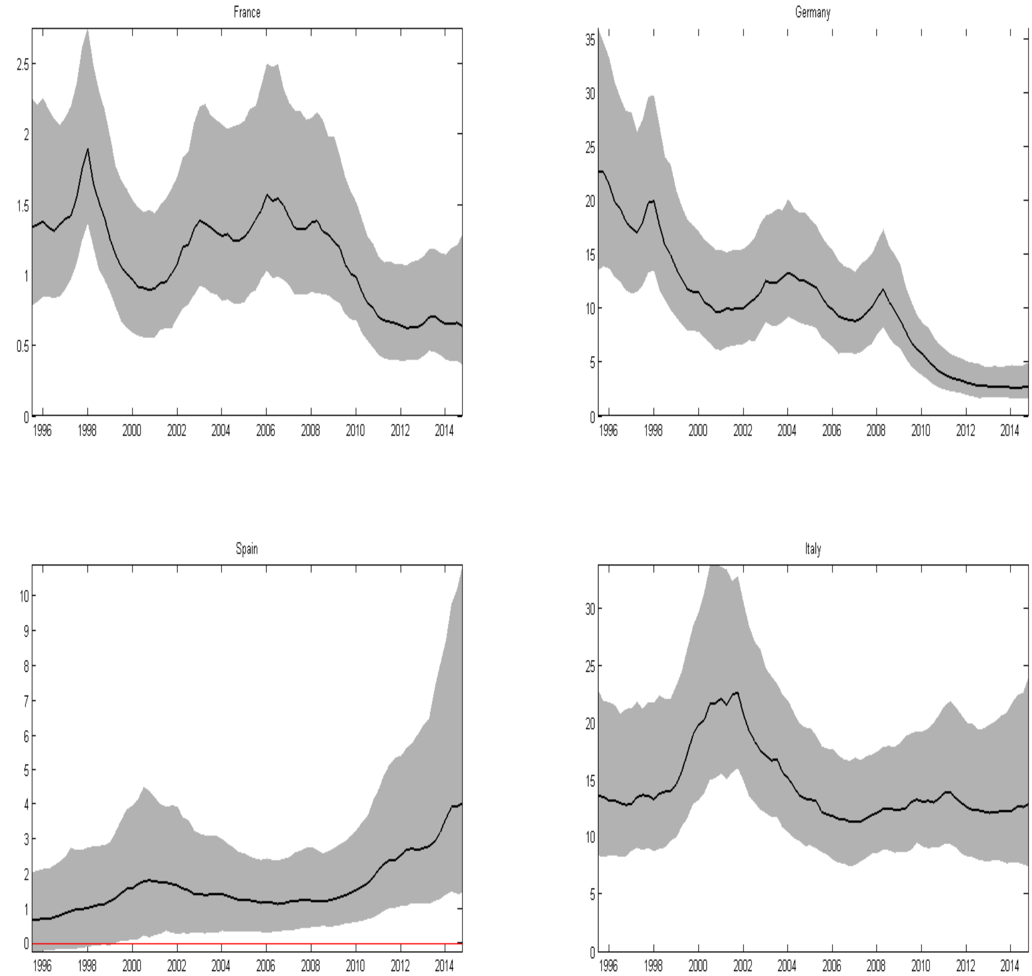


Figure 2.4: time-varying variance government spending. Solid line posterior median, grey area 68% confidence bands.

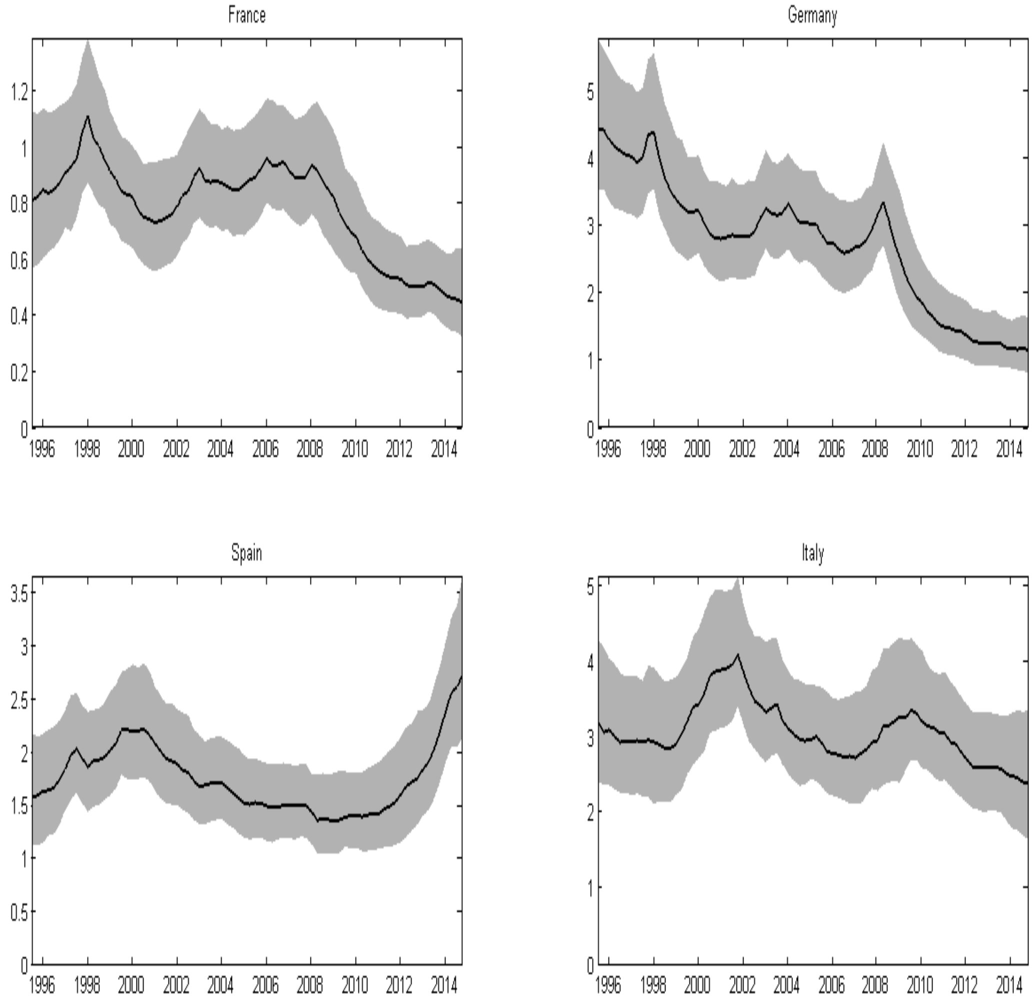


Figure 2.5: time-varying standard deviation of the government spending shock. The standard deviation is estimated by normalizing the effect of the shock on government spending of the home country equal to one. Solid line posterior median, grey area 68% confidence bands.

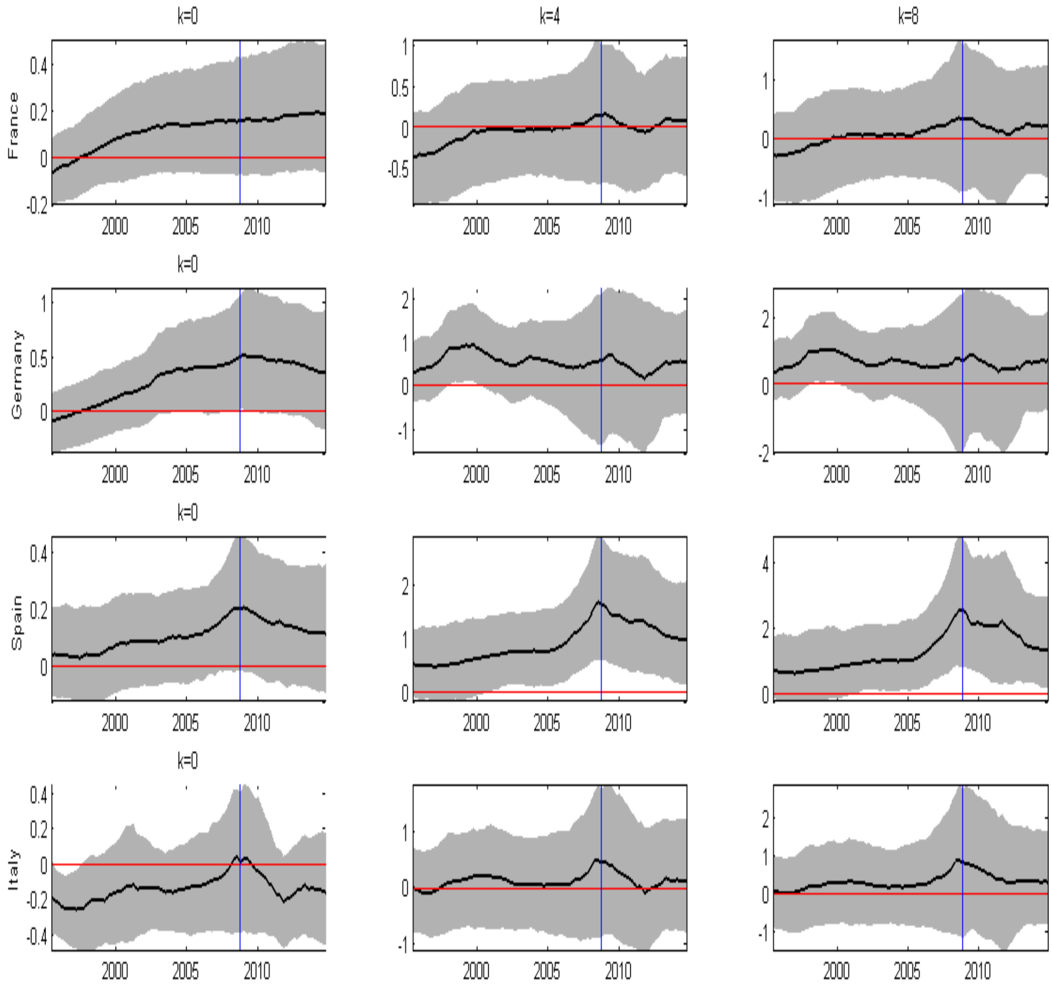


Figure 2.6: impulse response functions to a government spending shock in France.

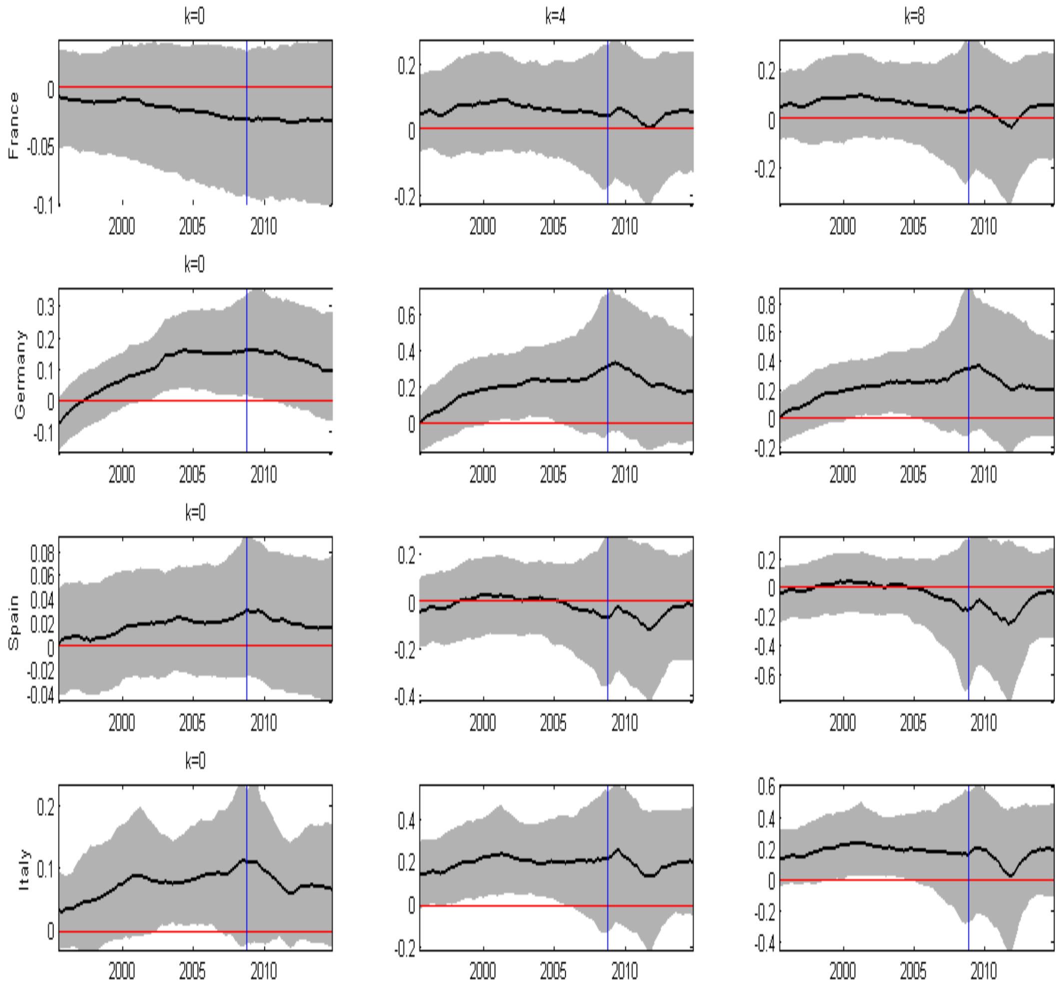


Figure 2.7: impulse response functions to a government spending shock in Germany.

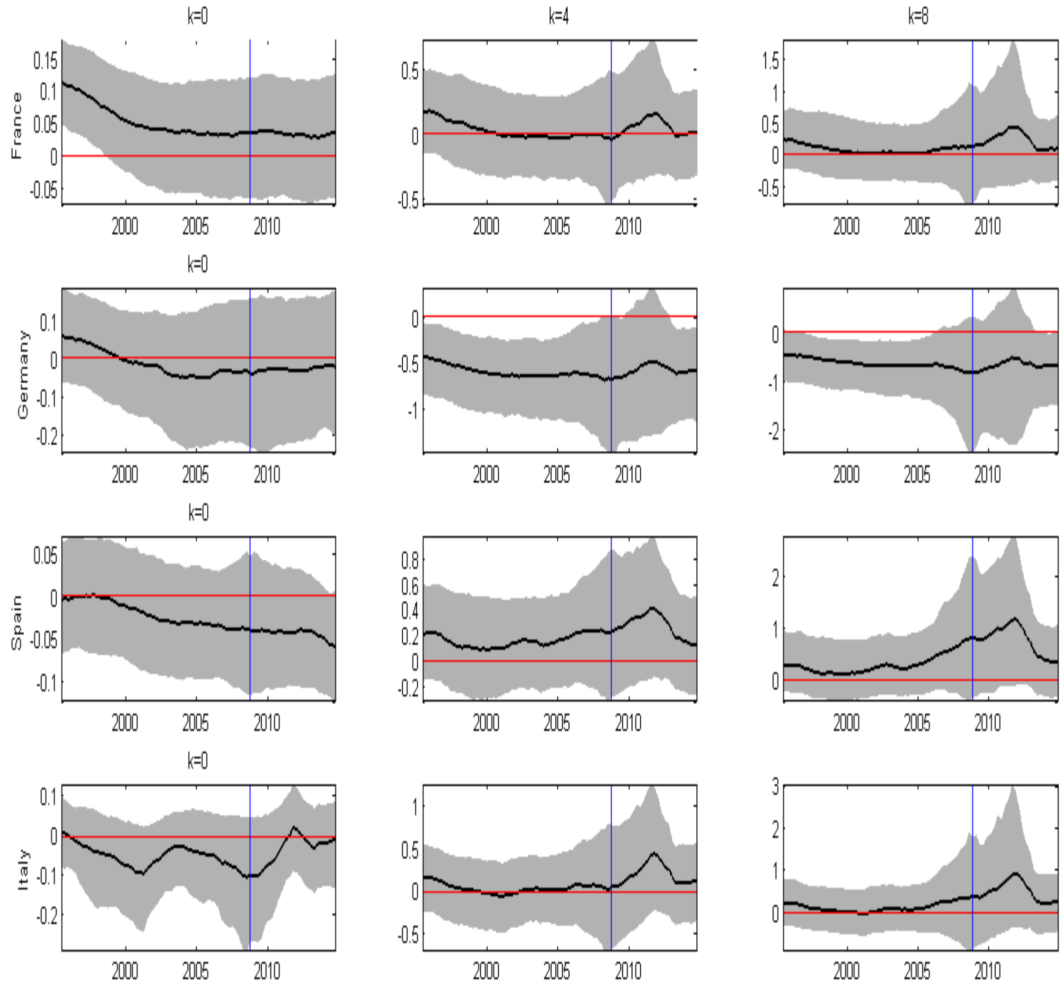


Figure 2.8: impulse response functions to a government spending shock in Spain.

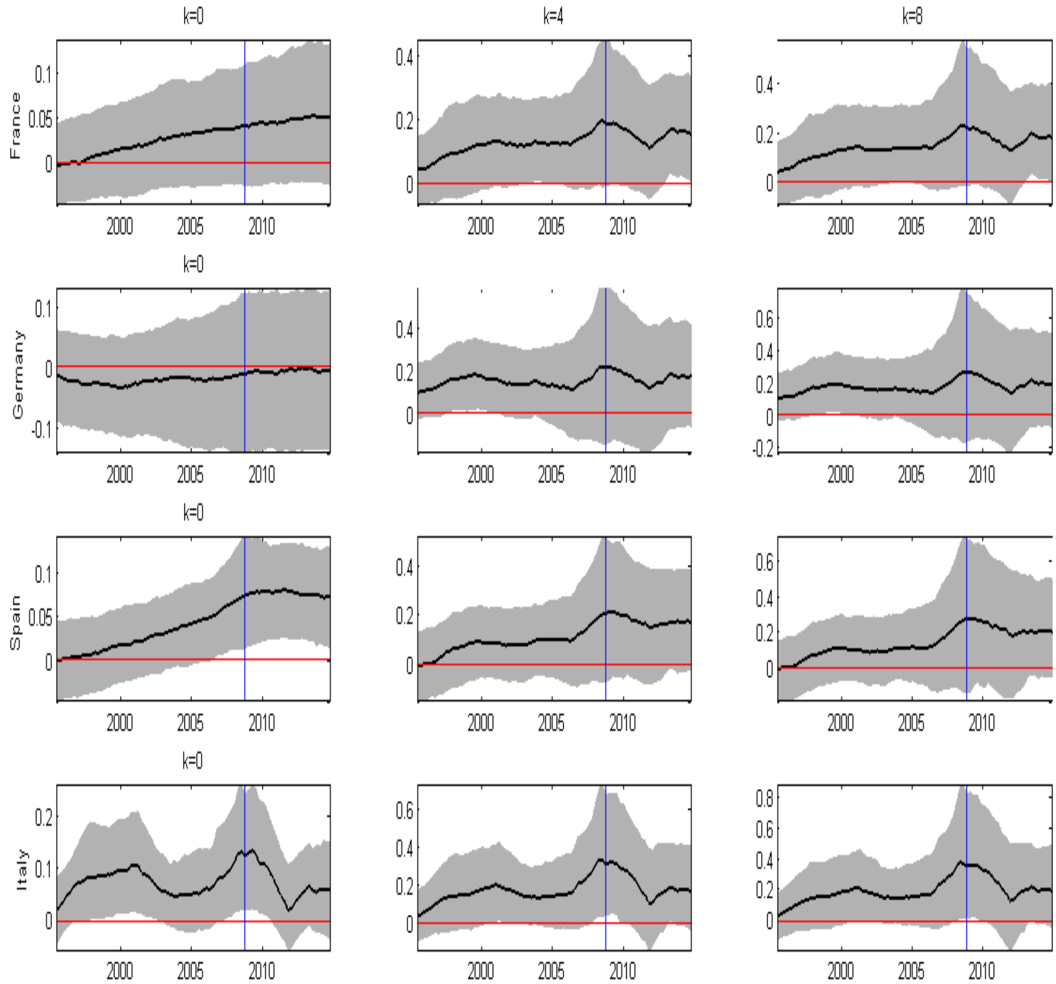


Figure 2.9: impulse response functions to a government spending shock in Italy.

Chapter 3

SVAR in the “miracle”: productivity of social capital, human capital, and output in the post-war Italy.

Abstract

This work explores the effects of productivity shocks on the growth profile of post war Italy. Namely, in a multi-sector context, we use a SVAR model to disentangle the relative contributions of productivity shocks of output, human capital and social capital.

Empirical results show that an increase in social capital productivity affects output positively. Conversely, it does not have any relevant effect on human capital accumulation. Also, consistently with endogenous growth theory, we find that human capital shocks affect GDP growth. This result is robust to different lags specifications and to exclusion of social capital from the analysis.

Finally, we find that social capital productivity accounts for a relevant portion of GDP movements. However, classical factors of development – namely human capital and TFP – still have a prominent role in explaining GDP variations.

JEL classification: A130, C320, N130, N140, O520.
Keywords: Social Capital, Trust, Human Capital, Growth, Italy, Multivariate Time Series.

3.1 The empirical question and motivation.

The debate on the determinants of growth is an ever lasting issue, which have been approached from various socioeconomic perspectives. On the one hand, neoclassical growth theorists – starting from Solow (1956) and Swan (1956) – stressed the importance of technological advances in explaining the growth path of an economy. Also, endogenous growth models – based on the contributions of Romer (1986), Lucas (1988) and Rebelo (1991) – shed some light on the role played by investment in human capital, innovation and knowledge in enhancing the economic performance of a country. On the other hand, more recent literature focused on alternative factors of growth, closely related to the structure of the society itself rather than to its economic features. Putnam et al. (1993), in their seminal work, paved the way to a new concept in development comparisons – the so called *"social capital"*. Their contribution originated a vast literature on the role of social capital in explaining regional differences (see for instance Beugelsdijk and van Schaik (2005); Helliwell and Putnam (1995); Knack and Keefer (1997)). This is particularly relevant when applied to the Italian case, where the north-south divide is sensibly persistent over the long run.

In studying this internal phenomenon the overwhelming majority of scholars relied on panel data analysis with non structural regression techniques. The reason for this is at least twofold: First, panel data is the most sensitive approach to perform cross-section comparisons. Second, data availability for Italy is strongly limiting the range of action, given that official figures are rarely made available by the *National Institute of statistics* (ISTAT) or by the *Bank of Italy* for periods preceding 1970. Thus, the bulk of the research is based on data reconstructed by historiographer for specific benchmark years – typically each decade. This naturally calls for panel data techniques.

Nevertheless, recent work carried forth in occasion of the 150^{th} anniversary of Italian Unification, allowed the *National Institute of Statistic* to publish a set of long term time series, covering different aspects of the social, political, and economic life of the country. This new data availability coupled with the existing historical reconstructions will allow us to approach the issue of the Italian growth and its determinants with econometric tools other that panel data.

In fact, our study makes use of multivariate time series methods to merge variables well-established in the growth literature – such as human capital and technology – with the more controversial concept of social capital. So far very little have been done through time series on this matter, both because of data limitations and because researchers have been much concerned with internal and cross-section inequalities. In this sense we depart from the preceding literature: we focus on the evolution of the whole national aggregate, trying to disentangle the relevance of specific structural shocks. More in detail, building on the idea of a multi-sector economy, we want to quantify the effects of productivity shocks of social capital, human capital, and output.

Our contribution is twofold: On the one hand we take advantage of recently released data, which have not been much exploited so far. On the other hand we propose a different methodological approach to study the role of social capital in the growth profile of Italy. While panel data techniques cannot escape the worries about the quality of the regressors and the need of instrumenting to correct for measurement errors, simultaneity and endogeneity, a time series approach can help to compensate these constraints, joining more series in a system in which all the variables are free to influence each other. The use of an alternative methodology, that to our best knowledge has not been applied to the specific subject so far, might allow to grasp a deeper understanding of social capital as a development factor and to test some theories on his role.

In the present study we proceed as follows: Section 3.2 starts with introducing some broad features to frame the concept of social capital. Then, we shape it in greater detail and we derive a measurement proxy coherent with the definition proposed. Section 3.3 preforms a growth accounting exercise to derive a time series for human capital. Our results are contrasted with other standard databases which report comparable information at benchmark years. Next, Section 3.4 summarizes the relevant characteristics of endogenous growth models dealing with social capital. This allows us to choose a sensible set of restrictions to properly identify productivity shocks in each sector. In Section 3.5 we briefly explain how to implement the identification scheme proposed, we deal with cointegration and finally we proceed to the SVAR analysis, performing impulse responses and variance decomposition. Finally, Section 3.6 summarizes and concludes.

3.2 Social Capital: definition and proxy.

Probably one of the main contributions of the economic literature of the 60s has been proposing that as physical capital could be represented by broadly defined productive equipment, by analogy, another form of asset – human capital – could be embodied in individuals, in their skills and capabilities (see for instance Schultz (1961); Becker (1962)).

If physical and human capital are nowadays well-established concepts in the literature, it is not the same for social capital whose dimensions and determinants, whose goods and evils and whose measurement are still object of debate in the literature (for a more extensive revision of the different approaches to social capital see Paldam and Svendsen (2000); Paldam (2000)).

To avoid ambiguities, we start with describing some broad features that characterize social capital and we give a definition of the concept within this framework. Then, we present the measurement proxy used to capture this controversial variable.

3.2.1 Some framing features.

Quoting from the celebrated 'Making Democracy Work' by Putnam et al. (1993): "*Social capital refers to features of social organization such as trust, norms and networks that can improve the efficiency of the society by facilitating coordinated action*". In this broad framework, social capital refers to a quite wide range of elements, but allows us to set two initial features that characterize it: it must relate to the **structure of the society (I)** and it should **facilitate interaction (II)** among agents – considered either individually or in groups.

Social capital is relative to a population $\mathcal{A}$ composed by $i = 1, \ldots, N$ individuals which can be thought of as people residing in a certain location (say a town or a village), as members of a corporation, as an ethnic group, etc. Depending on the size of $\mathcal{A}$ we can use "group" to refer to a relatively limited amount of agents and "population" when we consider a larger aggregate of individuals. Therefore, social capital is a micro concept that can be extended to macroeconomic applications (on which we want to focus indeed) by enlarging the size of $\mathcal{A}$ to include the whole national aggregate. Each individual in $\mathcal{A}$ has a certain quantity of social capital s_i and the population overall is endowed with an total amount $S_{\mathcal{A}}$, which is derived by aggregating the contributions s_i over the set of individuals. The population of object is therefore characterized by a level of $S_{\mathcal{A}}$ and, as underlined in point **(I)** above, by a structure of individuals' social capital.

Also, the dynamics implied in the social interactions between agents can provoke changes and adjustments in the individuals' s_i. As a consequence the aggregate level $S_{\mathcal{A}}$ might vary too. Therefore, another founding feature of social capital is that it can **evolve over time (III)**, allowing to describe it in terms of *stock* and *flows*, as is it generally done for other kinds of capital.

Moreover, as stressed by Coleman (1988), there are more parallels that can be established between social capital and the other types of assets. Like physical and human capital, social capital is also **productive (IV)**, making feasible the achievement of goals that would not be possible otherwise. Also, similarly to these assets, it is not completely fungible but it might be specific to a certain category of economic activities: A component of social capital that is very valuable in enhancing a given type of action can be useless or even harmful if applied in a different economic context. As an example, consider the connection in a network of a given population $\mathcal{A}$: If we are referring to the industrial organization of a set of firms, a network structure can be very helpful in stimulating the efficiency of the productive process – for instance by reducing transaction costs, or by facilitating logistics and distribution. Conversely, if we apply the same concept to criminal organizations, the network can provide with more intense illegal activity, with the consequent negative spillovers on the civil society. Thus, to properly define social capital is not enough to consider the mere structure of $\mathcal{A}$ (in our example not all networks equally generate social capital) and we should focus on those items that, at least potentially, generate positive influence on output.

Furthermore, there are some prominent differences between social, physical and human capital. Conversely to the latter two, the former is not to be found in the agents' qualities nor is lodged in any physical implement of the production. If fact, as underlined above, the endowment of s_i inheres more to the amount and to the intensity of the connections between individuals in $\mathcal{A}$, which define the *existence* and *structure* of a society. If the removal of such connections does not alter the inventory of physical and human capital – because in principle no machinery or skills are directly destroyed by removing links between agents – the same does not hold true for social capital. Indeed, isolated individuals do not form a society, and with no society there is no such thing as social capital. This is why social capital is a way more intangible asset and from here proceed the difficulties in clearly tracing his borders.

To sum up, and before digging in more specific details, we have to keep in mind four distinguishing features of social capital to be included in our definition:

(I) It relates to the *structure* of the *society* which is defined by a population $\mathcal{A}$ of individuals $i = 1, \ldots, N$ and the connections between them, individually or in groups.

(II) It should facilitate cooperation between different subsets of $\mathcal{A}$, that is, between single individuals or groups of individuals within a given society.

(III) Its endowment, on an individual s_i as well as on an aggregate level $S_{\mathcal{A}}$, can evolve over time thus generating a *stock* and *flow* dynamic.

(IV) It is productive, in the sense that it can foster output, making possible achievements that would not be reached otherwise.

3.2.2 Social capital: definition.

As seen in the previous section, one of the founding features of social capital is its ability to promote coordinated action between individuals. Other than Putnam, more authors stress this point: Guiso et al. (2006) first underline the relevance for economic output of "culture" identified as "*those customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation*". From this starting point they define social capital as "good culture", *i.e.* "*as the set of beliefs and values that foster cooperation among the members of a community*" (Guiso et al. (2008)). However, Dasgupta (2002) argues that interpreting all kinds of cooperative behavior as social capital can be misleading, given the too vast amount of incommensurable objects that can fall within this category.

Starting from this critique, we restrict our analysis on what Paldam (2000) named the *'trust-cooperation complex'* which is probably the most coherent category for defining social capital, given the context in which we want to apply it. To avoid ambiguities, it is convenient to have a closer glimpse at *trust* and its relation with the ease of cooperation between individuals. Also, we can detail how this concept is compatible with the framing features listed above.

Once more we have to face the problem of copiousness of trust definitions proposed by different social science. For instance, Gambetta (1988) states that trust is "*the probability that one economic actor will make decisions and take actions that will be beneficial, or at the least not detrimental to another*" – consequently making cooperation a strategy more profitable than competition. Other authors link trust to confidence, suggesting the existence of some limits to the agent's rationality. In fact, individuals take part in shared actions even if the stakes of getting hurt in case of betrayal are higher that the actual losses derived by non participating (for an extensive review of the various approaches to this concept see Hosmer (1995)).

Among the possible definitions available in the literature we privilege Healy (2002) [1], who suggests that trust is affected by personal experience and can be built in shared action.

Definition 1 (Trust) *Trust describes a belief about the good intentions and expected behavior of others. Trust arises from experience of other people trustworthy actions as well as innate or socially determined views about others.*

It is clear that trust refers to the relation between individuals who interact within a given society, thus trivially satisfying feature **(I)**. What is more interesting for our analysis is that trust can be an engine of coordinated action: People who trust each other work together more easily while without it cooperation is limited to activities that do not require intense monitoring. This is compatible with feature **(II)**. Furthermore, voluntary cooperation and trust are interwoven and posses some interactive simultaneity. On the one hand trust is crucial to most cooperation. On the other hand by working together people build further goodwill. Thus the key assumption is:

$$\text{trust} \Leftrightarrow \text{ease of voulntary cooperation} + e, \text{ where } e \text{ is a small error.}$$

In this context agents are subject to a double *learning process*, one that refers to the adjustment of individuals to the common level of trust and the other that concerns

[1] OECD definition emerged in the 'International Conference on Social Capital Measurement'.

the evolution of such level over time. As regards the former, suppose an agent has an uncommonly high level of trust. Such person will be the 'socialcholic' who is pushed to take part in too many cooperative acts, often being deluded by other people taking advantage of his goodwill. Conversely, if an individual has an unrealistically low level of trust he will be a 'misanthrope' who is under-cooperating in the society. This free rider, who exploits the participation of the others, is a potential parasite and might be subject to social sanctions after some time. Therefore, outliers with unrealistically high or low levels trust, might find it convenient to correct it and adjust to the general level of goodwill. Such learning processes are primary to the evolution of trust over time, thus making sensible its description in terms of stocks and flows, as requested by feature (**III**).

Following Paldam (2000) we are finally ready to characterize social capital:

Definition 2 (Social capital) *Social capital s_i is the amount of trust that individual $i \in \mathcal{A}$ has in other members of $\mathcal{A}$. The total amount of social capital $S_{\mathcal{A}}$ is obtained by aggregating the contributions s_i of each individual in $\mathcal{A}$.*

We have seen above that trust, and hence social capital in our definition, satisfies the framing feature (**I**) to (**III**). It remains to explain through which channels it can be productive (**IV**).

Advocates of the capital approach have interpreted social capital S as a factor of the production function, together with human and physical capital, H and K:

$$Y = F(K, H, S) \text{ with } \frac{\partial Y}{\partial S} > 0 \text{ and } \frac{\partial^2 Y}{\partial S^2} < 0.$$

This is a cheap way to justify that social capital is productive but it does not go without criticisms. In fact, it is generally assumed that production inputs are complement, hence $F(0, H, S) = F(K, 0, S) = 0$. Treating social capital in a similar fashion would imply $F(K, H, 0) = 0$. In other words, complete distrust ($S = 0$) paralyzes the productive system to a point that individuals are not able to generate any output – which is a quite extreme assumption.

It is more sensible to assert that social capital fosters output not as an input but rather as a factor that reduces frictions and makes the final good sector more virtuous. Trust can affect positively an economy by diminishing monitoring costs and by making transactions easier. Its role is to reduce frictions in a way that makes feasible achievements that would not be otherwise possible.

An example borrowed from Coleman on the wholesales of diamonds can clarify this point. In this market it is common practice that during the negotiation of a sale the merchant hands over a bag of stones to the potential buyer, who can examine them in private and at his own leisure. In doing so there is no formal insurance that the buyer will not try substitute one or more diamonds with other of inferior quality or with false replicas. The stakes at play are substantial, because of the high value of the merchandise, but this risky exchange of stones for inspection is a fundamental component of the good functioning of the market. This does not mean that there would be no trade of diamonds at all without this practice, but their exchange would be more cumbersome and way less efficient. In this sense the trust existing between the seller and buyer can enhance their economic relation, but it is not physically producing any diamond, nor is it *conditio sine qua non* of the trade.

Finally, there is a last clarification that is worth mentioning. Trust-based relations generate networks that can reduce transaction costs and enhance economic activity. However, networks can act in the opposite direction: a group may exploit its ties to achieve narrow internal interests, advantageous for the members and detrimental to the outsiders (for instance lobbying groups).

Sabatini (2008) divides social capital in three subcategories: *bonding*, *bridging* and *linking*. The word *bonding* has a negative connotation and refers to a small circle of homogeneous subjects that do not cooperate with other people outside the group. *Bridging* is used to define horizontal ties that link heterogeneous agents with different backgrounds. The term alludes to networks that generate a bridge between sectors of the society that would be otherwise disconnected, fostering the diffusion of information and trust among individuals. Lastly, *linking* social capital relates to vertical connections with subjects in position of political or financial prominence. This allow individuals to bring forward their issues and interests on higher levels.

Sabatini shows that bridging social capital has positive impact on human development and sustainable growth, and indeed this is the concept that more closely relates to our definition. Bearing in mind these details can guide us in the selection of a sensible measurement proxy that captures social capital spillovers on the economy.

3.2.3 Social capital: measurement proxy.

A first theoretical difficulty regarding our work was to define a concept which is as appealing as difficult to frame. Once this first issue is settled, there is still the problem of measuring such a poorly tangible object. This task is made harder by the empirical application on which we are focusing. In fact, we need a measure that is at the same time synthetic – capturing the macro evolution of social capital – and informative – reflecting the theoretical framework presented above. On top of this, we have to face the challenge of data availability over a wide time spam of time.

To circumvent the problem we can take inspiration from Putnam et al. (1993), who suggest the relevance of voluntary organizations as a measure of social capital. As a matter of fact, many empirical studies rely on such variable, under the presumption that groups and associations work as a "school of democracy" where values of participation, reciprocity and mutual confidence are easily socialized. Group membership facilitates the learning of cooperative behavior and increases the horizontal interaction between people, paving the way for the diffusion of trust and information. This is in line with the idea that trust and ease of voluntary cooperation are closely related. Moreover, as Paldam and Svendsen (2000) underlined, the so called *Putnam's Instrument*, *i.e.* the density of voluntary organizations, is an "easy-to-use proxy".

However, this measure is not exempt from critiques. For instance there exist the possibility of individuals self-selecting into an association group. As a result, the organization might gather people from similar backgrounds and might fail to have that connotation of heterogeneity which allows to bridge between different sectors of the society. Also, simple group belonging does not always imply interpersonal contact and value sharing. This is especially true in modern economies where membership can be limited to the payment of an annual subscription fee.

In the light of this, we use a slightly different measure which is based on the *number* of voluntary organizations (per capita) rather that on their *density*. The underlying idea is that the stock of associations reflects a general level of trust in the economy and thus can be used as an indicator of aggregate social capital. This measure is rougher than group density but has some clear advantage. First of all, it relaxes data issues on membership, which is not available for periods very distant in the past. Also, it satisfies the need of aggregation without escaping the general framing of social capital. Thus the measure we propose is at the same time handy and coherent, settling a reasonable compromise between synthesis and information.

Data on voluntary organizations is withdrawn from ISTAT 2001 census on industry and services. Specifically, we exploit a micro panel on no profit associations which was already used by Nuzzo (2006) for building a social capital index. At the moment of selecting which associations are suitable to represent social capital we have to be a cautious. As a matter of fact, no profit is a quite vast universe which the same Nuzzo classifies into three subsets: *pro-social*, *cultural* and *interest protecting - mutualistic*.

In our judgment the first category is the most accurate for representing those values of cooperation and civic norms that are generated by bridging social capital. Specifically we use data on volunteering, *comitati*, NGOs, and associations. Regarding this latter category, which accounts for the bulk of the no profits in Italy, we select *pro-loco* and those associations dealing with rights protection, environment, solidarity and civil protection.

The second subset, *cultural*, is discarded because it contains institution – as universities and research centers – that are better suited to capture education. Given that human capital will be later introduced in the analysis, it is wise to keep it clearly separated from social capital. This is why we avoid the use of organizations that might cause ambiguities between the two concepts.

The latter subset is also excluded from the proxy because it contains groups that show the characteristics of bonding social capital. A clear example is given by the "category association" which gather a specific profiles of subjects – merchants, farmers, artisans, etc. – with the scope of protecting their interest, promoting contacts among associates and preform actions of lobbying. This kind of groups are exclusive and lack the heterogeneity that is primary to the diffusion of trust between different sector of the society, thus are not suitable to measure bridging social capital.

Once we have identified the organizations that suit the definition of social capital, we have to build an estimate of their past stock along the whole series. We follow Nuzzo who takes advantage the year of foundation of each organization and we augment his approach with the *perpetual inventory* method. We assume that the accumulation rule of social capital follows:

$$S_t = I^s_{t-1} + (1-\delta)S_{t-1} \quad \text{for t} \in [T_0, T] \tag{3.1}$$

where S_t represents stock of social capital, I^s_t investment – *i.e.* the foundation of new associations – and δ is a depreciation factor assumed to be constant over time. Starting from T, simple recursive substitution allow reconstructing past observation by means of:

$$S_{T-h} = \frac{S_T}{(1-\delta)^h} - \sum_{j=0}^{h-1} \frac{I^s_{T-j}}{(1-\delta)^{h-j}}. \tag{3.2}$$

However, what we observe in the data are only organizations existing at time T, that is, the portion of past investment that survived depreciation. In other words, if at $t \in [T_0, T]$ the (unobservable) amount of new associations I^s_t was created, what we can see in the data is the quantity I^d_t that depreciated for $T-t$ consecutive years.

$$I^d_t = I^s_t(1-\delta)^{T-t} \tag{3.3}$$

In the appendix we show that from (3.2) and (3.3) we can express past stock of social capital as:

$$S_{T-h} = \sum_{j=T_0}^{T-h} \frac{I^d_j}{(1-\delta)^h} \tag{3.4}$$

which is all available information.

Finally, we fill the last years of the series with a linear projections based on a AR(4) process. We make sure that this is not affecting the VAR estimates by performing the analysis both till 2001 and till 2011. Lastly, we divide the series over population to obtain a per capita measure.

The limits of this procedure clearly reside in the accuracy of the historical reconstruction. The more we depart from a restricted time neighborhood of the census date the more information is lost, making the proxy less reliable. Also, the perpetual inventory alone cannot account for regime switches or world conflicts that might have indeed an impact on the level and evolution of social capital. This is why, even if numerically we can compute the complete series, we only perform the estimation using observations following 1946.

3.3 Human Capital and Growth accounting.

In this section we perform a growth accounting exercise, meant to obtain a complete time series of human capital H for the Italian economy. Many empirical and theoretical works have used human capital as a productive input, under the presumption that an educated labor force is better at creating, implementing, and adopting new technologies. For instance Lucas (1988) incorporated investment in H both as a determinant of the labor supplied (only time not dedicated to training and education can be devoted to production) and as a factor of production.

On this premise we adopt as a benchmark for our exercise Hall and Jones (1996, 1999), who modeled GDP Y as being engendered according to:

$$Y_t = K_t^{\alpha}(A_t H_t)^{1-\alpha} \tag{3.5}$$

where K is the aggregate capital stock, A is technology (TFP), H is human capital augmented labor and α is a constant. More specifically, H takes the form of:

$$H_t = e^{\phi(MYS_t)} L_t \tag{3.6}$$

where MYS is the average educational level measured in mean years of schooling, $\phi(\cdot)$ is a function of returns to education and L is the labor force.

Under the assumption that the production function does not change its functional form over the period in analysis, TFP could be derived as a residual once all the other quantities in (3.5) are computed. Baffigi and Broadberry et al. report data on GDP, physical capital accumulation and labor participation, hence the only variable we need to determine is H.

Nowadays human capital is a well established concept, whose formal theory was developed in the second half of the twentieth century by scholars such as Gary S. Becker, Theodore W. Schultz, and Jacob Mincer. However, it is also a non perfectly tangible asset and when it comes to empirical applications we have to face the issue of correctly quantifying it. To this scope the literature offers a wide range of alternative methodologies, but it is clear that education is a fundamental component of H and can be sensibly employed as a proxy for its measurement. For instance Azariadis and Drazen

(1990) and Romer (1989) relate human capital to the literacy level of the population, while Barro (1991) and Mankiw et al. (1992) prefer to use school enrollment rates instead (for a review of alternative proxies of human capital see Wößmann (2003)). As a matter of fact, according to the specification adopted, computing H translates into computing the mean level of education MYS and choosing an appropriate functional form for $\phi(\cdot)$ in (3.6).

Frequently in empirical growth studies the choice of proxies for MYS is dictated by data availability – especially when dealing with a wide spam of time – with the result that the analysis can be constrained to variables scarcely representing the underlying concept. To solve this issue we can use school enrollment data which offer a twofold advantage: This approach is quite standard in the literature, thus allowing for a sensible comparison with previous databases. Moreover, reliable figures on enrollment are available also for periods relatively distant in the past.

In order to compute aggregate years of schooling we use a simplified version of the perpetual inventory method designed by Nehru et al. (1995) and revised by Wößmann[2]. This technique presents the advantage of summing up data over time, making it possible to derive yearly observations of the series. In specific, the aggregate stock of schooling Sch embodied in the population at year t is given by:

$$Sch_t = Sch_t^{prim} + Sch_t^{sec} + Sch_t^{uni} \tag{3.7}$$

where the three members of the sum correspond to aggregate years of schooling imputed to primary school ($prim$), secondary school (sec) and university (uni).

Each of the three above categories is computed according to:

$$Sch_t^i = \sum_{\tau=t-A_h+D_0^i}^{t-A_l^i+D_0^i} \sum_g E_{g,\tau+g-1}\theta_{g,\tau+g-1,t} \quad \text{for } \ i = prim,\, sec,\, uni \tag{3.8}$$

where D_0^i is the age at which people enroll in the corresponding level of education

[2]Conversely to the original formulation of the proxy, we do not account for repeaters or for dropping-outs because specific figures are not available for the complete time spam. Furthermore, a glimpse to the available data shows that repetition rates are significantly decreasing over time, clashing with Wößmann's approach of assuming them constant. Hence we simply prefer not to correct for dropouts and repeaters, taking the risk of slightly overestimating MYS.

for the first time (6-14-19 respectively), A_h is the age of the oldest person in the population (set to 80), A_l^i the age at which individual with level of education $i = prim, sec, uni$ completes the corresponding school cycle and enters the labor force (14-19-23 respectively)[3], $E_{g,\tau}$ is the gross enrollment rate at period τ in the g^{th} year of the corresponding school level[4], and $\theta_{g,\tau,t}$ accounts for the "depreciation" of education and it is the probability that an individual enrolled in the g^{th} year of a school cycle at time τ survives till t. Finally, mean years of schooling MYS is expressed as a per capita measure:

$$MYS_t = Sch_t/N_t \tag{3.9}$$

where Sch was defined in (3.7) and N is national population.

Other databases, namely Barro and Lee (2010), UNDP-Unesco, Felice and Vasta (2012) and Cohen and Soto (2001), present comparable figures. Briefly, these authors observe the mean educational level of subjects within specific age bands and weight each age group to obtain the population average. This method is relatively simple but it requires a big deal of information which is usually available only at census dates. This is why these databases generally report observations at 5-10 year intervals, some of which computed with backwards or forwards extrapolations. The clear advantage of our methodology is that it needs less information to obtain more estimates. This allows us to compile a series of Italian MYS with a detail which is unprecedented in the literature, at least over such a wide spam of time. Moreover, even though our approach differs from the one of these authors, the underlying concept does not: doing

[3]We select this ages as benchmark under the generalization that school starts at the age of 6, primary education lasts 8 years (the old minimum compulsory schooling time), secondary education 5 years and university 4 more years. Indeed, if we did not brake the sum in (3.8) in three components, each of which with his extremes of summation, we would have a problem in the subscripts of (3.8). For instance suppose we set $A_l = 15$ for all categories, we would have that for $\tau = t - A_l + D_0$ there are individuals in the last year of university, i.e. in their fourteenth year of school ($g = 14$), for whom $\tau + g - 1 = (t - A_l + D_0) + g - 1 = t - 15 + 6 + 14 - 1 = t + 4$. This does not make any sense because the stock of Sch at t cannot depend on future values. Setting $A_l^i = 15, 19, 23$ and doing different summations we solve this problem. Notice that the interpretation of this is *not* that agents cannot study and work at the same time, since the years of lower school cycles are included in the summation also for those people continuing their studies. It follow that the correct interpretation of the index is that the active population is considered to be formed by agents aged 15-80, independently of their actual occupation.

[4]Notice that the support of g is also depending on the school level since in primary school $g \in [1, 8]$ for secondary $g \in [1, 5]$ and for university $g \in [1, 4]$. Hence, to be more precise we should have written a superscript g^i in (3.8), which we omitted to avoid too cumbersome notation.

a weighted average of mean educational levels is equivalent to dividing aggregate years of schooling by total population, thus we expect our results to be in line with previous estimates. As a matter of fact, Table 3.1 shows that the correlations both in levels and in first differences between our series and the existing databases are all high and significant. Figure 8 in the appendix makes this visually clearer.

Table 3.1: Mean year of schooling.

Database	Correlation coefficient ρ^1	
	Levels	First differences
Barro and Lee	0.998	0.932
	(0.000)	(0.000)
Cohen and Soto	0.9975	0.823
	(0.000)	(0.086)
Felice and Vasta	0.993	0.894
	(0.000)	(0.000)
Unesco - UNDP	0.971	0.667
	(0.000)	(0.025)

[1] Pearson's linear correlation coefficient between the databases specified and the mean years of schooling MYS obtained with the perpetual inventory method. Correlations are computed for data in levels and in first differences, selecting for MYS the observations at the same dates available in the source to be compared. P-values for testing no correlation against the alternative of nonzero correlation are reported in brackets.

Notice that Wößmann's techniques demands a lot of past information to be implemented. This is why – till 1941 – figures on MYS rely both on actual data and on backward projections of the enrollment rates. Notwithstanding this, our results are broadly in line with Felice and Vasta estimates for those years. However, to remove the uncertainty on the first part of the sample, we prefer to restrict the analysis on the years following 1946 for which all observations are computed on the basis of officially published data.

Finally, in order to compute the H series, it remains to make explicit the functional form of $\phi(\cdot)$ in (3.6). To this end we adopt the specification of Mincer (1974) who suggests a concave and piece-wise linear function whose slopes represent the average private return to schooling at different educational levels. On the spirit of Hall and Jones (1996) we use 13.4% for individuals with less than 4 years of school, which correspond to the sub-Saharan Africa returns estimated by Psacharopoulos and Patrinos (2004). As regards higher levels of education, we can rely on estimates more specific to the Italian case, namely we use 4.5% for individuals with 5–8 years of schooling, as in Brunello et al. (1999), and 2.3% for individuals with more than 8 years, based on Lorenz and Wagner (1990).

3.4 Theoretical background.

Even if empirical literature on social capital is quite copious, theoretical works are not equally abundant, especially when it comes to macro applications. This is probably because of the controversial nature of S, which makes it difficult to describe the channels and mechanism through which social capital acts on the economy.

A seminal contribution in this sense is due to Chou (2006) and to later works of Bofota et al. (2012) and Sequeira and Ferreira-Lopes (2011). These authors build on endogenous growth theory introducing social capital as a sate variable which affects the households' maximization problem and the equilibrium allocations. The basic ingredients of such models are: a multisectorial economy – including a final good sector, a human capital sector, and a third sector for social capital; competitive firms; and infinitely living agents maximizing a CRRA utility function. These authors add to the baseline of the Lucas - Uzawa model by introducing S as a factor in the production of H. In this fashion social capital gains a role in the aggregate economic outcome.

As customary in endogenous growth theory, the equilibrium result is that – in the balance growth path – the variables evolve at a constant rate g^*. In the Lucas - Uzawa baseline g^* depends (among other parameters) on the productivity of the H sector. The same holds true for models with social capital, in which the comparative statics underline how a better human capital production technology translates into a faster equilibrium growth. Conversely, there is no consensus on the role of the other sectors productivities, whose relevance for the equilibrium growth rate depends on author-specific assumptions.

Starting from these premises, we keep the idea of multiple sectors which relate to the time series at hand. What we advocate is that we can identify three structural shocks, one for each sector of the economy: a total factor productivity shock ξ^Y, a human capital productivity shock ξ^H and finally a social capital productivity shock ξ^S.

In a setting in which social capital produces human capital – which in turn is a factor of final output – it is intuitive how shocks propagate from the third to the second sector through S and similarly from the second to the first sector though H, but not all the way round. This means that ξ^Y only has transitory effects on H and S, and that ξ^H only has transitory effects on S. In other words, we can set three long run restrictions to zero. This is a sufficient condition to recover the implied structural shocks from the moving average reduced form.

The intuition behind this identification scheme is the following. First sector productivity (TFP) represents the efficiency with which labor and capital are combined to obtain output. A shock ξ^Y is therefore related to technological advance and there is no reason why technology *per se* should impact school enrollment or sociability. As regards the second sector, a shock ξ^H can be seen as an institutional reform, *e.g.* an increase in compulsory year of education. This can provide with a more skilled labor force – and consequently with more output – but should not affect long run trust, which is engendered with networking rather than with schooling. Lastly, regarding social capital, a positive productivity shocks endows the economy with higher S and, following the chain effects from one sector to the other, with more H and ultimately with more output. It can be argued that having S in the production of H is only a model assumption and that it is perfectly sensible to think that third sector productivity has no long run effects on education. However, we prefer to take a more agnostic stance on the role social capital and we avoid setting restrictions on its productivity shocks. In doing so, the effect of ξ^S will be delivered by the econometric analysis rather than by *a priori* imposed constraints.

For illustrative purposes, and to show that it is sensible to derive structural shocks from the reduced form, we provide with an example consistent with the theory and the restrictions presented above. Building on a simplified version of Bofota et al. (2012), we can focus on a subset of the equilibrium equations, concerning the production of the variables at hand:

$$Y_t = A_t H_t \tag{3.10}$$

$$H_{t+1} = B_t H_t^{\beta} S_t^{1-\beta} + (1-\delta) H_t \tag{3.11}$$

$$S_{t+1} = P_t S_t^{\eta} + (1-\delta) S_t \tag{3.12}$$

where β is in $[0, 1]$, $\eta > 0$ and A_t, B_t, P_t are the productivity parameters in the respective sectors. H is modeled as being produced by human and social capital with constant returns to scale, while S is produced with a technology that allows for non linearity. For simplicity, we assume full depreciation of both types of capitals ($\delta = 1$).

We can linearize the system with a log transformation, which delivers the interpretation of growth rates when we pass to first differences. Therefore, let small letters denote the natural logarithm of the variables, the above equations read:

$$y_t = a_t + h_t \tag{3.13}$$

$$h_{t+1} = b_t + \beta h_t + (1-\beta) s_t \tag{3.14}$$

$$s_{t+1} = p_t + \eta s_t \tag{3.15}$$

Next, we need to specify the dynamics of the productivity parameters, to be able to express the system as a function of present an past innovations of their processes. Regarding the third sector, taking first differences of (3.15) and exploiting the balanced growth path result $\Delta s_{t+1} = \Delta s_t = g^*$ is enough to infer that $(1-\eta)g^*$ can be interpreted as the deterministic component of the p_t process. As regards the two remaining sectors, we maintain the philosophy of endogenous theory – in which the productivity parameters are constant and growth comes as a result of the maximization problem – and thus posit processes for a, b which are constant in expectation. Specifically, given $a_0, b_0, p_0 > 0$ we assume:

$$a_t = a_{t-1} + \theta_y(L)\xi_t^y \tag{3.16}$$

$$b_t = b_{t-1} + \theta_h(L)\xi_t^h \tag{3.17}$$

$$p_t = p_{t-1} + (1-\eta)g^* + \theta_s(L)\xi_t^s \tag{3.18}$$

where ξ_t^y, ξ_t^h and ξ_t^s are zero mean and pairwise orthogonal innovations and $\theta_i(L)$ for $i = s,\ h,\ y$ are fundamental moving average processes of arbitrary length.

Now, subtracting from both sides of (3.14) and (3.15) h_t and s_t respectively we can express social and human capital as a function of g^* and of the productivity shocks.

After taking first differences and rearranging we have:

$$\Delta s_t = g^* + \frac{\theta_s(L)}{1-\eta}\xi_t^s \tag{3.19}$$

$$\Delta h_t = g^* + \frac{\theta_s(L)}{1-\eta}\xi_t^s + \frac{\theta_h(L)}{1-\beta}\xi_t^h \tag{3.20}$$

$$\Delta y_t = g^* + \frac{\theta_s(L)}{1-\eta}\xi_t^s + \frac{\theta_h(L)}{1-\beta}\xi_t^h + \theta_y(L)\xi_t^y \tag{3.21}$$

which in matrix notation reads:

$$\begin{pmatrix} \Delta s_t \\ \Delta h_t \\ \Delta y_t \end{pmatrix} = \begin{pmatrix} \mu_{11} \\ \mu_{21} \\ \mu_{31} \end{pmatrix} + \begin{pmatrix} \frac{1}{1-\eta}\theta_s(L) & 0 & 0 \\ \frac{1}{1-\eta}\theta_s(L) & \frac{1}{1-\beta}\theta_h(L) & 0 \\ \frac{1}{1-\eta}\theta_s(L) & \frac{1}{1-\beta}\theta_h(L) & \theta_y(L) \end{pmatrix} \begin{pmatrix} \xi_t^s \\ \xi_t^h \\ \xi_t^y \end{pmatrix} \tag{3.22}$$

where $\mu_{11} = \mu_{21} = \mu_{31} = g^*$. Notice that to obtain such result we made use of the balance growth path constancy of g^* which is likely to hold true in the long run, when the economy has reached an equilibrium. Thus, when we focus on the long run matrix ($L = 1$) it has a lower triangular form – which is indeed what our identifying restrictions would suggest.

$$\begin{pmatrix} \frac{1}{1-\eta}\theta_s(1) & 0 & 0 \\ \frac{1}{1-\eta}\theta_s(1) & \frac{1}{1-\beta}\theta_h(1) & 0 \\ \frac{1}{1-\eta}\theta_s(1) & \frac{1}{1-\beta}\theta_h(1) & \theta_y(1) \end{pmatrix}$$

3.5 Empirical results.

3.5.1 Cointegration.

Before running the estimation we have a glimpse at our time series, gathered in a single plot in Figure 1. As regards Y, Baffigi's data shows how GDP was growing at a slow pace of roughly 1% till 1945-46. The picture displays observations starting from the beginning of the so called "economic miracle" – after which Y boomed to a faster growth of 3% almost uninterrupted till the recent financial crisis. Also H, as computed in (3.6), shows an upward pattern which is consistent with the increase in the schooling level of the Italian population. The same goes for S which reflects the *per capita* increment of voluntary organizations. The picture suggests that the series are not stationary in levels and before running the VAR in log differences we need to address the question of possible common trends.

First, we check that each series (in log) is $I(1)$ – which is a necessary condition for cointegration. In order to do so, we select and appropriate number of lags, we estimate the univariate processes and test the residuals for autocorrelation. Then, depending on the number of lags and on the structure of the error term we run either the Phillips-Perron or the Augmented Dickey-Fuller test, to detect possible unit roots. Finally, we repeat the above procedure for the observations in log differences.

Test results show that the series in levels are non stationary, while the null of unit root is rejected for differenced data. This means that our processes are indeed individually $I(1)$ and further testing is needed to remove the concerns of cointegration.

In specific, we perform Engle and Granger's routine whose null hypothesis is no cointegration[5]. The test consists in regressing one series onto the others and checking how the residuals behave. If they are stationary, the regression coefficient represents a cointegrating vector – which delivers an $I(0)$ series out of a linear combination of $I(1)$ processes. Conversely, when the error term shows a unit root, the inference is that we cannot reject the null of no cointegration. Since test result might be driven by the choice of the LHS variable we repeat the routine for the three time series at hand. In Table 3.2 we report the values of the Augmented Dickey-Fuller test performed after each regression.

As it emerges from the table, the p-values relative to the specification suggested by the information criteria cannot reject the null of unit root. This means that residuals are not stationary and thus there there is no cointegration between the series.

[5]We privilege this test over Johansen's because the latter gives results that are too heterogeneous: depending on the number of lags and on the type of statistic used – either maximum eigenvalue or trace – the test suggests none, one or two conintegrating relations. This makes it difficult to do good inference on possible common trends and hence we prefer to use Engle and Granger's test which is independent of the lag structure chosen.

Table 3.2: Engle and Granger cointegration test.

	$\mathbf{s}^1$		$\mathbf{h}^1$		$\mathbf{y}^1$	
ADF lags[2]	tStat	pValue	tStat	pValue	tStat	pValue
1	−1.8018	0.8124*	−3.4024	0.1334*	−2.4319	0.5327*
2	−1.6068	0.8715	−3.3979	0.1345	−2.7084	0.4083
3	−2.0909	0.6861	−4.2850	0.0190	−2.6266	0.4451

[1] The columns **s**, **h** and **y** indicate which series is used as the LHS of the test regression.
[2] The Augmented Dickey-Fuller performed on the residuals z_t tests the the null hypothesis $H_0: \quad z_t = z_{t-1} + \beta_1 \Delta z_{t-1} + \cdots + \beta_p \Delta z_{t-p} + \epsilon_t$ under different lag specifications. Test statistics below the critical value of -3.8778 reject the null in favor of the alternative of no unit root. The symbol * on pValue marks the number of lags p suggested by the AIC, BIC and HQC information criteria.

3.5.2 Estimates.

After removing concerns about common trends, we can proceed to the estimation of our SVAR in first differences. Once more we make use of information criteria to select the number of lags to be included in the reduced form equations. Both the AIQ and the BIC suggest a VAR(1) – which we use as our baseline specification. However, the processes involved in the analysis are by their own nature slowly evolutionary (education and trust take time to be built over time) and few lags might lead to ignoring important information carried forth by past realizations of the series. For this reason and as a robustness check, we will also try richer lag structures.

Figure 2 contains the impulse responses obtained from the baseline specification of (**??**). Unit shock on growth rates are computed for 20 years and summed over the forecast horizons to obtain their cumulative effects. Other than point estimates, 90% confidence bands are obtained by bootstrapping.

As stated above, identification is reached via log rung zero restriction as in Blanchard and Quah (1989). Indeed, in the long run the matrix of cumulative multipliers is lower triangular and restricted impulse responses fade down to zero. This reflects how TPF movements have only transitory effects on H and S. More in specific, point estimates of ξ^y shocks are negative on such variables. In the light of endogenous growth models – in which individuals have to split their time between working, studying and socializing – this can be interpreted as a reallocation of resources from a sector to another. An increase in TPF is an incentive in optimally devoting more time to final good sector, which is now more productive. This is done at the expenses of second and third sectors and turns into a temporary reduction of human and social capital. Nevertheless, this reallocation effect is small: a 1% increase in final sector productivity would imply a short run decrease in S and H of the order of 0.5% and 0.2% respectively, and non significant in the latter case[6].

As regards ξ^h shocks, the null effects on S appear not only in the long run but also on impact, where bootstrap bands are so wide that not even reducing the confidence level would be enough to grant significance. Conversely, the effects on final good sector are clearly positive – which is expected given that H is an input of the production function.

Moreover, if we focus on the 2×2 bottom right subsystem given by H and Y, the graphs are consistent with Lucas and Uzawa's theory (which does not include social capital). As discussed above, the balanced growth path result of this model is that the growth rate g^* is a direct function of human capital productivity but not of TFP. This implies that first sector shocks are only temporary while ξ^h is relevant for long run economic growth. Namely, our estimates would suggest an almost 3% response of output to a unit increase in education productivity.

In order to check that this result is not a fluke driven by the introduction S in the SVAR, we replicate the estimation in a two-dimensional setting, using H and Y alone. Under the same long-run triangular restrictions we obtain results compatible with the ones presented in this section. Figure 6 in the appendix shows that impulse responses look alike in the baseline model and in the two-dimensional SVAR. Specifically, in the latter case, a 1% shock in ξ^h implies roughly a 2.5% long run increase in output.

Finally, let's have a look at the third sector. Not surprisingly, the effects of ξ^s on S itself are positive (of the order of 1.5%) which – under our identification scheme – implies that the dynamics of social capital are mainly driven by changes in its own productivity. Also, we find evidence of positive effects on Y, which stand in favor of the literature advocating that social capital fosters output.

What is more astonishing, is the non significant response of H to ξ^s at all horizons.

[6]However, recall that plotted bootstrap bands represent 90% confidence intervals. Shrinking the bands down to a conventional 68% would be enough to make the latter shock statistically different from zero.

This seems to clash with the theoretical literature presented above, in which social capital is assumed to be an input in the second sector. To see if we can recover impulse responses consistent with those models we perform the estimation again, adding more lags of the independent variables. Figure 3 compares the effects of a ξ^s shock in the baseline VAR(1) with the ones obtained in a VAR(4). Apart from the responses plotted in figure 3, the other graphs are similar in sign and significance across specifications, as can be seen in figure **??** in the appendix, which reports the complete set of impulse responses obtained from the VAR(4). However, this latter specification amplifies the effects of social capital productivity on Y threefold – from 2% to 6% – which is quite unrealistic. Moreover, significance of ξ^s shocks on H is obtained only by reducing the confidence level to 68%.

This detracts from having S in the production function of H, which surely does the algebra and gives relevance to social capital in theoretical models, but does not find empirical confirmation. That is, when we work with the baseline specification (but the same holds true for a VAR of order 2 or 3), ξ^s shocks seem to be irrelevant for human capital dynamics. This poses the theoretical challenge of modeling an alternative way through which social capital affects final good production.

As a last exercise, we compute the relative importance of the identified shocks for the implied changes in output. Table 3.3 contains the variance decomposition of y on impact and after 1, 5, 10, 15 and 20 years. In the baseline specification, we can see that ξ^s shocks explain a percentage of output variation that ranges from a 9% on impact up to a 18% in the long run. This suggests that social capital evolves slowly and takes 5-6 periods to exhaust its positive spillovers on the economy.

In what concerns ξ^h, it comes as no surprise that it explains a high share of GDP variance. In fact, endogenous growth models agree on the fact that H productivity positively affects the economic outcome – both in the balanced growth path and in the comparative statics. Therefore, a portion of the variance decomposition of around 45% looks perfectly sound for this productivity shock.

Finally, also TFP movements are relevant both on impact (41%) and in the long run (37%). The relative decrease of their percentage over time might reflect technological obsolescence: if on the one hand ξ^s slowly gains relevance over time, on the other hand, technology highly affects the economy immediately but its effects fade away faster.

Table 3.3: Output y variance Decomposition

		horizons					
		0	1	5	10	15	20
	ξ^s	0.0912	0.1612	0.1840	0.1842	0.1842	0.1842
VAR(1)	ξ^h	0.4926	0.4649	0.4429	0.4427	0.4427	0.4427
	ξ^y	0.4156	0.3738	0.3731	0.3731	0.3731	0.3731
	ξ^s	0.4086	0.4246	0.4208	0.4200	0.4232	0.4242
VAR(4)	ξ^h	0.4204	0.4001	0.3673	0.3631	0.3595	0.3584
	ξ^y	0.1710	0.1752	0.2119	0.2170	0.2173	0.2174

For completeness, and to give a picture of how the effects of ξ^s are amplified when we increase the number of lags, Table 3.3 also reports the values obtained from a VAR(4). As it clear comparing the two subsections of the table, results concerning human capital productivity are not excessively sensitive to lag specification. Conversely, as regard social capital, a richer lag structure increases the share of output variance attributable to ξ^s fourfold on impact and more than twice overall, placing it around an unrealistically high 40%. Again, this goes in favor of the baseline specification, which is not only the one suggested by the information criteria but also delivers more sensible point estimates.

3.6 Conclusions.

Empirical literature concerned with cross-section heterogeneity found that social capital has a significant role in explaining disparities in between regions. Starting from this point, we shifted our attention on the aggregate economy, to disentangle the role of social capital productivity shocks on the growth profile of Italy.

Using a measure of social capital based on trust and voluntary cooperation and exploiting enrollment data to proxy for human capital, we obtained the observations needed to address the issue in a time series setting. The novelty of the work does not only reside in the application of techniques other than panel data, but also in the use of a long term data set recently published by ISTAT.

Borrowing the idea of a multi-sectoral economy from endogenous growth models, we proposed a SVAR approach in order to identify the effects of productivity shocks in each sector – with special attention for their effects on output. Tackled the issue of cointegration, we proceeded to the estimation a stationary VAR in first differences and we derived structural shocks out of the reduced form using long run triangular restrictions.

A first point worth underlying is that our approach proved to be consistent with the features of the baseline Lucas and Uzawa model and of other endogenous growth models, whose balance growth path depends on second sector productivity. This results is robust to lag specification and can be replicated also in a two dimensional framework (excluding social capital from the VAR).

Furthermore, our main finding is that third sector productivity shocks have indeed positive effects on output. This seems to confirm previous empirical literature describing social capital as a relevant explanatory variable in economic growth. Namely, our estimates suggest a 2% response of output to a 1% increase in third sector productivity. However, the impulse responses failed to find any significant effect on human capital. This clashes with theoretical models in which S is a production factor of H and poses the question of the rethinking such model assumption.

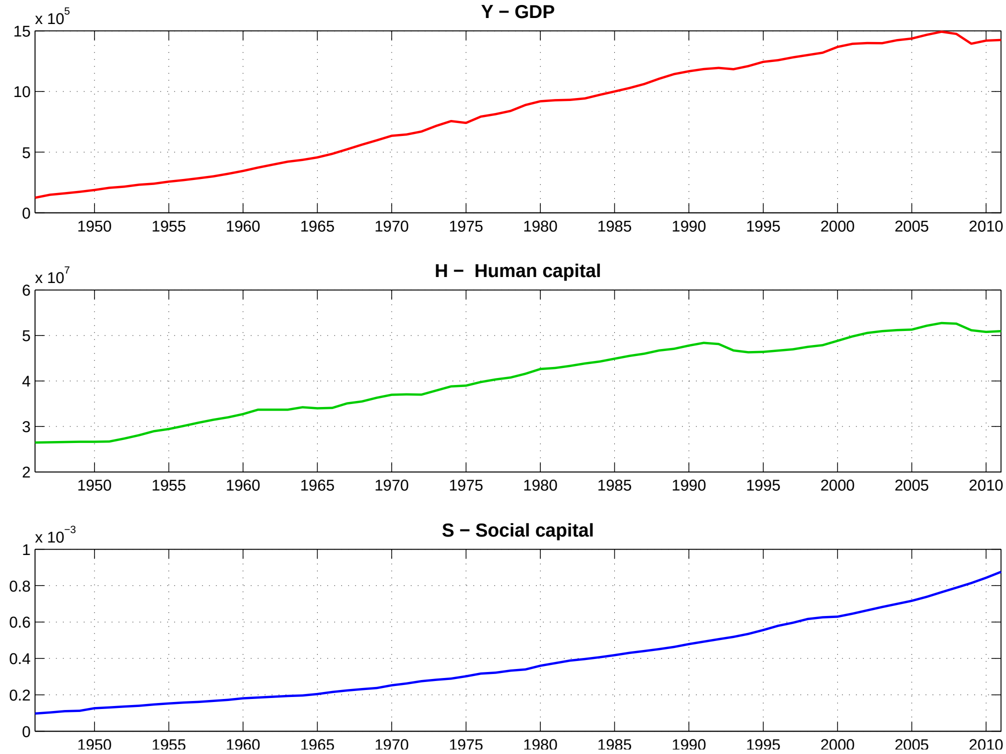
Finally, a comment is worth making on the output variance decomposition. Our baseline specification assigned to S productivity shocks roughly 18% of the long run variability of Y. Also, enriching the lags structure of the VAR this portion increased twofold, proving that estimates are not robust to lag specification. This calls for a refinement of the social capital measure, which at present day we could not compare with other databases. In specific, when new census micro-data will be made available, it might be interesting to compare them with past panels, in order to derive more specific survival probabilities for each voluntary organization. Awfully, this will allow a more precise reconstruction of the past stock of S, thus delivering more robust estimates of the variance decomposition.

At last, we hope that new and more accurate data will be made available soon not only because of the mantra "better data, better results" but also in the hope of obtaining a longer social capital time series, reliably dating back to Italian unity. This would pave the way to compare and contrast the role of social capital before and after WWII in a country that evolved from a relatively backward situation to be a member of the club of the developed G8 economies.

Appendix.

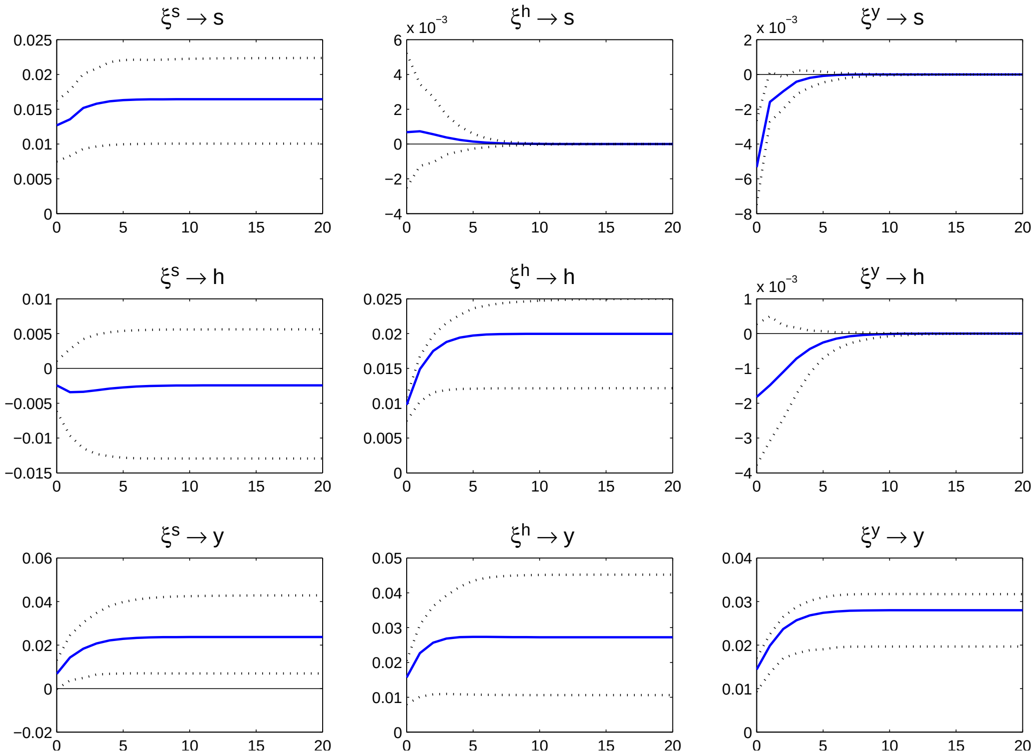
.1 Figures.

Figure 1: The time series.



Notes: Y comes from Baffigi (2011) and it is expressed in millions 2005 €. H is education augmented labor force as computed with Hall and Jones (1996, 1999) methodology. S is measured in number of voluntary organization *per capita*, estimated from ISTAT 2001 census on industry and services.

Figure 2: Structural IR – baseline model.



Notes: Structural impulse responses from a 3-D VAR(1) estimation of (**??**). ξ^y,ξ^h and ξ^s are 1% shock in first, second and third sector technology respectively. 90% confidence bands are obtained with bootstrap procedure.

Figure 3: Compare IR.

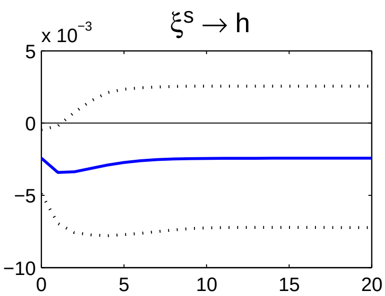


Figure 4: VAR(1)

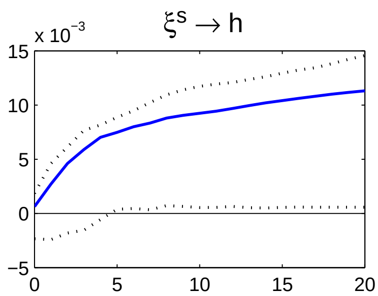


Figure 5: VAR(4)

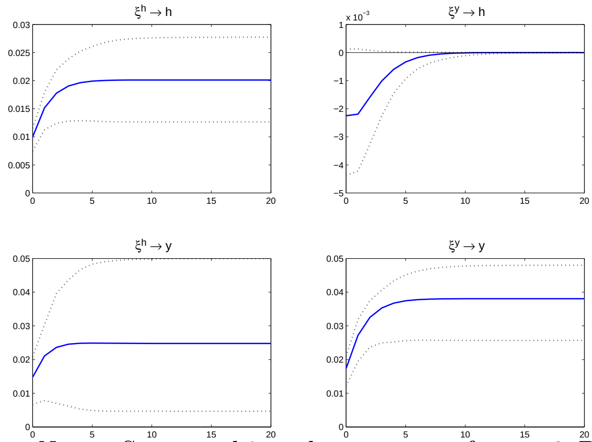
Notes: Comparison of h responses to a 1% shock in third sector productivity. The estimation of the the 3–D VAR in (**??**) is performed with one lag (left panel) and 4 lags (right panel). Bootstrap bands are set conventionally to 68% in both pictures.

.2 Data source and time series estimation.

.2.1 Social Capital.

Data on voluntary organizations comes from ISTAT 2001 census on industry and services. Hereby we provide in greater detail the derivation of (3.4) from (3.3) and (3.2).

Figure 6: Structural IR 2–D VAR(1).



Notes: Structural impulse responses from a 2–D VAR(1) estimation of (??) with H and Y. ξ^y and ξ^h are 1% shock in TFP and second sector technology respectively. 90% confidence bands are obtained with bootstrap procedure.

Plugging the former into the latter we have:

$$\begin{aligned} S_{T-h} &= \tfrac{S_T}{(1-\delta)^h} - \textstyle\sum_{j=0}^{h-1} \tfrac{I^d_{T-j}}{(1-\delta)^{T-(T-j)}(1-\delta)^{h-j}} \\ &= \tfrac{S_T}{(1-\delta)^h} - \textstyle\sum_{j=0}^{h-1} \tfrac{I^d_{T-j}}{(1-\delta)^h}. \end{aligned} \tag{23}$$

Now recall that – by construction – the total amount of voluntary organizations at census date is the sum over all years of the observed I^d_t, that is:

$$S_T = \sum_{j=T_0}^{T} I^d_j = \sum_{j=T_0}^{T-h} I^d_j + \sum_{j=T-h+1}^{T} I^d_j. \tag{24}$$

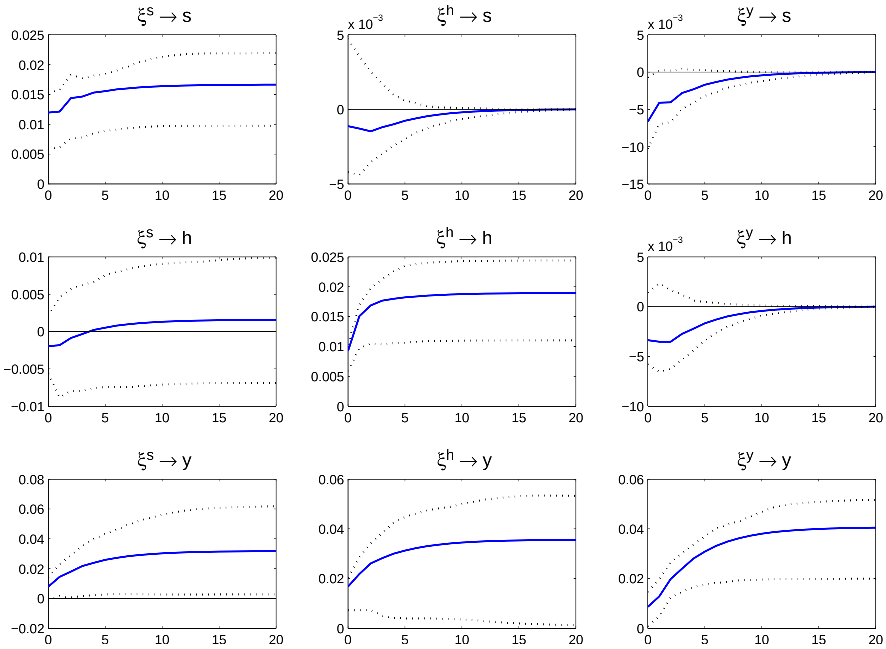
Rearranging the counter in the second part of the summation in (24) we can express S_T as:

$$S_T = \sum_{j=T_0}^{T-h} I^d_j + \sum_{j=0}^{h-1} I^d_{T-j} \tag{25}$$

which plugged in (23) reads:

$$S_{T-h} = \sum_{j=T_0}^{T-h} \frac{I^d_j}{(1-\delta)^h}.$$

Figure 7: Structural IR – VAR(2).



Notes: Structural impulse responses from a 3-D VAR(2) estimation of (**??**). ξ^y,ξ^h and ξ^s are 1% shock in first, second and third sector technology respectively. 90% confidence bands are obtained with bootstrap procedure.

.2.2 Human capital.

1. **Survival probabilities**. Data on mortality divided in age bands are withdrawn from http://timeseries.istat.it/:

   Table 2.8 - Mortality tables by sex and age – Years 1899-1902; 1921-22; 1930-32; 1950-52; 1960-62; 1970-72; 1981; 1991; 2001; 2007

   The survival probability from t till $t+1$ relative to the age band j is obtained as $1 - mortality\ rate_t^j$. Missing observations have been obtained by linear interpolation together with projections of future and past mortality values. Both for backwards and forwards reconstruction we used second degree polynomials, and made sure that all observations fall in the $[0, 1]$ support. $\theta_{g,\tau+g-1,t}$ in the human capital index is computed as by multiplying the one-year survival probabilities (in the correct age band) for the appropriate number of years.

2. **Enrollment and mean year of schooling**. Data on enrollment are available at http://timeseries.istat.it/:

   Table 7.3 - Enrolment in pre-primary, primary, secondary and tertiary school by school or academic year - Years 1861/62-2008/09.

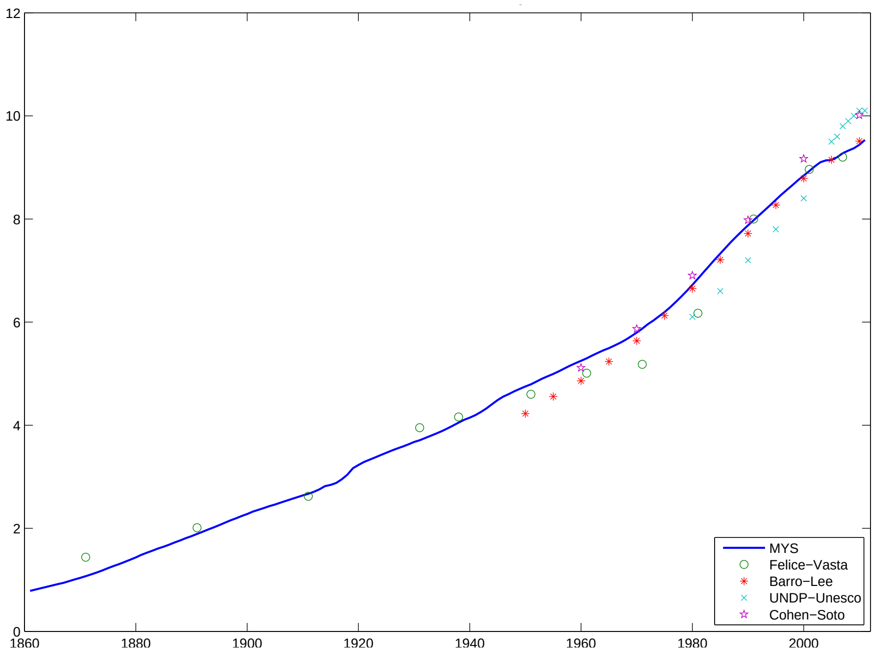
   I.Stat: data warehouse for recent observations 2009/2011

   Missing values have been filled with linear interpolation. Data on enrollment is collected by educational level and more specific figures relative to each grades are not available. In order to compute MYS, we assumed uniform distribution of the enrolled in the different grades of each school cycle.

   Moreover, to compute MYS over a 150 years, we needed to reconstruct the enrollment series till 1803. In order to do so, we used second degree polynomials and a subset of observations specific to each series. Data preceding 1963, 1880 and 1908 was used respectively for primary, secondary and tertiary education. Backward projections have been designed in order to show the smallest possible discontinuity with the existing series and to ensure that under no circumstances enrollment levels fall below zero.

   This exercise is necessary only to obtain observations preceding 1941, which are not used in the analysis. However, it allows us to make comparisons not only with Barro and Lee (2010), Cohen and Soto (2001), UNDP-UNESCO but also with Felice and Vasta (2012) whose database goes back in the liberal age. Results of our procedure are plotted in figure 8 together with the benchmark estimates of these sources.

Figure 8: Mean Years of Schooling.



Notes: MYS obtained with the perpetual inventory method are plotted as a solid line and compared with the benchmark estimates of Barro and Lee (2010), Cohen and Soto (2001), UNDP-UNESCO and Felice and Vasta (2012).

.2.3 Output and Labor.

1. **Output**. Data on value added and GDP Y are derived from Baffigi (2011):

   Alberto Baffigi (2011), Italian National Accounts. A project of Banca d'Italia, Istat and University of Rome "Tor Vergata", in "Economic History Working Papers, Banca d'Italia", n. 18

   This work, done in the occasion of the 150^{th} anniversary of the unification, is the state of the art – and nearly the only[7] – historic reconstruction of the figures

[7] Actually Daniele and Malanima (2007) in "Il prodotto delle regioni e il divario Nord-Sud in Italia (1861-2004)" have their own time series both for the aggregate and for two macro areas (Center-North and South-Islands). However, their work has been criticized because their

regarding Italian national accounts over the last century and a half.

2. **Labor**. As regards labor L, we use data on workers headcount done by Broadberry et al. (2011) in:

   Source: Broadberry, S.N., Giordano, C. and Zollino, F. (2011), "A Sectoral Analysis of Italy's Development, 1861-2011", Economic History Working Papers, Banca d'Italia, N. 20

   which present the figures on the labor force divided by occupational sectors.

reconstruction does not show clear north-south divide in value added in 1861, from which the authors suggest that the reason of underdevelopment of the south of the peninsula is to be found in a predatory attitude of the north and not in different initial conditions. Even though our study does not go into this matter, we privilege Baffigi's series whose figures are less controversial.

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