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"The dynamic effects of technological and non technological shocks in the energy sector: a case study for Italy"

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Sources of productivity growth in Italian energy sector: A structural vector autoregressive approch

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Abstract

By using a vector autoregressive model, this paper decomposes labor productivity of the Italian energy sector, into technological and *non* technological shocks. We take the innovative approach to use economic theory, about long-run impacts of different shocks, to identify the empirical model, and to measure the labor productivity response to each shock, separately. The key identifying restriction is that the level of productivity is determined in the long-run by shocks to technology. We find that: (1) productivity responds positively to technological shocks, leading to a transition from one equilibrium to another; (2) capital accumulation shows a persistent decline in response to a positive technological shock, revealing that, in energy sector, technology and capital stock are substitutes. Yet, *non* technological shocks play a minor and transitory role in explaining productivity change. Results show that shocks that move the productivity at business cycle frequencies may also affect the dynamics of the energy sector in the long-run.

JEL codes: C32, O47, Q4,Q43.

Key words: Energy Sector, SVAR, Productivity, Shocks.

1 Introduction

This paper studies the relationship between labor productivity and technology advances in energy sector. Measuring the correlation between these variables requires an appropriate proxy of technological progress. We extract such a series by controlling for *non* technological effects in labor productivity: varying capital accumulation, oil price, interest rates and unemployment. With respect to the previous literature on productivity change in the energy sector we take an innovative approach to characterize the dynamic relationship between productivity and technological progress. We attempt to identify and estimate the components of labor productivity associated to technological shocks, on the one hand, and *non* technological shocks on the other. That decomposition is carried out using a structural vector autoregressive (SVAR) model, in which the long run properties of the variables are determined by a simple neoclassical growth model.

An extensive literature on productivity and technological progress in energy sector, however, exists. Prior to the 1990s, especially in US, a large number of contributions have been made to investigate how regulation and technological advances affected the generation of electricity and the associated level of productivity. This intensive research has produced a great deal of empirical evidence which is not yet conclusive. For a good review of the literature, on methodologies and applications, see Abbott (2005).

Traditionally, the standard procedure is to compute index number of partial or total factor productivity (TFP). Partial productivity measures the output generated with a given set of inputs. For example, labor productivity is the ratio of real value added to labor inputs employed in industries. In turn, TFP is computed decomposing the growth of output per worker into the contribution of capital per worker and a remaining term, the *Solow residual*. This residual is called TFP, and it is interpreted as a measure of the contribution of the technological progress (Solow, 1957). Kendrick (1961) was the first to assess *partial* productivity change measurements, using labor hours and capital stock, in the electricity industry. He estimated, over the period 1904-1953, a global growth rate of 5.5% of the electricity utilities in the US. This pioneering contribution has been refined in subsequent papers (Kendrick, 1973; Kendrick and Grossman, 1980).

Later models have, however, questioned about Kendrik's results. Basically, the main criticism was that energy sector is a capital intensive industry with partial productivity depending strongly on technology. This would imply that empirical research should investigate directly upon the contribution of technological progress to control the effects of technology change on partial productivity. Using *growth accounting,* Cowin, Small and Stevenson (1981), Nelson and Wohar (1983) and Callan (1991) conducted similar researches for the US electricity industry. They find that over the period 1970-1990 the TFP growth is the main component of labor productivity. Its deceleration (2.3% on average in the 1970s, versus 1.4% in the 1980s) explains the productivity slowdown recorded in the US electricity industry during that period.

More recently, alternative approaches have been suggested to estimate TFP in energy sector. One of this is the *data envelopment analysis* (DEA) pioneered by Charnes el al. (1978). DEA is a linear programming technique which estimates organizational efficiency by measuring the ratio of total inputs employed to total output produced for each organization. This ratio is then compared to others in the sample group to derive an estimate of relative efficiency (Fare et al. 1983, 1990). A range of works has been conducted in a number of countries (Whiteman and Bell, 1994). In recent years, this approach has been used by Abbott (2006). In his work, which uses data of the Australian electricity supply industry, he shows that the acceleration in productivity growth after 1990 has been driven by a marked increase in the level of TFP.

The drawback of these studies is, however, that they give a good indication of the degree to which there is scope to improve productivity to world's best practice, *but* they do not give any indication of the reasons why the energy sector has improved its performance over the past decade (Whiteman, 1999). Further, these contributions do not provide any indication of disturbances (or shocks) moving energy sector away from some "potential" level of productivity. Indeed, inputs like labor, capital and technology determine the level of production per worker in the long-run, but they can fluctuate in the short-run because of business cycle. As a consequence, caution should be taken when comparing TFP among countries because different levels of productivity, and its variations, can be influenced either by the phase of the cycle, which can be diverse in the different countries, or by the *relative* improvements of efficiency in energy sector.

But, even the most updated literature on productivity in energy sector fails in exploring this topic in depth (Ang and Zang, 2000; Ang, Liu and Chung, 2004). For example, the recent paper by Wang (2007), based on a distance function approach computed using DEA, decomposes *energy pro-*

ductivity into several components, with technology as the most important source of growth, but it does not provide any adding information about the nature of the shocks affecting the technological progress, and about the possibility that shocks that move the economy at business cycle frequencies may also affect the economy in the long-run.

To the contrary, in the present paper we view *partial* productivity fluctuations in energy sector as arising from mixture of shocks. Our goal is to disentangle these shocks. We focus on labor productivity. We present an alternative approach to analyze how labor productivity responds to a large range of shocks. Further, we ask if the effects of these shocks are transitory or permanent.

1.1 Aims and scope

In principle, a wide range of changes (shocks) can explain the movement of productivity in energy sector, including changes in the rate and direction of technological progress, changes in capital accumulation, changes in incentives and regulation, fluctuations of the oil price, changes in aggregate demand, or any combination of these.

This problem of identification may well account for the mixed empirical results found by several authors on the *general* relationship between productivity and technological progress. For example, Hansen and Wright (1992), Chirinko (1995) and Christiano et al. (2003), Galì (1999, 2004), Galì et al. (2002) find evidence of procyclical productivity to technological improvements in the short run. In turn, Christiano et al. (2001), Smets and Wouters (2003) and Saltari and Travaglini (2009) find evidence which requires a variety of stochastic disturbances to capture the evolution of productivity over time.

That said, it must be noted that in energy sector new technologies enable shifts in the trajectory of productivity in many different ways. A study by Carraro et al. (2003) has already shown that research and development, and learning-by-doing, affect both life and productivity of a technology in the energy sector. Additionally, Van der Zwaan and Seebregts (2004) have shown that learning-by-doing rates are highest in the initial stages of energy technology deployment, declining over time because of saturation and senescence.

Finally, in recent years, many analyses of the productivity-technology relationship depart from all previous methodologies. Some recent contributions have attempted to incorporate empirical data on technological change into computational models of energy sector in order to quantify the impact of technological progress on productivity. Numerical calibration and parametrization are the standard methods employed to implement this approach (Pizzer and Popp, 2008; Fisher-Vanden and Sue Wing, 2008). However, the drawback to numerical solutions is that it is often difficult to determine why results come out the way they do, and this disadvantage may tend to obscure the underlying economics.

Thus, how can the relationship between technological progress and productivity be investigated? One of the most fertile areas of contemporary applied research concerns macro-econometric models where data are assumed to be consistent with a flexible representation of the economy. This approach is called vector autoregressive (VAR). In this framework each variable included in the model is treated symmetrically, and it is modelled as an autoregressive and distributed-lag process.

In this paper we employ this econometric methodology. More precisely, our purpose is to identify the shocks which induce movements in labor productivity, and to measure the productivity response to each shock separately. Our approach is similar to the approach taken by Blanchard and Quah (1989) and Galì (1999). We impose identifying restrictions to decompose labor productivity into two structural shocks, at least. The key identifying restriction underlying our model is that the level of labor productivity is determined in the long-run by shocks to technology. This assumption does not exclude that other shocks also account for short-run movements in productivity.

On this basis, we find that (1) labor productivity in energy sector responds positively to technological shocks leading to a transition from one equilibrium to another; further, (2) capital accumulation shows a persistent decline in response to a positive technological shock, revealing that, in energy sector, technology and capital stock are substitutes. Yet, we do not assume that all fluctuations in labor productivity are attributable to technological shocks. Specifically, *non* technological shocks can affect permanently capital accumulation, but play a minor and transitory role in explaining productivity growth.

The paper is organized as follows. In the next two sections we use economic theory about long-run impacts of shocks to identify our empirical model. Section 4 gives the precise econometric specification. In Section 5 we present our estimates. Section 6 concludes.

2 Sources of growth and fluctuations

It is widely accepted that labor productivity is a unit root process. Theoretical models, like Solow growth model, predict a positive correlation between productivity and technological shock, and the empirical performance of these models explains the mechanisms through which shocks impact the economy and are propagated over time. However, if labor productivity is affected by shocks of different nature the interpretation of simulations becomes difficult. In that case the moving-average representation of productivity is some combination of the dynamic response of productivity to each shock.

It is helpful for our analysis to classify shocks into two classes each uncorrelated with the other, and to assume that the first shock has a long-run effect on productivity while the other do not. We assume that there are two types of structural shocks: (1) *technological shocks*, that is changes in the technological progress. As discussed above, technological progress affects labor productivity in the long-run. However, productivity can deviate in the short-run from its balanced growth path, and these deviations can be induced by diverse shocks; (2) *non technological shocks* that is all the other shocks, impinging on the economy, that can affect labor productivity *temporarily* through its effects on capital accumulation and aggregate demand.

We focus on the long-run properties of the model. Basically, according to the Solow growth model, movements in labor productivity are attributed to changes in technology and capital accumulation. As we will explain later, we refer to these changes as *technological* and *non technological shocks*. Our aim is to quantify the role of these shocks in determining the productivity growth by making minimal and plausible assumptions. We begin our analysis estimating a restricted VAR model. More precisely, to decompose labor productivity into its sources we impose restrictions on the long-run multipliers of a vector autoregressive model containing the differenced log of real labor productivity (Δy) and the differenced log of real capital stock (Δk). This procedure is known as structural VAR, and use theoretical restrictions to separate shocks into technological and *non* technological components (Shapiro and Watson, 1988; Blanchard and Quah, 1989). Other variables can be accommodated into the empirical model, but according to the theory they capture only the short-run evolution of the economy.

2.1 Neutral and biased technological progress

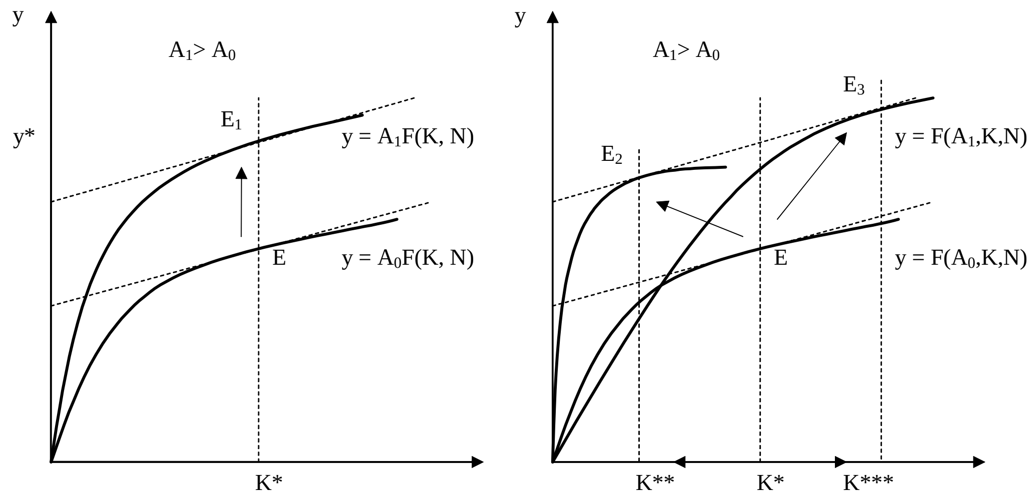
The effects of technological shocks on labor productivity and capital stock can be easily explained using a basic version of the Solow model (Stern, 2004).

The model assumes that output Y increases at a decreasing rate as the amount of capital K employed rises. Since we are interested in the relationship among labor productivity, technological progress and capital accumulation, we suppose a constant size labor force $N = \bar{N}$.

The simplest concept of technological progress is to suppose that it increases the output Y for given inputs, without affecting the way the inputs interact. Let's assume that the aggregate production function has the Cobb-Douglas form and is given by $Y \equiv AF(N,K) = A_0 N^{\alpha} K^{1-\alpha}$, where A_0 is the initial stock of technology. Output Y is a function of capital K and of labor N.

This equation can be written in per capita term as $y = B_0 K^{1-\alpha}$, where $y = Y/\bar{N}$ is a measure of labor productivity, while $B_0 \equiv A_0 \bar{N}^{\alpha-1}$ is a measure of the technology, given the constant size of $\bar{N}$. The curve of diagram (a) in figure 1 shows the relationship between output per worker y and capital K. Suppose now that the technology variable A is growing, so that $A_1 - A_0 > 0$. In this framework, the technological progress – that is, a higher A, or, correspondingly, a higher value of B – is "neutral" in the sense that for a given $\bar{N}$, if input prices were constant, the marginal rate of substitution between inputs is unchanged, and so is K^{*}. All that happens is that the production function in per capita term shifts upward; and the steady state moves from E to E_1, rising labor productivity y as well. Nonetheless, the relative income distribution is unchanged after the technological improvement.

This neutrality assumption may not strike you as plausible. For a more general production function, $Y = F(A,K,N)$, alternative assumptions would be that technological progress either (1) decreases the use of capital K with respect to labor, or (2) rises the use of K with respect to labor. In either case, given the input prices, technological progress is "biased". In case (1) the effects of technological improvements would decrease the optimal K in the long run. Such progress is, therefore, called *capital-saving*. In case (2) the effect would be the rising of the optimal K. Such progress is therefore called *capital-intensive*. The diagram (b) in figure 1 is the graphical counterpart of the two long-run "biased" equilibria E_2 and E_3, where $K^{**} < K^{*}$ and $K^{***} > K^{*.}$



(a) "neutral" technological progress.

(b) "biased" technological progress.

Figure 1: The effects of technological progress on labor productivity and capital stock.

The relevance of this result will become clear shortly. In our empirical estimation we do not impose any *a priori* restriction about the nature of the technological progress in energy sector. Hence, the effective correlation between technology and capital can be positive or negative, depending on the nature of the technological progress. In particular, suppose that technology A and capital K are *complements*. Then, an advance in technology induces an increase in capital accumulation with respect to labor, and because of complementarity this change is biased towards capital. Conversely, if A and K are *substitutes* an increase in A will lead to a decline in K, and now because of substitutability this induces a slowdown in capital accumulation (Kumar and R. Russell, 2002; Acemoglu, 2009).

This framework is clearly only illustrative. More complex productivity and capital dynamics, such as in Jones (2002), will also satisfy the long-run properties of the model. This basic model is nevertheless a useful vehicle to discuss our interpretation of permanent and transitory shocks in energy sector.

Finally, note that this model has also another basic property. Independently from the nature, neutral or biased, of the technological progress, no economy can grow in perpetuity merely by accumulating capital, due to the diminishing returns to capital accumulation. The only cause of continuing growth is technological progress which rises the labor productivity in the long-run. In the simple model being examined, technological improvements, $A_1 - A_0 > 0$, shifts the production function upward, and so the long-run equilibrium of the labor productivity rises.

These properties of the model allow us to decompose labor productivity into the components arising from technology and from capital input. Labor productivity is influenced by technological progress in the long-run. To the contrary, capital accumulation does not affect labor productivity in the long-run because of diminishing returns, but it can be influenced by technological progress as time passes.

3 Identification of shocks

We begin estimating the two variable VAR system

$$D(L)Z_t = \mu_t \tag{1}$$

where $Z_t = (\Delta y, \Delta k)'$ and μ_t is the vector of disturbances. Δy is the differenced log of real labor productivity, and Δk the differenced log of real capital stock. This (stationary) autoregressive model can be interpreted in terms of an infinite-order moving average model of the form

$$Z_t = G(L)\mu_t \tag{2}$$

where $G(L) = D(L)^{-1}$. Since the elements of μ_t are in general contemporaneously correlated, we cannot interpret them as structural shocks. We orthogonalize them by imposing restrictions on the long-run multipliers in the system.

Our previous assumptions about shocks provide the identifying restrictions for the structural VAR. There are two types of structural shocks affecting Δy and Δk. The first shock, namely the technological shock ϵ^T, has a long-run impact on the (log of) labor productivity and capital accumulation. The second shock, the *non* technological shock ϵ^N, has a long-run effects on the log of capital accumulation, but it has no long-run affect on labor productivity. These two restrictions are implied by the Solow growth model.

Using these restrictions we obtain an alternative representations of Z_t which is called *structural VAR* (SVAR). Formally, it can be written as

$$Z_t = C(L)\epsilon_t \tag{3}$$

where $\epsilon_t = \left(\epsilon^T, \epsilon^N\right)'$ is now composed by two structural shocks, where ϵ^T is the technological shock, ϵ^N is the *non* technological shock.

Given our identifying restrictions, the matrix of the long run multipliers $C(1)$ can be written as:

$$C(1) = \begin{bmatrix} C_{11}(1) & 0 \\ C_{21}(1) & C_{22}(1) \end{bmatrix} \tag{4}$$

Assuming the shocks are ordered technological and *non* technological, the above restrictions says that the secular component in labor productivity originates in the technological shocks, and the coefficient $C_{11}(1)$ identifies the long-run multiplier of this shock. In turn, the zero in matrix (4) implies that *non* technological shocks do not affect the log of productivity in the long-run (however, they may well have short and medium run effects on it), but that the secular component of the log of capital accumulation depends on both technological shock, $C_{21}(1)$, and *non* technological shocks, $C_{22}(1)$.

4 Empirical evidence

To estimate our model we proceed in two steps.

In this section we report evidence based on a bivariate SVAR model estimated using Italian data, which employ only labor productivity and capital stock. Then, we will show that the main qualitative results obtained in this model also hold for an augmented model that includes a number of nominal and real variables in addition to labor productivity and capital accumulation.

The data used to estimate the bivariate SVAR are real value added, employment in hours worked and real capital stock of the Italian energy sector. We compute (log) labor productivity y as the ratio of real value added to labor inputs. k is the log of capital accumulation. Data are quarterly. The period goes from 1981:1 to 2005:1.[1]

[1] The database employed in the econometric analysis is extracted by the Productivity Database provided by Istat (2010) for the Italian economy.

The SVAR requires that the first difference (Δ) of the log of productivity y and capital accumulation k are stationary. This preliminary assumption has been tested by the standard Dickey-Fuller test and Phillips-Perron test which reject the null of unit root when applied to the first differences of logs (table 1). More precisely, the t-statistic for the null hypothesis of a unit root in the first difference of each series has been tested with 4 lags and the intercept, at 5% significance critical values. Δy is an integrated process which accepts the assumption of mixed-trend difference stationary process. But, Δk is a stationary process which accepts at most the presence of an intercept in its autoregressive process. For this reason we include the intercept in the estimation of the original VAR.[2]

Δk presents a break point in 1992. When we allow for a change in capital accumulation we simply remove the different sample means before estimating the VAR. Three different specifications of the time series in VAR are run to test the robustness of the result. In the first case (specification A) we remove means by Δk. In the second case, we remove the mean growth shift for both productivity and capital accumulation after 1992. In the third case we employ the raw data including a linear trend. Since the results for the three specifications are similar, we present below only the outcomes for specification A. The information criteria AIC and SC can be used for model selection such as determining the lag length of the VAR, with smaller values of the information criterion being preferred. The values of the lag criteria suggest to include two lags in the original VAR. All the criteria reported in table 2 are discussed in Lütkepohl (1991).

As explained above, in order to estimate the SVAR we need to provide long-run identifying restrictions. These restrictions are specified in terms of the elements of the long-run multipliers in the form of zero restrictions. In our model the restriction means that the (accumulated) response of labor productivity to the *non* technological shock is zero in the long-run. The point estimates, standard errors, and z-statistics of the estimated free parameters are reported together with the maximized value of the log likelihood in table 3.

[2]There is the issue to how handle the apparent time trend in productivity. To focus this point we have estimated an augmented VAR including a linear trend. The results are qualitatively similar to those for the base case discussed in the paper.

	Δy	Δk
ADF	-3.29 (-2.89)	-3.09 (-2.89)
PP	-3.67 (-1.94)	-2.25 (-1.94)

Table 1: Augmented Dickey-Fuller test and Phillips-Perron test for unit root, with 4 lags and intercept. Critical t values in parentheses.

	Δy	Δk
$\Delta y(-1)$	1.523 (21.32)	-0.011 (-1.081)
$\Delta y(-2)$	-0.707 (-10.23)	0.007 (0.733)
$\Delta k(-1)$	-0.741 (-1.822)	1.751 (27.80)
$\Delta k(-2)$	0.606 (1.524)	-0.785 (-12.74)
intercept	0.511 (3.966)	0.028 (0.921)
R-squared	0.91	0.98
S.E. equation	0.94	0.14
F-statistic	239.4	1963.9
Log likelihood	-127.3	49.7
Akaike AIC	2.78	-0.94
Schwarz SC	2.91	-0.80
Log likelihood	-74.5	
Akaike information criterion (AIC)	1.78	
Schwarz criterion (SC)	2.04	

Table 2: Vector Autoregression Estimates. Sample (adjusted): 1981:3-2005:1. t-statistic in parentheses.

	Coefficient	Std. Error	z-Statistic
$C_{11}(1)$	5.79	0.420	13.78
$C_{21}(1)$	-2.20	0.443	-4.98
$C_{22}(1)$	4.03	0.292	13.78
Log likelihood		-79.720	

Table 3: Structural VAR estimates.

4.1 Impulse response functions

Figures 2-3 show the impulse response functions estimated from the empirical model. The responses along with the confidence intervals (± 2 standard error) are provided as recommended by Runkle (1987). Shocks are positive by construction.

The panels of figure 2 show the (log) labor productivity y and (log) capital accumulation k responses to a one unit technological shock. We interpret this shock as an advance in technology. Both productivity and capital accumulation are permanently affected by a positive technological shock. The accumulated responses are, however, of opposite sign. We find a positive impact for labor productivity which shifts towards the new steady state, but a negative long-run impact on capital accumulation. More precisely, in response to a positive one unit technological shock, labor productivity experiences an immediate increases of about 1.3 percent, stabilizing after 40 quarters at an higher level. Conversely, capital accumulation experiences an immediate decrease of 2.2 percent, eventually recovering in the long-run. These responses can be in principle be reconciled with the idea that the initial negative impact of the technological shock on investment may be partly offset by a positive comovement between technology advance and capital accumulation in the long-run, induced by technological improvement. Nonetheless, figure 2 displays that the cumulated impulse responses of capital accumulation to the technological shock is, on the whole, negative and persistent. As time passes, the cumulated responses in productivity and capital accumulation become mirror images to each other because technological progress tends to replace capital stock in the production function. Figure 2 illustrates the tight inverse relation between productivity and capital accumulation. The values of the long-run coefficients suggest an implied long-run elasticity (in absolute value) of about 0.38 percent. Hence, in Italian energy sector technology and capital are substitutes: a positive technological shock will lead to a rise in y_t and a decline in k_t. However, the same relationship is weaker in the short-run: during the initial periods, the responses of capital accumulation to technological shocks are more gradual than that of labor productivity.

Then, figure 3 displays the responses of time series to one-unit *non* technological shock. We can interpret these responses as the shift of economy to changes in nominal variables, like input prices or regulation, which impinge upon capital accumulation in energy sector. *Non* technological shock leads to a persistent increase in capital stock, with a peak response of 16 at 20 quarters. On the other hand, the productivity response is initially positive. A one percent *non* technological shock has a 0.23 percent impact effect on productivity in the short-run. But, after 6 to 13 quarters, the *non* technological shock leads to a decrease in productivity of roughly 1 percent. Then, productivity returns to its original level, and the effects of the *non* technological shock vanishes over time. Conversely, the shock has a sizable permanent impact on capital accumulation, thus emerging as the main source of unit root detected in capital accumulation. Hence, in the long-run, the rise in (log) capital accumulation is associated to an unchanged level for (log) productivity. This dynamic response is consistent with the standard properties of the Solow growth model, and with the traditional view of transitory effects of aggregate demand disturbances (i.e., accelerator models) on labor productivity .

4.2 Variance decomposition

Table 4 presents the forecast error variance decomposition for the two variables y, k at various horizons. The forecast error variance decomposition tell us the proportion of the movements in a variable due to its "own" shocks versus shocks to the other variables. Table 4 gives this variance decomposition for our basic specification. It has the following interpretation. Define the t quarter ahead forecast error in productivity as the difference between the actual value of productivity and its forecast from equation (3) as of t quarter earlier. This forecast error is due to unanticipated technological and *non* technological shocks in the last t quarters. The number for labor productivity at horizon $t = 1, 5, 10, 20$ gives the percentage of variance of the t quarter ahead forecast error due to the two shocks. A similar interpretation holds for capital accumulation.

Technological shocks account for most of the variation in labor productivity in energy sector under all specifications. Specifically, they explain under the basic case the $67.5 - 82.8$ per cent of the variation in productivity at all horizons. *Non* technological shocks account for $75.2 - 87.6$ percent of the forecast error variance of capital accumulation. Note that the results are stable across alternative treatments of break, trend and mean.

One principal conclusion emerges from this table. Estimates of the relative contributions of the different shocks for both productivity and capital accumulation show that only one shock captures most of the corresponding variation over time. Thus, in the case of productivity after 20 quarters most

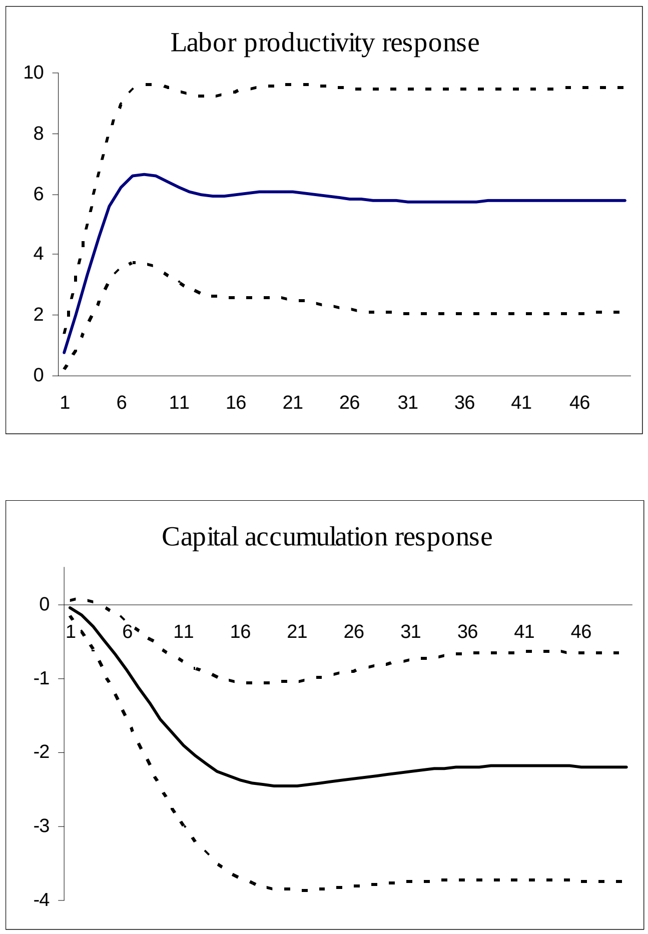


Figure 2: Responses to technological shocks from the bivariate VAR model.

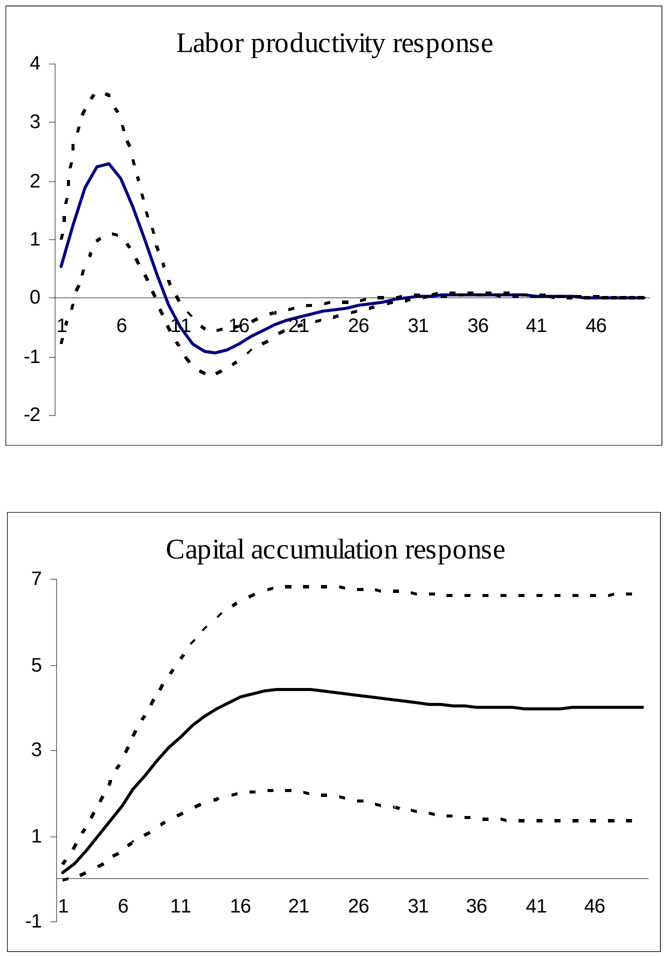


Figure 3: Responses to *non* technological shocks from the bivariate VAR model.

of the productivity variation is due to technological shocks (71.3%), with a marginal response to *non* technological shocks. Alternatively, accumulation variation is largely explained by *non* technological shocks (75.2%) with a minor effect for the other structural shock. In all cases, technological shocks appear to be quite important for productivity fluctuation and growth at all horizons.

4.3 Evidence from an augmented model

To check the robustness of the results, we estimate a higher dimensional SVAR model. This augmented SVAR allows for four orthogonal *non* technological shocks, still identified assuming that they do not affect the level of labor productivity. This augmented model provides information regarding the effects of technological shocks on a larger number of variables than was the case for the bivariate SVAR. As before, we are mainly interested in the relationship between technology and capital accumulation.

We add data on crude oil price, real interest rates and unemployment rate. Data are from Eurostat. The nominal interest rate is the three-month Italian Treasury Bill (BOT) rate. The deflator of the Italian GDP is used to compute the real interest rate. Finally, the national Italian unemployment rate is used to extract the structural aggregate demand shocks. Data are quarterly, and cover the period from 1983:1 to 2005:1.

Standard ADF and PP tests reject the null of unit root in oil price growth (Δp), real interest rate (r), and the unemployment rate (u) at a 5 percent significance level. However, for u as well as r, tests accept the assumption of mixed-trend difference stationary processes. For this reason, to estimate the augmented SVAR we include a linear trend together with the intercept and two lags. Then, we impose our restriction that only technological shocks have a permanent effect on labor productivity.

Figure 4 displays the responses of the time series to a one unit technological shocks. The pattern of labor productivity and capital accumulation are very similar to that obtained in the bivariate model: a positive technological shock increases permanently productivity, but implies a corresponding decline in capital accumulation. The elasticity of the variation (in absolute value) is close to 0.4, a value very similar to that estimated with the bivariate SVAR.

Note that the response of real interest rate r to the technological shock is positive and persistent, in accordance with theory, given the higher returns to capital induced by the technological advance. Further, the response of oil inflation Δp is negative and persistent because a technological advance as well as a higher labor productivity would imply an improvement in efficiency with a reduction of oil demand in the long-run.

Finally, the bottom panel of figure 4 shows that unemployment rate u increases temporarily in response to a one unit technological shock, to go back afterwards to the original steady state. This dynamic pattern seems consistent with the hypothesis of natural unemployment rate.

5 Conclusions

The purpose of this paper was to investigate the relationship between labor productivity and technological progress in energy sector. To study this issue we employed a parsimonious SVAR, measuring the labor productivity response to technological and *non* technological shocks. We contemplated the case of Italy.

Estimates show that technological shocks have permanent effects on the level of productivity leading to a transition from one equilibrium to another. Further, most of the variation in productivity is due to technological shocks which account for roughly two-third of the productivity variation. For the Italian data, it appears that technology and capital accumulation in energy sector are substitutes. Additionally, favorable *non* technological shocks affect permanently capital accumulation, but play a minor and transitory role in explaining productivity growth, capturing only the residual fraction of productivity fluctuations at high frequencies.

Thus, our findings tell us a story about the sources of shocks affecting productivity in energy sector. The data support the idea that technological progress is necessary to gain a strong and persistent advance in labor productivity. But, while the model provides a positive answer to the question of the relative importance of technological shocks in growth of energy sector, it is more prudent about the role of *non* technological shocks. That is, our estimates suggest that components other than technological progress are less important in driving productivity growth than markets and policy makers expect.

This outcome has an important implication for energy policies. European reforms of energy sector and national legislations formulated, in recent years, mainly to support investments in the emerging "green" economy, may affect

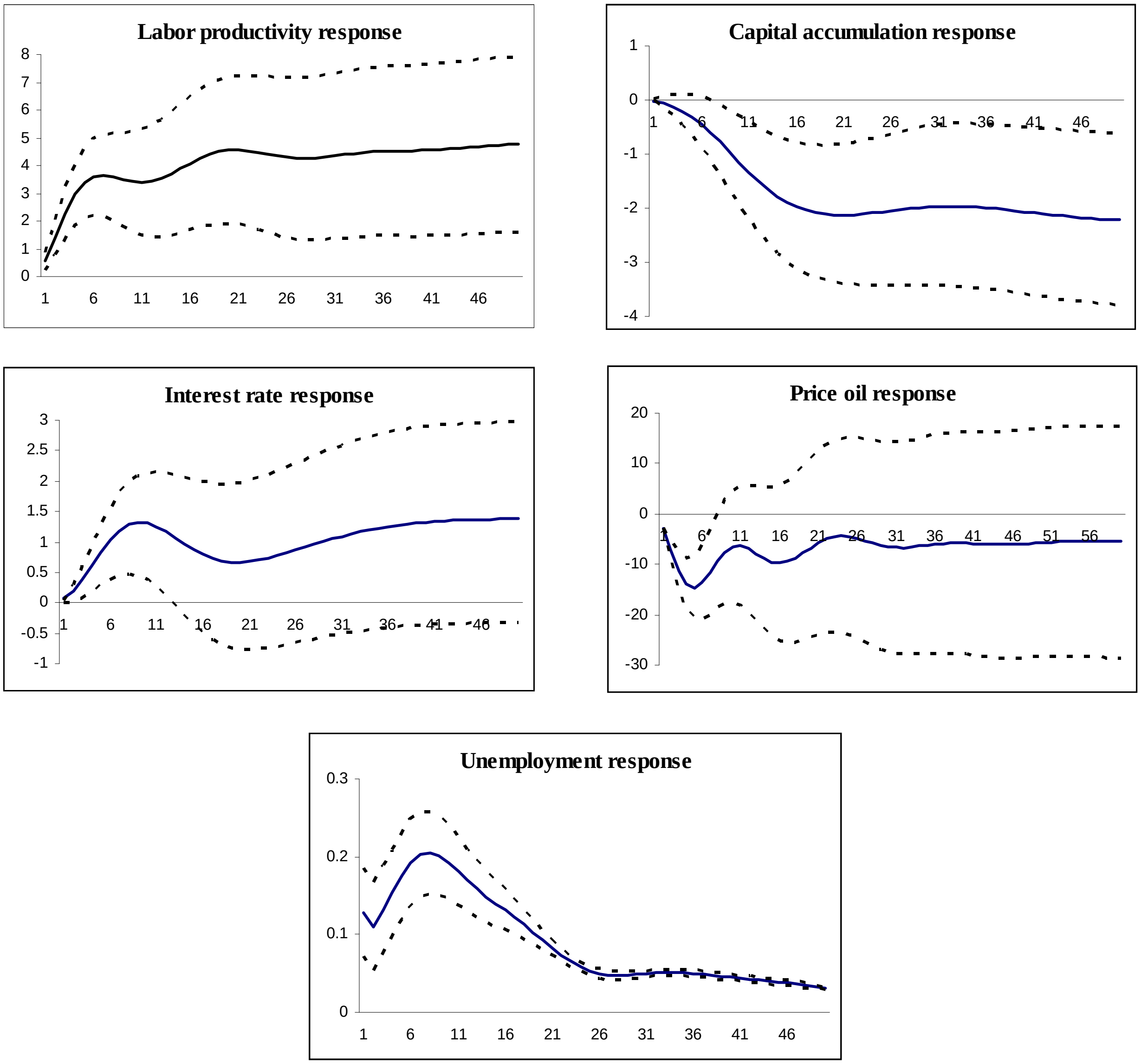


Figure 4: Responses to technological shocks from the augmented VAR model.

capital accumulation, but cannot guarantee the *jump* of technology necessary to rise up labor productivity in the long-run. Remedying this problem will require the development of new policies aimed at promoting the rate of technological progress in the energy sector.

Finally, from the methodological point of view, VARs do not eliminate omitted variable biased. Impulse response functions and forecast errors depend on structural shocks. A larger set of shocks could change the sensitivity of variables in the system to each single shocks. Nonetheless, we believe that the empirical model must be based on economic theory which captures the main characteristics of the economy. Our model is a macro-economic parsimonious representation of the energy sector: technological progress and capital accumulation capture the main components of the labor productivity, and they allow to represent the dynamic changes of its structure over time. As we have discussed, even considering a larger number of variables the properties of the empirical model remain unchanged, and the effects of the *non* technological shocks remain small compared to those of the technological shocks.

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	Productivity		**Accumulation**	
periods ahead	**Technological**	**Non Technological**	**Technological**	**Non Technological**
1	**67.5**	**32.5**	**12.4**	**87.6**
5	**82.8**	**17.2**	**20.9**	**79.1**
10	**73.3**	**26.7**	**25.3**	**74.6**
20	**71.3**	**28.7**	**28.8**	**75.2**

Table 4: Forecast error variance decomposition.