CSEF
Centre for Studies in Economics and Finance

WORKING PAPER NO. 137

Interpreting Aggregate Fluctuations Looking at Sectors

Antonio Acconcia and Saverio Simonelli

April 2005

This versione September 2006

University of Naples Federico II
University of Salerno
Bocconi University, Milan

CSEF - Centre for Studies in Economics and Finance – UNIVERSITY OF SALERNO
84084 FISCIANO (SA) - ITALY
Tel. +39 089 96 3167/3168 - Fax +39 089 96 3167 – e-mail: csef@unisa.it

WORKING PAPER NO. 137

Interpreting Aggregate Fluctuations Looking at Sectors

Antonio Acconcia* **and Saverio Simonelli****

Abstract

This paper relies on sectoral-level data to interpret aggregate fluctuations of labor productivity and employment in US as due to exogenous disturbances. A shock determining permanent effect on the real investment good price may reasonably be interpreted as an investment-specific technology shock, since it mainly produces long-run effect on labor productivity in the durable goods producing sector. A transitory shock on the real investment price may instead be interpreted as a sectorneutral disturbance since it homogeneously affects the labor productivity across sectors. Finally, sectoral evidence suggests that the near-zero correlation between aggregate productivity and employment growth rates may be explained as the overall outcome of positive and negative correlations within, respectively, the durable and nondurable goods producing sectors.

JEL classification: C10, E32, O41.

Keywords: Dynamic Factor Model, Long-Run Restriction, Sectors, Technology shock.

Acknowledgements: Different versions of this paper have been presented at the University of Bari, the University of Hamburg, the University of Padova, ECARES, the University of Roma La Sapienza, the Csef-Igier Symposium on Economics and Institutions held in Capri (2005), the 20th Annual Congress of the European Economic Association held in Amsterdam (2005), the 2005-6 European Forum held in Florence (IUE), and the Royal Economic Society Annual Conference held in Nottingham (2006). We are grateful to Domenico Giannone, Morten O. Ravn, Lucrezia Reichlin, and Randall Verbrugge for many helpful suggestions and discussions. We thank Efrem Castelnuovo, Jordi Galí, Marco Lippi, Bernd Lucke, Argia Sbordone, Paolo Surico, Guglielmo Weber, Philippe Weil, and Michael Woodford for comments. We are also grateful to Jason Cummins and Gianluca Violante for the US price of equipment data. An earlier draft was written while the second author visited ECARES and circulated with the title *Revisiting the one type permanent shocks hypothesis: Aggregate fluctuations in a multi-sector economy.* Saverio Simonelli acknowledges the RSCAS (IUE) for the financial support received as Jean Monnet fellow in the 2005-6 European Forum program 'Growth Agenda for Europe'.

* University of Naples "Federico II" and CSEF - E-mail: saverio.simonelli@iue.it

** University of Naples "Federico II", CSEF and IUE. Corresponding address: Robert Schuman Centre for Advanced Studies, European University Institute, Villa La Fonte - Via delle Fontanelle, 20 I - 50016 San Domenico di Fiesole (FI) - Italy. E-mail: saverio.simonelli@iue.it

Contents

1 Introduction

This paper investigates the cross-sectoral effects of economy-wide and sector-specific efficiency disturbances by estimating a dynamic factor model (DFM) with data on two-digit U.S. manufacturing industries. First, it is argued that the dynamic pattern of sectoral labor productivity is consistent with the assumption of two sources of productivity disturbances, interpreted as investment-specific technical changes and sector-neutral innovations. Second, it is provided a novel interpretation of the near-zero correlation between aggregate labor productivity and employment growth rates. This emerges as the overall outcome of both positive and negative correlations arising within the durable and nondurable goods producing sectors, respectively. The former is due to the investment-specific technical changes while the latter is traced to the sector-neutral productivity disturbances.

Following Blanchard and Quah (1989), economically motivated long-run restrictions and vector autoregression (VAR) have been usually exploited for interpreting economic fluctuations. A popular strategy recently put forward by Galí (1999) allows to recover technology and nontechnology components of business cycle under the assumption that any other source of fluctuations, but the technical change, has a merely transitory effect on labor productivity. Restricting to a single permanent component, we make use of that long-run restriction to identify the cross-sectoral effects determined by two types of innovations: one which influences permanently the *aggregate* (Manufacturing) labor productivity — the technology shock — and the other which, by construction, has only transitory effect on it — the nontechnology shock. As expected, we find that a technological improvement induces positive and statistically significant long-run effects for almost all industries considered. Thus, on this respect sectoral results appear to be fully consistent with the aggregate one and support the modelling of technological changes in terms of sector-neutral innovations. Looking at the effects of a nontechnology shock, however, a drawback of such identifying approach emerges. We find that this shock — which by construction does not influence the long-run aggregate labor productivity — conversely does influence the labor productivity of some industries, suggesting the possibility that the technology component of the data has not been correctly disentangled. To check the robustness of this conclusion we also recover the nontechnology and technology components under the identifying assumption that the former determines the minimum long-run impact on a weighted average of the labor productivity across industries. We find again, however, that for many industries the long-run effects of both types of shocks are statistically significant.

Previous evidence can be rationalized admitting that two distinct sources of innovations are relevant for the behavior of the labor productivity in the long-run. Greenwood et al. (2000, 1997) argue that the investment-specific technological change is a main source of growth and business cycle, and provide the theoretical framework for identifying this type of technology. In particular, for an economy characterized by both exogenous sector-neutral innovations and investment-specific technological changes, Fisher (2005) notes that the long-run behavior of the relative price of equipment is solely affected by investment-specific shocks. Under this long-run restriction our DFM suggests that a (positive) investment-specific technical shock increases, both on impact and in the long-run, the labor productivity of 7 out of 10 industries which are characterized by the production of durable goods. Moreover, the effect of the shock is estimated positive and statistically significant for both the durable goods producing sector and the Manufacturing sector as a whole. Conversely, looking at the nondurable goods producing sector we do not ascertain any effect. Arguably, these results support the identifying assumption. Finally, as concerns the second source of permanent innovations, we estimate widespread positive effects across sectors resembling those of sector-neutral innovations.

Sectoral-level data allows a deep explanation of a well-known empirical finding, that is the near-zero correlation between aggregate labor productivity and employment growth rates. Proponents of real business cycle (RBC) models explain it as the outcome of a positive conditional correlation induced by a technology shock and a conditional correlation of opposite sign due to a nontechnology shock. Galí (1999), instead, provides evidence that a technology shock determines a negative correlation while the opposite is true for a nontechnology one. Hence, the lack of aggregate unconditional correlation is explained by reversing the effects of its sources respect to what predicted by standard RBC models.[1] Assuming sector-neutral and investment specific shocks, Fisher (2005) estimates an increase of employment after an investment-specific technological improvement and a contraction after a positive neutral shock. In this paper we provide evidence that the lack of aggregate correlation is due to the positive correlation between the two variables in the durable goods producing sector — conditional to the investment-specific innovation — and the negative correlation between the same variables in the nondurable goods producing sector — conditional to the neutral shock. Thus, the aggregate evidence may be interpreted as the overall outcome of different sectoral dynamics after investment-specific and sector-neutral disturbances.

The rest of the paper is organized as follows. Section 2 presents the empirical model and the estimation strategy. In section 3 we determine the number of

[1] A similar conclusion is provided by Kiley (1997), who identifies the Galí's technology component independently for each two-digit U.S. manufacturing industries, and by Francis and Ramey (2005), who show the robustness of such conclusion to different ways of implementing the basic identifying assumption. Conversely, Chang and Hong (2005) show that for a large number of four-digit U.S. manufacturing industries technological progress significantly increases hours in the short-run, if one looks at the relationship between hours and total factor productivity.

dynamic factors, while in sections 4 and 5 we examine the implications of the two identifying strategies regarding the effect of a shock across sectors. Section 6 contains the sectoral interpretation of the near-zero correlation between growth rates of labor productivity and employment. Finally, in section 7 we summarize the main findings.

2 The econometric framework

The empirical framework we refer to is the generalized DFM developed by Forni et al. (2000). Let X denotes the n-dimensional vector of variables relevant for what we are going to study, that is the log-difference of labor productivity and hours worked at both aggregate and sectoral levels. The starting point of our investigation is the following moving average representation

$$X_t = \widetilde{X}_t + \xi_t = \Gamma(L)\varepsilon_t + \xi_t. \tag{1}$$

where L denotes the lag operator, ε_t is an m-dimensional vector of orthogonal shocks, which explain a substantial part of aggregate and sectoral fluctuations, the matrix $\Gamma(L)$ captures the mechanism through which the shocks propagate over time and across sectors, and ξ_t is an $n \times 1$ vector of transitory idiosyncratic shocks — each one orthogonal to those in ε_t.[2]

A matter of importance of equation (1) is that each series is decomposed into two orthogonal parts: the common component, $\Gamma(L)\varepsilon_t$, and the idiosyncratic component, ξ_t. The common component captures global comovement, as it is explained by common shocks with loadings specific to each variable. The idiosyncratic com-

[2]Equation (1) is based on the assumption that both productivity and hours are integrated of order one. This assumption is in line with many other empirical investigations on the same topic (see, for example, Galí, 1999).

ponent, instead, would capture shocks the effects of which do not propagate widely across sectors.[3] We argue that a DFM is ideally suited to investigate the main question of this paper for at least three reasons:

- The number of rows in the vector ε_t depends on the total number of relevant shocks in the economy. Formally, this question is related to the rank of the spectral density matrix of X_t. The implementation of the dynamic factor analysis provides an estimate of the relevant stochastic dimension of the sectoral economy. In other words, it makes possible to find out the number of shocks, m, which emerge from the behavior of many sectors as responsible for the business cycle features.

- When both the cross-section and the time-series dimensions of a panel tend to infinity, the two orthogonal components $\Gamma(L)\varepsilon_t$ and ξ_t are identifiable even though the shocks in ξ_t are not mutually orthogonal. All we need is that the idiosyncratic disturbances, although eventually shared by two or more units, have their effects concentrated on a finite number of cross-sectional units and tending to zero as the cross-sectional dimension of the data tends to infinity. This feature of the DFM is of interest for our application. In fact, it would be unrealistic to assume lack of cross correlation among idiosyncratic components when a set of industries is involved with strong relationships. In this case, it is reasonable to suppose that when an idiosyncratic shock hits any industry it propagates its effect around. The DFM allows for such cross correlations.

- The key point of our empirical model rests on the possibility of interpreting the observed variations in labor productivity and employment across a large

[3] An alternative explanation for the term ξ_t involves the possibility of measurement errors in the data.

number of sectors as originating in a low number of sources of exogenous disturbances, ε_t. Starting from equation (1), it is possible to identify the m common shocks ε_t and to estimate the $n \times m$ impulse response functions $\Gamma(L)$. As in the structural VAR literature, the common shocks are identified up to a static rotation R, where R is an orthonormal matrix of dimension $m \times m$. Hence, the identification consists in selecting R such that economically motivated restrictions on the matrix $\Gamma(L)R$ are satisfied. In particular, as the matrix R is orthonormal $m(m-1)/2$ restrictions are required. Therefore, adopting a dynamic factor approach we can use information on n variables to identify m shocks, with n much larger than m. Moreover, this implies that even a small set of economically motivated restrictions generates testable over-identified restrictions. Indeed, the indeterminacy problem of a structural factor model does not depend on n (as it is generated by an m-dimensional rotation), while the impulse response functions estimated are n. For example, exploiting just one economically motivated restriction on a given variable which characterizes different sections of the panel, we can obtain n responses for which such identification has to be valid. Therefore, it is possible to test the restriction imposed on such a variable.

2.1 The estimation strategy

In order to estimate our empirical model we follow the procedure proposed by Giannone et al. (2005). Thus, consider the following static version of equation (1):

$$X_t = \mathcal{F} f_t + \xi_t \tag{2}$$
$$f_t = A f_{t-1} + S\varepsilon_t$$

where $f_t = (\varepsilon_t' \; \varepsilon_{t-1}' \; \dots \; \varepsilon_{t-s}')'$ is the $r \times 1$ vector of so-called static factors, $\mathcal{F}$ is the $n \times r$ matrix of loadings, and S is an $r \times m$ matrix.[4]

- First, we need to choose both the numbers of dynamic and static factors, that is m and r.

  To fix m, we look at how many common shocks explain most of the variance of the data-panel. In particular, we exploit the circumstance that the variance explained by the i-th dynamic factor, at each frequency ϑ, is given by

  $$\frac{\lambda_i(\vartheta)}{\sum_{j=1}^{n} \lambda_j(\vartheta)} \qquad \text{for } i = 1 \dots n$$

  where $\lambda_i(\vartheta)$ denotes the i-th eigenvalue of the spectral density matrix of the panel, ranked in descending order of magnitude.

  A formal way of determining the number of static factors would be to apply the testing-strategy proposed by Bai and Ng (2000). However, by means of Monte Carlo simulations the authors show that the test is reliable when both N and T are extremely large.[5] As the dimension of our panel does not fit this requirement, we prefer to investigate the sensitivity of the estimates to different values of r. Results, however, will reveal to be not qualitatively sensible to the choice of r.

- Second, principal component analysis is employed to estimate the parameters of model (2). More precisely, by adopting the principal component estimator proposed by Stock and Watson (1999, 2002), we estimate the static factor

[4] In the literature the number of static factors refers to the $r = m(s+1)$ entries of f_t, while the number of dynamic factors identifies the stochastic dimension m of the model.

[5] Technically, for our relatively small panel the algorithm proposed by Bai and Ng does not reach a local minimum.

space related to the first r principal components of our panel, that is

$$\widehat{f}_t = W' X_t$$

where W is the $n \times r$ matrix of the eigenvectors corresponding to the first r largest eigenvalues of the sample covariance matrix of the panel, that is $\frac{1}{T}\sum_{t=1}^{T} X_t X_t'$. Then, we regress X_t on the estimated factors to estimate the factors loadings:

$$\widehat{\mathcal{F}} = \sum_{t=1}^{T} X_t \widehat{f}_t' \left(\sum_{t=1}^{T} \widehat{f}_t \widehat{f}_t' \right)^{-1}.$$

Finally, in order to estimate the parameters of the second equation of model (2) we run a VAR on the estimated factors. It follows

$$\begin{aligned}
\widehat{A} &= \sum_{t=2}^{T} \widehat{f}_t \widehat{f}_{t-1}' \left(\sum_{t=2}^{T} \widehat{f}_{t-1} \widehat{f}_{t-1}' \right)^{-1} \\
\widehat{\Sigma} &= \frac{1}{T-1} \sum_{t=2}^{T} \widehat{f}_t \widehat{f}_t' - \widehat{A} \left(\frac{1}{T-1} \sum_{t=2}^{T} \widehat{f}_{t-1} \widehat{f}_{t-1}' \right) \widehat{A}' \\
\widehat{S} &= B H^{-1}
\end{aligned}$$

where H is the diagonal matrix having on the diagonal the square roots of the first m largest eigenvalues of $\widehat{\Sigma}$ and B is the $r \times m$ matrix whose columns are the eigenvectors corresponding to those eigenvalues.

- Third, estimated parameters are replaced into model (2):

$$\begin{aligned}
X_t &= \widehat{\mathcal{F}} f_t + \xi_t \\
f_t &= \widehat{A} f_{t-1} + \widehat{S} \varepsilon_t.
\end{aligned}$$

Hence, by means of the Kalman filter we re-estimate the factors and we get the estimates of the common shocks:

$$\widehat{f}_t = \text{Proj}[f_t|X_1', \ldots, X_T'],\ t = 0, 1, \ldots, T$$
$$\widehat{\varepsilon}_t = H^{-1}B'(\widehat{f}_t - \widehat{A}\widehat{f}_t').$$

- Fourth, we recover the impulse response functions of the common component by inverting the factor-VAR-representation and substituting out in the first equation of model (2):

$$\begin{aligned}\widetilde{X}_t &= \widehat{\mathcal{F}}(I - \widetilde{A}L)^{-1}\widehat{S}R\varepsilon_t \\ &= \widehat{\mathcal{F}}(I + \widehat{A}L + \widehat{A}^2L^2 + \ldots)\widehat{S}R\varepsilon_t \\ &= \widehat{\Gamma}(L)R\varepsilon_t\end{aligned} \tag{3}$$

  where the entries of R depend on the identifying assumption. We will discuss later this issue.

3 Sectoral comovements

In the following we deal with a panel of US annual data on labor productivity and employment relative to the Manufacturing sector, the durable and nondurable goods producing sectors, and the 2-digit SIC manufacturing industries. Employment is measured as hours worked while productivity is measured as deflated value of production over employment; the time span is 1949-2000.

The first step of the empirical analysis consists in determining if labor productivity and hours worked comove across sectors, particularly at business cycle and lower frequencies. If so, this would imply that few shocks can explain the dynamics of the sectoral variables. As said before, one approach to measuring the degree of comovements is to determine the number of dynamic principal components which are sufficient to explain the bulk of labor productivity and employment variances. If the number is small, few shocks are relevant for sectoral dynamics.

Looking at hours worked, Figure 1 (Plot b) shows that the first principal component explains about 75% of the sectoral variance at the business cycle frequencies. Adding a second principal component substantially improves the explained variance at the long-run horizon, which increases by almost 20%. Two principal components also explain most of the variance for labor productivity (Figure 1, Plot a), with the second principal component determining increments ranging from 15% to 30%. Thus, in general two principal components are responsible for large shares of total variances for each sets of time series, denoting strong comovements across sectors for both labor productivity and employment. This conclusion is reinforced if we merge the two sets of data and carry out the same analysis for a single panel (Figure 1, Plot c). Now two principal components explain more than 60% of the variability at any frequency.

A complementary way to asses the commonality across sectors is to examine the goodness of fit of the projection of the sectoral variables of interest onto the first two principal components. By such analysis we show that, across industries, the average variance explained for hours is about 80%, while for labor productivity is about 62%. In particular, the common component almost always explains more than 50% of the variance of the two variables for each industry (see Table 1).[6]

Resting on previous evidence, we assess that two shocks explain the main bulk of variance at both short- and long-run horizons. Thus, in the following we will settle $m = 2$.

[6]The only two exceptions concern the labor productivity for the Food and Kindred Products and Furniture and Fixtures industries.

4 One permanent shock and sectoral dynamics

Much of the recent empirical work on business fluctuations rests on the identifying assumption that the long-run variability of labor productivity is traced to a single shock source, generally interpreted as an aggregate, sector-neutral, technology shock; any other disturbances recovered in the data are restricted to have a purely transitory influence. In this framework, the empirical evidence about what happens after a technology shock is related to the relevant issue of which class of economic models correctly interpret the dynamic behavior of market economies. For instance, by estimating a bivariate VAR with employment and labor productivity data, the long-run restriction allows to readily estimate the sequence of shocks — usually interpreted as aggregate demand shocks — which by construction have transitory effects on the level of labor productivity and those shocks affecting this variable permanently. The possibility that favorable technology shocks lead to declines in employment, while demand shocks rise both output and hours, is viewed as conflicting with the relevance of the technology-driven business cycle idea.

4.1 Identification I: Aggregate variables

Results reported in section 3 suggest that two shocks appear to explain most of the variance for both labor productivity and employment for the US, so focusing on two shocks with aggregate data does seem to be plausible. Hence, as a first instance we exploit the Galí's identifying assumption and interpret as technology shock the only shock with long-run effect on the aggregate productivity.[7] Technically, this

[7]Note that for aggregate we refer to the Manufacturing sector.

identification can be imposed by choosing $\widehat{\vartheta}$ such that

$$D\text{vec}[\widehat{\Gamma}(1)R(\widehat{\vartheta})] = 0$$

where $\widehat{\Gamma}(1)$ is the matrix of estimated long-run impulse responses.[8]

Figure 2 reports the effects of the technology and nontechnology shocks on aggregate employment and labor productivity for $r = 2$. It is noteworthy that our results look quite similar to those of Galí (1999) and others, despite the fact that we have applied a very different econometric technique and used annual rather than quarterly data. In particular, we find that just after the technology shock hours worked declines, supporting the theoretical predictions of both new keynesian models and less orthodox versions of flexible price models.

If the technology (permanent) component of the data has been correctly disentangled then the technology shock should determine positive widespread long-run effects on the labor productivity at sectors level while, more important, the nontechnology (transitory) shock should not have any long-run effect on that variable across sectors. Hence, this argument suggests that we can question the reliability of the aggregate long-run restriction looking at the dynamic effects of the shocks across sectors.[9] Figure 3 reports the responses of the labor productivity after a (positive) technology shock for the 18 manufacturing industries, the durable and nondurable goods producing sectors, and the Manufacturing sector as a whole. The figure shows that for 16 out of 18 industries the shock produces a positively and statistically significant effect in the long-run. In particular, a technology shock

[8] The D matrix, of dimension 1×84, is such that it selects only the response of the aggregate labor productivity to the transitory shock, that is all the elements but one are equal to zero.

[9] Exploiting the Galí's assumptions, Kiley (1997) also investigates the dynamic effects of technology and nontechnology disturbances at sectoral level. However, differently from the present paper, the two components of the data are recovered looking at each sector separately. Hence, the potential impact of cross-sectoral linkages are not taken into account.

determines quantitatively relevant increments of the labor productivity mainly for Chemicals and Allied Products, Rubber and Miscellaneous Plastic Products, Transportation Equipment, and Electrical Machinery. At a more aggregate level, the figure suggests that the impact of a technology shock is quantitatively more relevant for the durable goods sector than the nondurable goods one: The labor productivity increment of the former (latter) is estimated higher (lower) than that of the Manufacturing. Food and Kindred Products and Primary Metal industries are the only two industries which do not appear to be affected by a technology shock neither in the short-run nor in the long-run. Overall, our results would suggest that the identifying strategy correctly isolated the effect of a shock which can be labelled as a neutral technology shock.

The support of the Galí methodology weakens, however, when we look at the effects of the shock which by construction does not influence the aggregate labor productivity in the long-run. The impulse responses reported in Figure 4 clearly shows that for many industries such shock has a statistically-significant long-run impact. This is mainly true for 4 industries out of 8 caracterised by the production of nondurable goods (Paper and Allied Products; Printing, Publishing, and Allied Industries; Chemicals and Allied Products; Petroleum Refining and Related Products) and for 5 durable goods industries out of 10 (Stone, Clay, Glass, and Concrete Products; Primary Metal Industries; Fabricated Metal Products; Machinery; Transportation Equipment). In those cases the shock determines a positive and statistically significative effect both on impact and in the long-run. At a more aggregate level, it happens that after a nontechnology shock the labor productivity in the durable goods producing sector rises on impact and settles on a positive and statistically significant value in the long-run; consistently with the assumption the nondurable goods producing sector, instead, does not appear to be affected by the shock at all.

Previous results are based on estimates of equation (1) under the assumption of two static factors, that is $r = 2$. As showed before, this choice is appealing because it determines, on aggregate, results qualitatively similar to those reported in previous studies on the same topic. In principle, however, a different parameterization could undermine the main conclusions we achieved. Thus, we re-estimate our DFM for values of r up to 7 and replicate, for each value of r, exactly the same analysis presented before. Overall we corroborate previous findings; again, the main message is that after a transitory-nontechnology shock the labor productivity of some manufacturing industries is permanently affected. To give a flavor of the results we achieved, Figure 5 reports the effects of a nontechnology shock on the labor productivity for 4 manufacturing industries — the left-hand side is relative to $r = 4$ while the right-hand side is relative to $r = 7$. The impulse responses confirm that looking at the long-run behavior of aggregate labor productivity to identify the technology and nontechnology components of the data may neglect a relevant piece of information.[10]

4.2 Identification II: Sectoral variables

The empirical approach proposed above rests on the view that if we identify the effect of a shock by imposing a long-run restriction on a given aggregate variable, then the same restriction should characterize that variable for each sector. This argument appears to be quite plausible if one interpret, as usual, the transitory shock as nontechnology shock. It can be argued, however, that the long-run-neutrality across sectors is a too strong requirement to question the assumption that a single source of permanent innovations is responsible for the long-run behavior of labor

[10] Erceg et al. (2005) find a substantial bias in the estimated technology shock responses under the Galí assumption and show that such bias is related to the difficulty of identifying the technology schocks.

productivity. Now we follow a different route. We define the nontechnology shock for a sectoral economy as the one with the minimum impact on the weighted average across industries of the long-run labor productivity responses. Technically, this identifying assumption implies a value of $\widehat{\widehat{\vartheta}}$ such that

$$\widehat{\widehat{\vartheta}} = \underset{\vartheta}{\operatorname{argmin}} \left\{ \text{vec}[\widehat{\Gamma}(1)R(\vartheta)]'\widetilde{D}' \right\} \left\{ \widehat{\text{Var}} \left(\widetilde{D}\text{vec}[\widehat{\Gamma}(1)R(\vartheta)] \right) \right\}^{-1} \left\{ \widetilde{D}\text{vec}[\widehat{\Gamma}(1)R(\vartheta)] \right\}$$

where Var(.) denotes the variance operator.[11]

The main message of Figure 6 is that such nontechnology shock affects the long-run labor productivity. In particular, a shock determining a positive long-run effect for Manufacturing induces a similar effect for the nondurable goods producing sector. Moreover, results for different values of r, not reported, confirm the evidence of Figure 6.[12] These findings reinforce our main conclusion that the dynamic behavior of the labor productivity across US sectors does not fully support the single-source permanent shock hypothesis.

5 Neutral and sector-specific innovations

By estimating a DFM under the assumption that just sector-neutral technology shock determines persistence in aggregate (Manufacturing) labor productivity, we showed that: (a) some key features which characterize previous work with aggregate data and VAR methodology can be replicated; (b) sectoral responses to the identified shocks provide evidence which questions the identifying assumption. Thus, in the following we assume two distinct and potentially important sources of business fluctuations and long-run persistence. One source of fluctuations con-

[11]Note that we estimate the matrix $\text{Var}(\widetilde{D}\text{vec}[\widehat{\Gamma}(1)R(\widehat{\vartheta})])$, of dimension 18×18, by means of the variance-covariance matrix of the long-run impulse responses of the bootstrapped time series.

[12]Results for different values of r are available upon request.

sists of shocks which originate in the investment goods producing industries and propagate through the entire economy, possibly via the adoption of new equipment. The second source of fluctuations consists of sector-neutral shocks, which can be interpreted as economy-wide efficiency disturbances.[13] Greenwood et al. (1997) and Fisher (2005) provide, respectively, the theoretical framework for modelling the investment-specific technical change and the empirical assumptions to identify variables' dynamic responses to exogenous neutral and investment-specific technology shocks. The latter are summarized as follows.[14]

Assumption 1. Only investment-specific technology shocks affect the real investment price in the long-run.

Assumption 2. Only neutral or investment-specific technology shocks affect labor productivity in the long run.

Assumption 3. Exogenous investment-specific technology shocks which lower (raise) the real investment good price by an amount x, raise (lower) labor productivity in a known fixed proportion to x.

In order to identify the DFM in terms of the above assumptions we add to the data-panel the price of equipment series constructed by Cummins and Violante (2002), entered as a ratio to the consumption goods deflator. First, consider the aggregate responses to the investment-specific shock, reported on the right-hand side of Figure 7. For both labor productivity and hours, the effect of the shock is positive and statistically significant on impact and in the long-run. These results agree with those of Fisher (2005). Consider now the effects of the sector-neutral shock, reported on the left-hand side of the figure. The labor productivity re-

[13] For a systematic analysis of the role of sector-specific shocks when comovements across sectors are related to the economy's input output structure see, for example, Long and Plosser (1983); Hornstein and Praschnik (1997); Horvath and Verbrugge (1997); Horvath (2000). In particular, Horvath and Verbrugge (1997) provide an investigation of the sources of US fluctuations allowing for both aggregate and sector-specific shocks and conclude that at medium term independent sectoral shocks are prominent to explain forecast error variance for aggregate output.

[14] We refer to Fisher (2005) for further details.

sponds positively both on impact and in the long-run; the effects of the shock are always statistically significant. Hours, instead, responds negatively on impact before returning slowly back towards zero. The behavior of hours and labor productivity after a neutral shock are very similar to those we recovered as due to a technology shock under the Galí assumption (see Figure 2) as well as to those that Galí (1999) and Fisher (2005) estimated as due to, respectively, a technology shock and a neutral shock.[15]

Now, look at the sectoral responses. Figure 8 documents statistically significant positive effects in the long-run after a positive neutral shock for 15 labor productivities out of 18. Of course, the effect of the shock is estimated positive for the durable and non durable goods producing sectors and the Manufacturing sector, too. The main exception relates to Primary Metal Industries which appears to be not affected at all by the shock.[16] Hence, sectoral results confirm that this shock can be reasonably labelled as a sector-neutral shock.

The investment-specific shock determines heterogeneous effects across sectors (Figure 9). After a positive shock, 12 out of 18 industries document an increase of the labor productivity in the short- as well as in the long-run. The shock permanently affects the labor productivity of 5 industries which are part of the non-durable goods producing sector and of 7 industries which are part of the durable goods producing sector. At a more aggregate level, however, a significant effect is only estimated for the durable goods producing sector. Actually, this sector is responsible for the positive effect displayed on impact and in the long-run by Manufacturing. Thus, sectoral results validate the interpretation of this shock as an investment-specific technological improvement.[17]

[15]Note that the responses of the relative price of investment are in line with what expected.

[16]It is interesting to note that we previously estimated no effect at all for the labor productivity of Primary Metal Industries after a technology shock of the Galí type. In general the present results are qualitatively very similar to those we recovered under the Galí's identifying assumption.

[17]Results for hours, not reported, show that the investment shock determines positive and statistically

6 Sectors and the productivity-employment correlation

Many authors locate evidence for a strong positive correlation between aggregate hours and output, and a near-zero correlation between aggregate hours and labor productivity. Advocates of RBC models suggest that technology shocks are the main driving force behind aggregate fluctuations and that business cycles in market economies are consistent with the competitive neoclassical equilibrium.[18] In particular, a standard RBC model predicts a high positive correlation between employment and labor productivity conditional to technology shocks; thus, the nearly zero unconditional correlation between the two variables calls for another set of shocks which produce a conditional correlation of negative sign. Some proponents of the new keynesian paradigm suggest, instead, models based on nominal rigidities and variable labor effort, and focus on aggregate demand shocks, mainly monetary and public spending shocks, as the main source of macroeconomic fluctuations. For instance, under the assumption that just one type of shock can have permanent effects on labor productivity, Galí (1999) — who interprets this shock as technological — argues that the nearly zero unconditional correlation can be interpreted as the outcome, respectively, of the negative correlation due to technology shocks and the positive correlation due to demand shocks. Thus, the lack of unconditional correlation between productivity and employment is explained by reversing the effects of its sources respect to what predicted by standard RBC models.[19] Moreover, Francis and Ramey (2005) argue that the labor-productivity-permanent-shock can be plausibly interpreted as technological and confirm Galí's

significant impacts on employment across sectors at any horizons. At the same time, sectoral responses of hours to the neutral shock are often negative.

[18]King and Rebelo (2000) argue that a standard RBC model augmented with persistent exogenous technological shocks implies unconditional dynamic patterns for aggregate variables similar to those exhibited by actual time series.

[19]Blanchard (1989) and Blanchard and Quah (1989) also provide such empirical findings which they interpret as consistent with the traditional keynesian framework.

findings.[20] Christiano et al. (2003) and Chang and Hong (2005) challenge, however, previous conclusion showing that such negative conditional correlation is not robust, respectively, to the way one models the low frequency component of employment and to different measures of productivity.[21] All previous work departs from assuming a single source of permanent innovations in labor productivity interpreted as sector-neutral technology disturbances. Allowing also for investment-specific technological improvement, Fisher (2005) shows that the latter determines an increase of employment.

Conditional on the sector-neutral and investment-specific sources of business cycle, we now offer a new interpretation of the low correlation between productivity and hours worked which arises looking at sectoral data. In fact, Table 2 offers a way to interpret the aggregate unconditional correlation in terms of strong sectoral correlations. In particular, the table shows the unconditional correlations and the correlations conditional on, respectively, the investment and neutral shocks, for Manufacturing and for the durable and nondurable goods producing sectors.[22] For Manufacturing, we replicate the well-known near-zero unconditonal correlation between the two variables. However, looking at the second and third rows of the table it appears that the lack of aggregate unconditonal correlation is the net effect of, respectively, the positive correlation in the durable goods producing sector and the negative correlation in the nondurable goods one. In particular, the conditional estimates suggest that behind the lack of correlation between the two variables, on aggregate, hides a strong positive correlation in the durable goods

[20] Francis and Ramey (2005) note, however, that some variants of a standard dynamic general equilibrium model, with habit formation in consumption and adjustment costs in investment or with a high degree of complementarity between inputs in the short run, can produce the negative conditional correlation.

[21] By assuming that per capita hours worked is a stationary process Christiano et al. (2003) find that employment rises after a positive technology shock, while the converse is true if one assume that per capita hours is a difference stationary process. By looking at the total factor productivity sector by sector, Chang and Hong (2005) also show that employment rises after a positive technology shock.

[22] For technical details on how to compute conditional correlations see Galí (1999).

producing sector, conditional to the investment shock, and a negative correlation in the nondurable goods producing sector, conditional to the neutral shock. This result highlights that sectoral fluctuations provide a relevant piece of information to properly interpret aggregate evidence and suggests to look at sectoral models in order to improve our understanding of business cycle.

7 Conclusions

A very popular strategy to identify VAR models aimed at explaining business fluctuations rests on the assumption that a single source of shocks, usually interpreted as efficiency gains neutral across sectors, is responsible for the long-run persistence of labor productivity. Any other shock is restricted to just have transitory effect on this variable. An alternative strategy departs from assuming two potentially important sources of business fluctuations, one sector-neutral and the other sector-specific. The latter is usually interpreted as investment-specific technological change. By estimating a DFM with data referring to the US two-digit manufacturing industries we investigate on the reliability of the two identifying strategies. Overall our results seems to be more consistent with a framework characterized by two sources of innovations determining long-lasting effects on labor productivity. At a more general level, we argue that sectors do provide useful information in explaining the business cycle. In particular, sectoral data allows for a more deep explanation of an important empirical puzzle, namely the near-zero correlation between aggregate labor productivity and employment.

When we recover the thechnology vs nontechnology components of the data under the assumption that a single source of shocks — usually interpreted as efficiency gains neutral across sectors — is responsible for the long-run persistence of labor productivity, we find that a nontechnology shock permanently affects the labor productivity of some industries, mainly those caracterised by the production of durable goods. We argue that this result is at odds with the spirit of the identifying assumption. Of course, the aggregate transitory shock may be interpreted as a sectoral-shift shock such that it improves the labor productivity of one sector and lowers the productivity in an other one; to be consistent with the identifying assumption, however, we should assume that the effects of sectoral-shift shock across sectors are such that they exactly cancel out on aggregate. When we identify, instead, the DFM by recovering the sector-neutral and investment-specific shocks we find that, as expected, the investment shock permanently affects the labor productivity of the durable goods producing sector. Conversely, the effect of the shock is estimated not statistically significant in the nondurable goods producing sector. Finally, resting on the assumption of two potentially sources of permanent innovations we show that the near-zero correlation between aggregate productivity and employment growth rates can be interpreted as due to the positive correlation between the two variables, in the durable goods producing sector, and the negative correlation between the same variables in the nondurable goods producing sector. The positive correlation is determined by investment-specific shocks while the negative correlation is mainly traced to sector-neutral shocks.

A Data Description

Labor is measured as the hours worked by all persons engaged in a sector. The sources for employment and average weekly hours data are the BLS Current Employment Statistics program and Current Population Survey. Sectoral output is based on the deflated value of production, less that portion which is consumed in the same industry. This treatment is consistent with a production function which represents the industry as if it were a single process. Real production equals the deflated value of shipments and miscellaneous receipts plus inventory change. Intra-industry transactions are removed from all output and material input series used in this study, using transactions data contained in the various input-output tables for the U.S. economy prepared by the U.S. Bureau of Economic Analysis (BEA). It should be noted that this intra-sector transaction for total manufacturing is greater than the sum of intra-sector transactions for two-digit industries. For each two-digit industry, intra-sector transactions are those between establishments in the same industry; for total manufacturing, the intra-sector transaction consists of all shipments between domestic manufacturers, regardless of industry.[23]

It follows the list of sectors for which we have collected the above variables:

- Manufacturing
- Nondurable Goods
- Food and Kindred Products
- Textile Mill Products
- Apparel
- Paper and Allied Products
- Printing, Publishing, and Allied Industries
- Chemicals and Allied Products

[23]The definitions are taken from Bureau of Labor Statistics, US Department of Labor, sept. 2000, Measurement Framework and Methods.

- Petroleum Refining and Related Products
- Rubber and Miscellaneous Plastic Products
- Durable Goods
- Lumber and Wood Products (except furniture)
- Furniture and Fixtures
- Stone, Clay, Glass, and Concrete Products
- Primary Metal Industries
- Fabricated Metal Products (except machinery)
- Machinery (except electrical)
- Electrical and Electronic Machinery, Equipment, and Supplies
- Transportation Equipment
- Measuring and Controlling Instruments
- Miscellaneous Manufacturing Industries

The series of price is the price of equipment, as a ratio to the consumption goods deflator, constructed by Cummins and Violante (2002).

B A model with neutral and investment-specific shocks

In this appendix we solve the two-sector model. The economy is characterized by the following equations:

$$U(C, N) = \theta \ln C_t + (1-\theta)\ln(1-N_t) \tag{B.1}$$

$$C_t = Z_t K_{c,t}^{\alpha_c} N_{c,t}^{1-\alpha_c} \tag{B.2}$$

$$I_t = Q_t Z_t K_{I,t}^{\alpha_k} N_{I,t}^{1-\alpha_k} \tag{B.3}$$

$$K_{t+1} = (1-\delta)K_t + I_t \tag{B.4}$$

$$\ln Z_t = g_z + \ln Z_{t-1} + \varepsilon_{z,t} \tag{B.5}$$

$$\ln Q_t = g_q + \ln Q_{t-1} + \varepsilon_{q,t} \tag{B.6}$$

Equation (B.1) is the instantaneous utility function of the representative household, where C and N denote consumption and labor respectively. The durable, I, and the non-durable, C, goods are produced using capital and labor accordingly to the equations (B.2)-(B.3). Total factor productivity is affected by technological changes. In particular, changes in Z affect both sectors in a direct way, while changes in Q are investment specifics. Finally, equation (B.4) represents the accumulation law for total capital, while equations (B.5) and (B.6) model the evolution of technological change.

Competitive equilibrium With W, R, and P we denote respectively the wage, the rental price of capital, and the relative price of investment goods.

1. **Representative agent**. – She maximizes the expected present value of lifetime utility as given by

$$E_0\left[\sum_{t=0}^{\infty}\beta^t U\left(C_t, N_t\right)\right]$$

subject to

$$K_{t+1}P_t - \left(\frac{R_t}{P_t} + 1 - \delta\right)K_t P_t - W_t N_t + C_t = 0$$

and equations (B.5)-(B.6).

2. **Firm**. – The maximization problems of the firm in the two sectors are:

$$\max_{K_{c,t},N_{c,t}} \pi_{c,t} = Z_t K_{c,t}^{\alpha_c} N_{c,t}^{1-\alpha_c} - R_t K_{c,t} - W_t N_{c,t}$$
$$\max_{K_{I,t},N_{I,t}} \pi_{I,t} = P_t Q_t Z_t K_{I,t}^{\alpha_k} N_{I,t}^{1-\alpha_k} - R_t K_{I,t} - W_t N_{I,t}$$

3. **Equilibrium**. – Defining with $\varsigma = (K, Z, Q)$ the aggregate state of the

economy, a competitive equilibrium is a set of allocation rules $C = \mathcal{C}(\varsigma)$, $I = \mathcal{I}(\varsigma)$, and $N = \mathcal{N}(\varsigma)$, a set of pricing functions $W = \mathcal{W}(\varsigma)$, $R = \mathcal{R}(\varsigma)$, and $P_t = \mathcal{P}(\varsigma)$, and an aggregate law of motion for the capital stock $K' = \mathcal{K}(\varsigma)$ such that:

(a) The agent solve the problem taking as given the aggregate state of world and the form of pricing functions, with the equilibrium solution to this problem satisfying the allocation rules.

(b) Firms solve the problem given the aggregate state of world and the form of pricing functions, with the equilibrium solution to this problem satisfying $K_c + K_I = K$, and $N_c + N_I = N$.

Balance growth We seek a balanced growth path where all endogenous variables grow at constant rates. Dividing equation (B.4) by K_{t+1}, we have that $g_I = g_k$, where with g_y we refer to the mean rate of growth of a generic variable y. Then, using the above results and the production functions (B.2) - (B.3), it is possible to show that $g_I = g_k = \frac{1}{1-\alpha_k}(g_q + g_z)$ and $g_c = \frac{1-\alpha_k+\alpha_c}{1-\alpha_k} g_z + \frac{\alpha_c}{1-\alpha_k} g_q$. Finally, considering that $R = \mathcal{R}(\varsigma)$ is by definition the same for the two sectors, we have that $g_p = \frac{\alpha_c-\alpha_k}{1-\alpha_k} g_z - \frac{1-\alpha_c}{1-\alpha_k} g_q$.

Stationary economy We transform our economy in a no-growth economy. For this task, we take the ratio of each non stationary variable with respect to the relative stochastic trend. By studying the balance growth we know that the stochastic component for consumption is $Z_t^{\frac{1-\alpha_k+\alpha_c}{1-\alpha_k}} Q_t^{\frac{\alpha_c}{1-\alpha_k}}$, for capital and investment is $(Q_t Z_t)^{\frac{1}{1-\alpha_k}}$, while for the relative price of the investment goods is $Z_t^{\frac{\alpha_c-\alpha_k}{1-\alpha_k}} Q_t^{-\frac{1-\alpha_c}{1-\alpha_k}}$.

Indicating such ratio with lower case letter, we rewrite (B.1) - (B.4) as follow:

$$\begin{aligned} U(c, N) =& \theta \ln c_t + (1-\theta)\ln(1 - N_c - N_I) + \\ & \theta \frac{1-\alpha_k+\alpha_c}{1-\alpha_k} \ln Z_t + \frac{\theta\alpha_c}{1-\alpha_k} \ln Q_t \end{aligned} \tag{B.1'}$$

$$(e^{g_z+g_q+\varepsilon_{z,t+1}+\varepsilon_{q,t+1}})^{\frac{1}{1-\alpha_k}} k_{t+1} = (1-\delta)k_t + i_t \tag{B.4'}$$

Efficiency Condition We solve the transformed consumer problem maximizing the following Lagrangian:

$$\begin{aligned} \mathcal{L} =& E_0 \left\{ \sum_{t=0}^{\infty} \beta^t U(c_t, (1-N_t)) \right\} \\ &+ E_0 \left\{ \sum_{t=0}^{\infty} \Lambda_t \left[-(e^{g_z+g_q+\varepsilon_{z,t+1}+\varepsilon_{q,t+1}})^{\frac{1}{1-\alpha_k}} k_{t+1} p_t + \left(\frac{r_t}{p_t} + 1 - \delta \right) k_t p_t + w_t N_t - c_t \right] \right\} \end{aligned}$$

The first order conditions are as follow

$$\theta c_t^{-1} - \lambda_t = 0 \tag{B.7}$$

$$(1-\theta)(1-N_t)^{-1} - \lambda_t w_t = 0 \tag{B.8}$$

$$E_t \left\{ -\lambda_t (g_z g_q)^{\frac{1}{1-\alpha_k}} p_t + \beta\lambda_{t+1} \left(\frac{r_{t+1}}{p_{t+1}} + 1 - \delta \right) p_{t+1} \right\} = 0 \tag{B.9}$$

$$-(e^{g_z+g_q+\varepsilon_{z,t+1}+\varepsilon_{q,t+1}})^{\frac{1}{1-\alpha_k}} k_{t+1} p_t + \left(\frac{r_t}{p_t} + 1 - \delta \right) k_t p_t + w_t N_t - c_t = 0 \tag{B.10}$$

where $\lambda_t = \Lambda_t/\beta$. The solutions of the firm problem are:

$$MPk_{c,t} = r_t = p_t \times MPk_{I,t} \tag{B.11}$$

$$MPN_{c,t} = w_t = p_t \times MPN_{I,t} \tag{B.12}$$

where with $MP\Upsilon$ we indicate the marginal productivity of the generic variable Υ.

Log-linearization We now linearize our economy taking the log-deviation from the steady-state path (let's denote with $\widehat{}$ the variable in log-deviation). Following King et al. (1988) we can represent our economy by the following two equations systems:

$$M_{cc}\begin{bmatrix}\widehat{k}_{I,t}\\ \widehat{N}_{I,t}\\ \widehat{N}_{t}\end{bmatrix}=M_{cs}\begin{bmatrix}\widehat{k}_{t}\\ \widehat{\lambda}_{t}\end{bmatrix}\tag{B.13a}$$

$$M_{ss}(L)\begin{bmatrix}\widehat{k}_{t+1}\\ \widehat{\lambda}_{t+1}\end{bmatrix}=M_{sc}(L)\begin{bmatrix}\widehat{k}_{I,t+1}\\ \widehat{N}_{I,t+1}\\ \widehat{N}_{t+1}\end{bmatrix}+M_{se}\begin{bmatrix}\varepsilon_{z,t+1}\\ \varepsilon_{q,t+1}\end{bmatrix}\tag{B.13b}$$

where the matrices are functions of the deep parameters of the model, and $M_{ss}(L)$ and $M_{sc}(L)$ are polynomials in the lag operator of order one. Inverting M_{cc}, the combination of (B.13a) - (B.13b) implies:

$$M_{ss}^{*}(L)\begin{bmatrix}\widehat{k}_{t+1}\\ \widehat{\lambda}_{t+1}\end{bmatrix}=M_{se}\begin{bmatrix}\varepsilon_{z,t+1}\\ \varepsilon_{q,t+1}\end{bmatrix}.\tag{B.14}$$

Premultiplying by the inverse of M_{ss0}^{*} the previous system, we write the fundamental dynamic system of our two-sectors economy

$$\begin{bmatrix}\widehat{k}_{t+1}\\ \widehat{\lambda}_{t+1}\end{bmatrix}=V_1\begin{bmatrix}\widehat{k}_{t}\\ \widehat{\lambda}_{t}\end{bmatrix}+V_2\begin{bmatrix}\varepsilon_{z,t+1}\\ \varepsilon_{q,t+1}\end{bmatrix}\tag{B.15}$$

where $V_1=-\left[M_{ss0}^{*}\right]^{-1}M_{ss1}^{*}$ and $V_2=\left[M_{ss0}^{*}\right]^{-1}M_{se}$. Defining with μ the stable eigenvalues of the matrix V_1, and partitioning the matrix V_2 as $\left(\begin{smallmatrix}-\frac{1}{1-\alpha_k} & -\frac{1}{1-\alpha_k}\\ \upsilon_{\lambda,z} & \upsilon_{\lambda,q}\end{smallmatrix}\right)$ we can express the dynamic process for the capital in the following way:

$$\widehat{k}_{t+1} = \mu\widehat{k}_t - \frac{1}{1-\alpha_k}\varepsilon_{z,t+1} - \frac{1}{1-\alpha_k}\varepsilon_{q,t+1} \tag{B.16}$$

While the endogenous variables can be expressed as functions of the deviation of the capital from the stochastic trend, that is

$$\begin{aligned} \widehat{k}_{I,t} &= \omega_{k_I,k}\,\widehat{k}_t \\ \widehat{N}_{I,t} &= \omega_{N_I,k}\,\widehat{k}_t \\ \widehat{N}_t &= \omega_{N,k}\,\widehat{k}_t. \end{aligned} \tag{B.17}$$

State-Space Representation The task of this appendix is to recover the state-space representation of our model. In particular, we want to show how the endogenous variables can be expressed as a function of a vector of state variables. We take advantage of equations (B.16) - (B.17) and the definition of log-deviation from the steady state of the transformed variables, that is

$$\ln \Upsilon_t = \ln \Upsilon_t^p + \ln \Upsilon + \widehat{\Upsilon}_t$$

where with Υ_t^p we indicate the permanent component of a generic variable Υ.

Taking the first differences of the previous equation and plugging in equations (B.16) - (B.17), we have:

$$X_t^* = \mathcal{F} f_t \tag{B.18}$$

where $f_t' = [\widehat{k}_{t-1}, \varepsilon_{z,t}, \varepsilon_{q,t}]$, X_t^* is a vector composed by the centralized first differences of $\ln C_t$, $\ln I_t$, and $\ln Y_t$ and by the centralized level of $\ln N_{c,t}$, $\ln N_{I,t}$, and

$\ln N_t$, and the matrix $\mathcal{F}$ is as follows

$$\mathcal{F} = \begin{pmatrix} \omega_{c,k}(\mu-1) & \frac{1-\alpha_k+\alpha_c-\omega_{c,k}}{1-\alpha_k} & \frac{\alpha_c-\omega_{c,k}}{1-\alpha_k} \\ \omega_{I,k}(\mu-1) & \frac{1-\omega_{I,k}}{1-\alpha_k} & \frac{1-\omega_{I,k}}{1-\alpha_k} \\ \omega_{y,k}(\mu-1) & \frac{1-\alpha_k+\alpha_c-\omega_{y,k}}{1-\alpha_k} & \frac{\alpha_c-\omega_{y,k}}{1-\alpha_k} \\ \omega_{N_c,k}(\mu-1) & -\frac{\omega_{N_c,k}}{1-\alpha_k} & -\frac{\omega_{N_c,k}}{1-\alpha_k} \\ \omega_{N_I,k}(\mu-1) & -\frac{\omega_{N_I,k}}{1-\alpha_k} & -\frac{\omega_{N_I,k}}{1-\alpha_k} \\ \omega_{N,k}(\mu-1) & -\frac{\omega_{N,k}}{1-\alpha_k} & -\frac{\omega_{N,k}}{1-\alpha_k} \end{pmatrix}$$

For the vector f_t the following VAR holds:

$$f_t = Af_{t-1} + S\varepsilon_t \tag{B.19}$$

where $A = \begin{pmatrix} \mu & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$, $S = \begin{pmatrix} -\frac{1}{1-\alpha_k} & -\frac{1}{1-\alpha_k} \\ 1 & 0 \\ 0 & 1 \end{pmatrix}$, and $\varepsilon_t = [\varepsilon_{z,t}, \varepsilon_{q,t}]$. Finally, by inverting equation (B.19) and substituting for f_t in (B.18) it follows the MA representation:

$$X_t^* = \mathcal{F}[I - AL]^{-1}S\varepsilon_t = \Gamma(L)\varepsilon_t. \tag{B.20}$$

References

Bai, J., Ng, S., 2000. Determing the number of factors in approximate factor models. Econometrica 70, 191–221.

Blanchard, O. J., 1989. A traditional interpretation of macroeconomic fluctuations. American Economic Review 79, 1146–64.

Blanchard, O. J., Quah, D., 1989. The dynamic effect of aggregate demand and supply disturbances. American Economic Review 79, 655–673.

Chang, Y., Hong, J. H., 2005. Do technological improvements in the manufacturing sector raise or lower employment? American Economic Review 96, 352–368.

Christiano, L. J., Eichenbaum, M., Vigfusson, R., 2003. What happens after a technology shock? NBER Working Paper No. 9819.

Cummins, J. G., Violante, G. L., 2002. Investment-specific technical change in the us (1947-2000): Measurement and macroeconomic consequences. Review of Economic Dynamics 5, 243–284.

Erceg, C., Guerrieri, L., Gust, C., 2005. Can long-run restrictions identify technology shocks? Journal of the European Economic Association 3, 1237-1278.

Fisher, J. D. M., 2005. The dynamic effects of neutral and investment-specific technology shocks. Mimeo.

Forni, M., Hallin, M., Lippi, M., Reichlin, L., 2000. The generalized dynamic factor model: Identification and estimation. Review of Economics and Statistics 82, 540–554.

Francis, N., Ramey, V. A., 2005. Is the technology-driven real business cycle hypothesis dead? Shocks and aggregate fluctuations revisited. Journal of Monetary Economics 52, 1379–1399.

Galí, J., 1999. Technology, employment, and the business cycle: Do technology shocks explain aggregate fluctuations? American Economic Review 89, 249–71.

Giannone, D., Reichlin, L., Sala, L., 2005. Monetary Policy in Real Time. In Gertler, M., Rogoff, K. (Eds.) NBER Macroeconomics Annual 2004. The MIT Press, Boston, pp. 161-224

Greenwood, J., Hercowitz, Z., Krusell, P., 1997. Long-run implications of investment-specific technological change. American Economic Review 87, 342–362.

Greenwood, J., Hercowitz, Z., Krusell, P., 2000. The role of investment-specific technological change in the business cycle. European Economic Review 44, 91–115.

Hornstein, A., Praschnik, J., 1997. Intermediate inputs and sectoral comovement in the business cycle. Journal of Monetary Economics 40, 573–595.

Horvath, M., 2000. Sectoral shocks and aggregate fluctuations. Journal of Monetary Economics 45, 69–106.

Horvath, M., Verbrugge, R., 1997. Shocks and sectoral interactions: an empirical investigation. Mimeo.

Kiley, M. T., 1997. Labor productivity in u.s. manufacturing: Does sectoral comovement reflect technology shocks. Mimeo.

King, R. G., Rebelo, S. T., 2000. Resuscitating real business cycles. NBER Working Paper No. 7534.

King, R., Plosser, C., Rebelo, S., 1988. Production, growth and business cycles ii: New directions. Journal of Monetary Economics 21, 309–341.

Long, J. B., Plosser, C. I., 1983. Real business cycles. Journal of Political Economy 91, 39–69.

Stock, J. H., Watson, M. W., 1999. Forecasting inflation. Journal of Monetary Economics 44, 293–335.

Stock, J. H. and Watson, M. W., 2002. Macroeconomic forecasting using diffusion indexes. Journal of Business and Economic Statistics 40, 147–162.

Table 1: Percentage of Variance Explained by the First Two Dynamic Principal Components

INDUSTRY	**Labor Productivity**	**Hours**
Manufacturing	0.78	0.91
Nondurable Goods	0.54	0.91
Food and Kindred Products	0.46	0.57
Textile Mill Products	0.60	0.83
Apparel	0.64	0.81
Paper and Allied Products	0.54	0.82
Printing, Publishing, and Allied Industries	0.64	0.58
Chemicals and Allied Products	0.76	0.75
Petroleum Refining and Related Products	0.63	0.55
Rubber and Miscellaneous Plastic Products	0.67	0.91
Durable Goods	0.76	0.90
Lumber and Wood Products	0.57	0.87
Furniture and Fixtures	0.48	0.91
Stone, Clay, Glass, and Concrete Products	0.60	0.90
Primary Metal Industries	0.77	0.86
Fabricated Metal Products	0.58	0.86
Machinery (except electrical)	0.70	0.78
Electrical and Electronic Machinery	0.69	0.79
Transportation Equipment	0.61	0.77
Measuring and Controlling Instruments	0.57	0.78
Miscellaneous Manufacturing Industries	0.59	0.77

Note. The table describes the share of the variance of the growth rates of labor productivity and hours worked explained by the common component.

Table 2: Conditional Correlation Estimates

	Unconditional	Conditional	
		Investment	Neutral
Manufacturing	-0.16	0.52**	-0.63**
Nondurable goods	-0.32**	0.18	-0.74**
Durable goods	0.20	0.73**	-0.22

Note. The table reports estimates of unconditional (data) and conditional correlations between the growth rates of labor productivity and hours for Manufacturing, Nondurable and Durable goods producing sectors. Significance is indicated by one asterisk (10-percent level) or two asterisks (5-percent level).

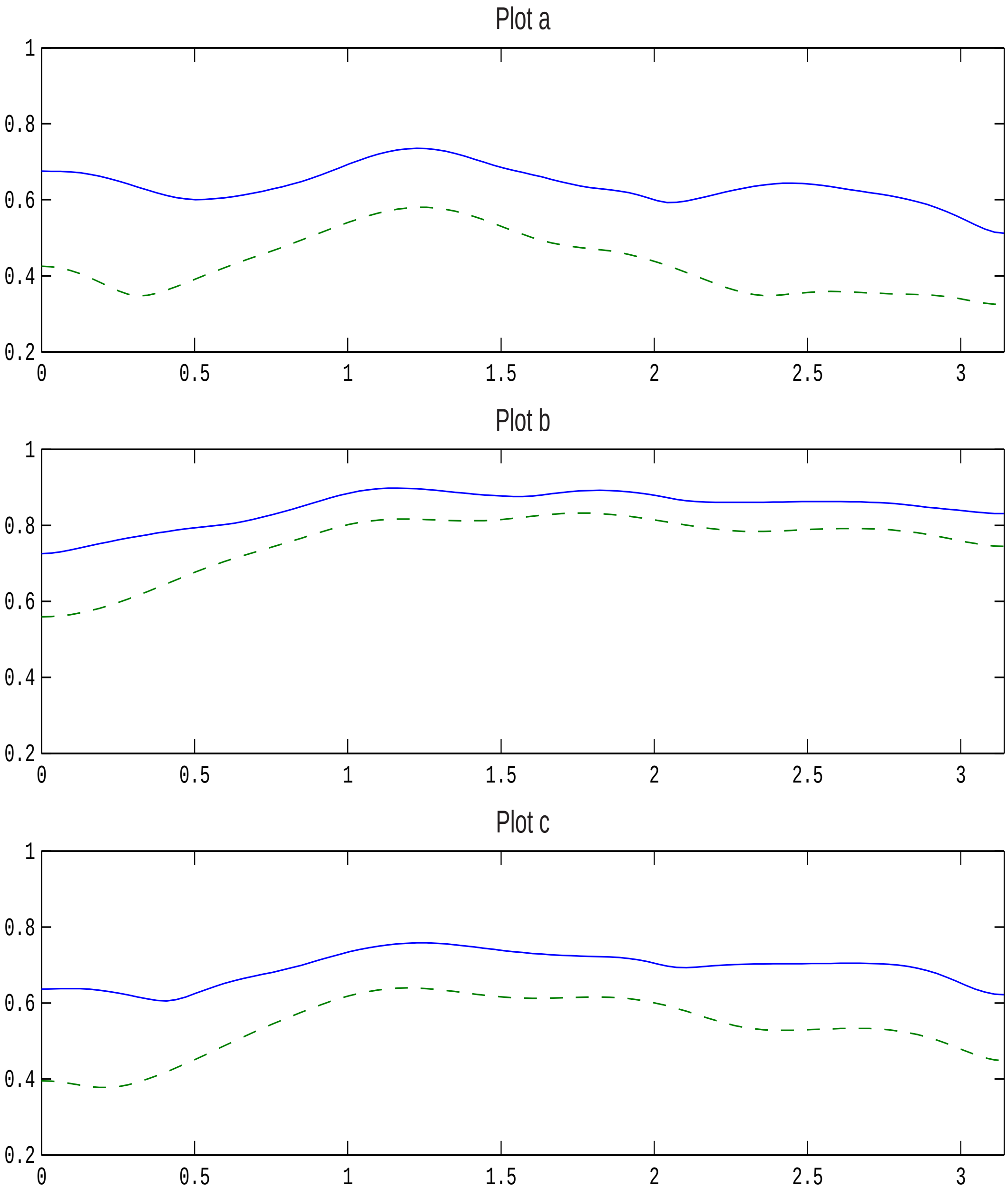

Figure 1: Shares of total variance of growth rates of labor productivity (Plot a), hours worked (Plot b), and both labor productivity as well as hours worked (Plot c) explained by the first component (dashed line) and the first two components (solid line) at each frequency.

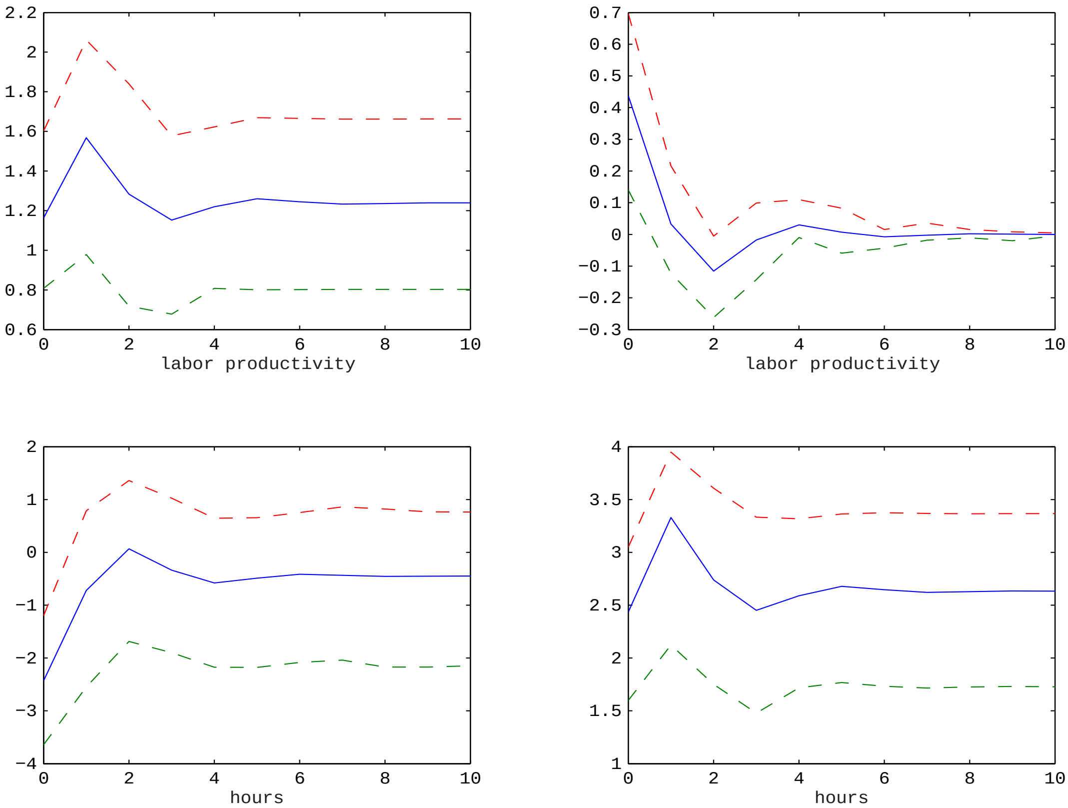

Figure 2: Impulse response functions relative to the Manufacturing sector under the Galí assumption. Plots on the left hand-side report the effects of a technology shock while plots on the right hand-side report the effects of a nontechnology shock, that is a shock with transitory effects on aggregate labor productivity.

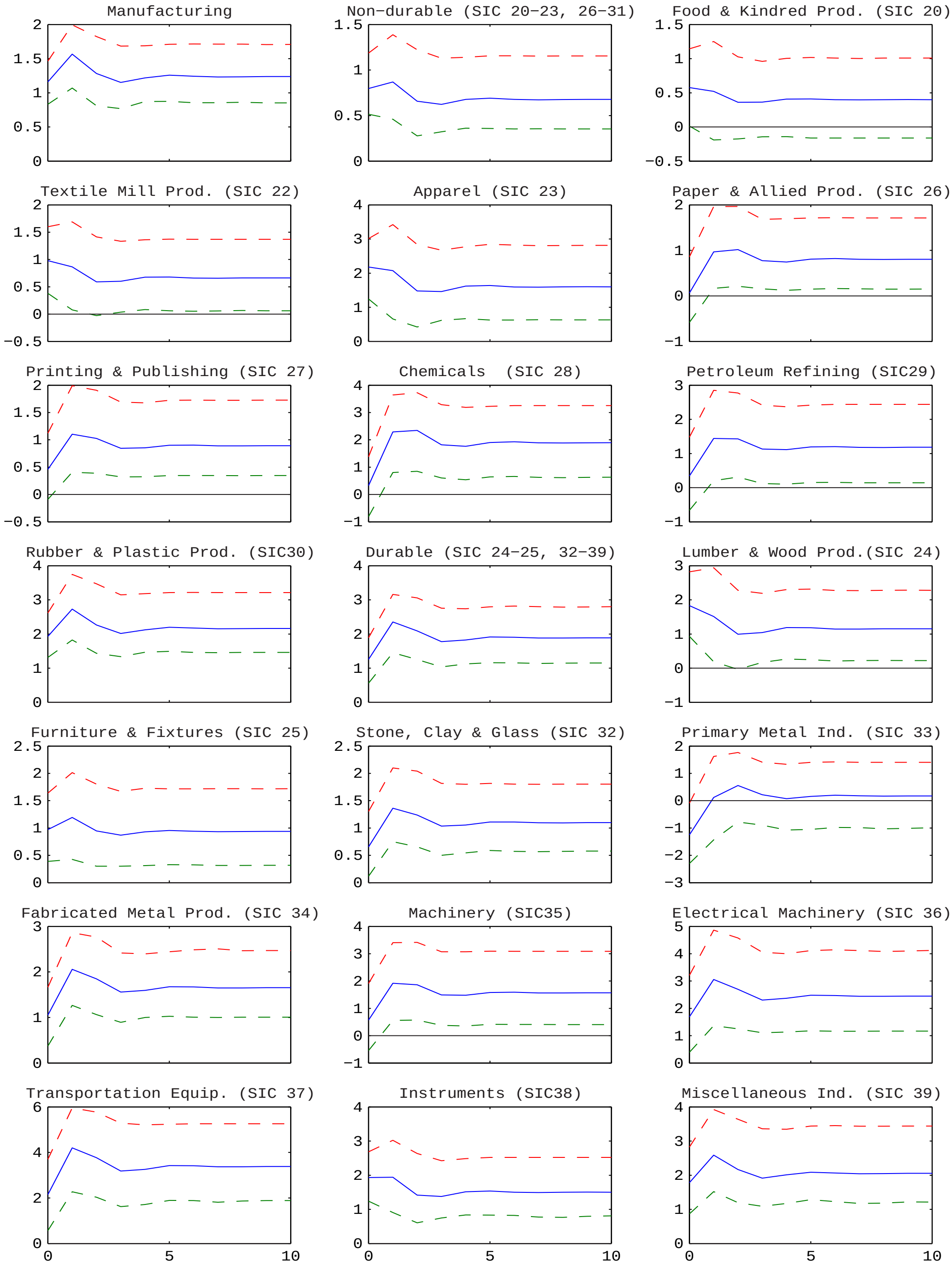

Figure 3: Response functions of the labor productivity across manufacturing sectors after a technology shock, under the Galí assumption ($r = 2$).

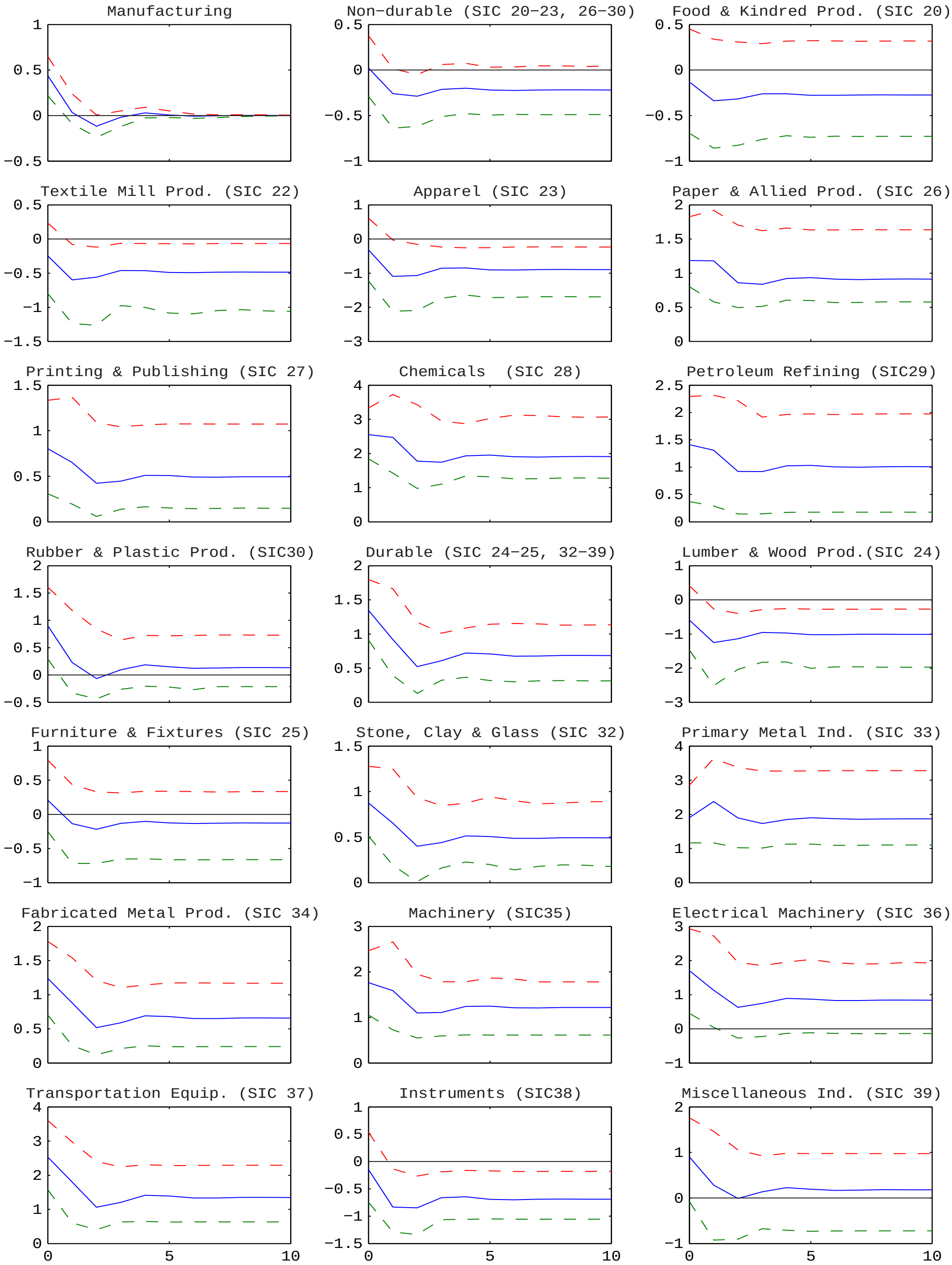

Figure 4: Response functions of the labor productivity across manufacturing sectors after a nontechnology shock, under the Galí assumption ($r = 2$).

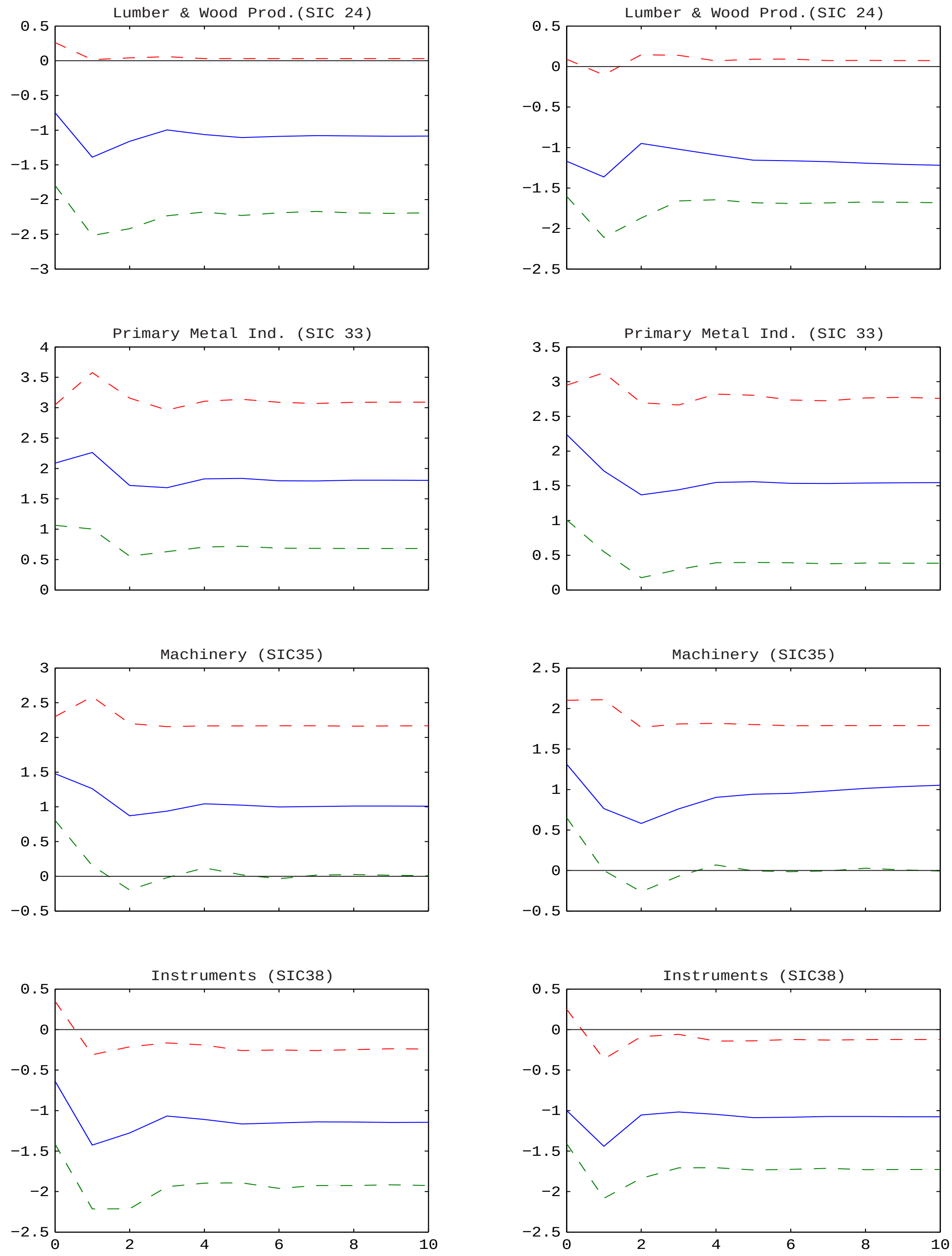

Figure 5: Response functions of the labor productivity to a nontechnology shock, under the Galí assumption, for $r = 4$ (left-side) and $r = 7$ (right-side).

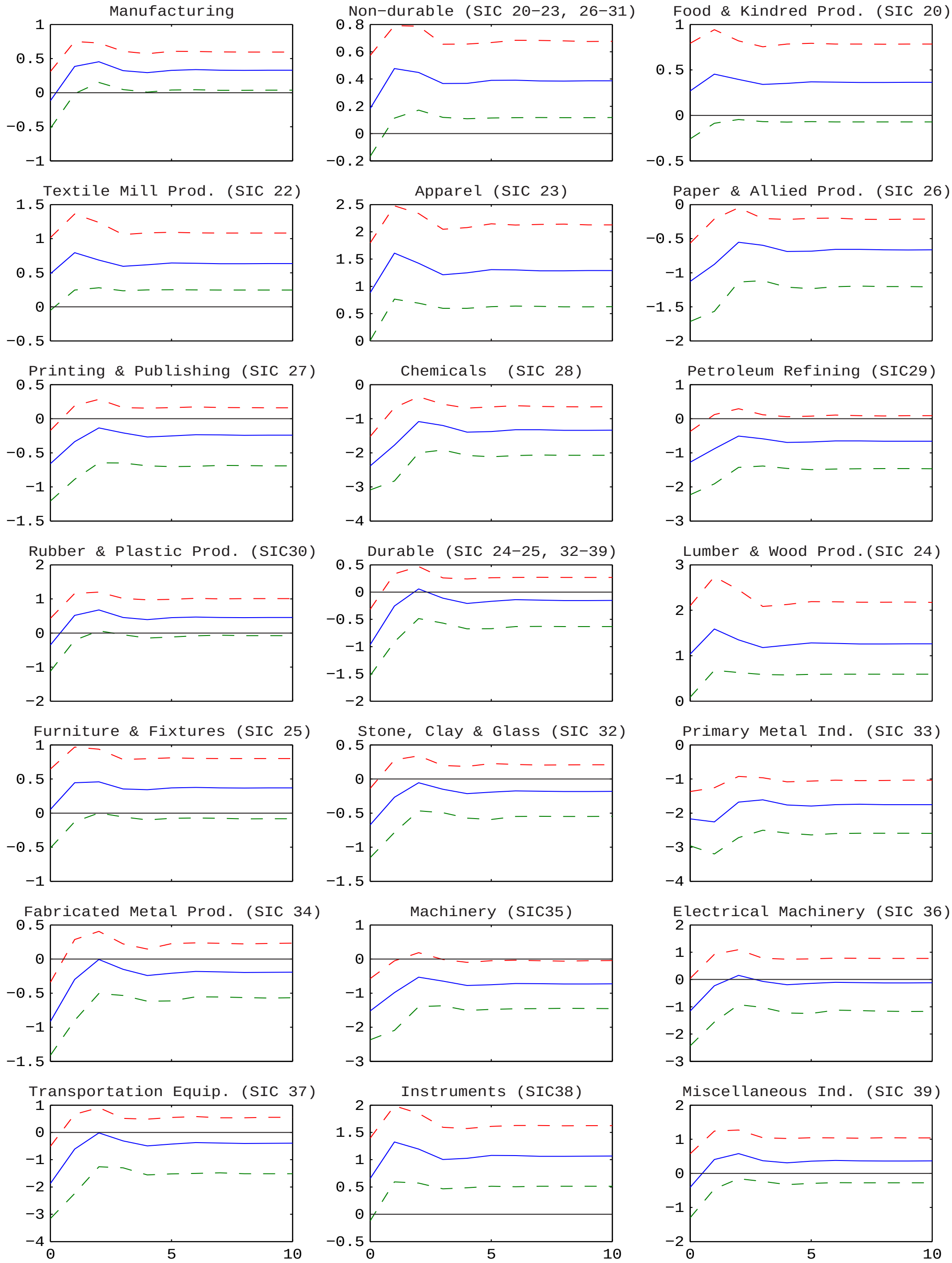

Figure 6: Response functions of the labor productivity to a shock determining the minimum long-run impact on sectoral labor productivities ($r = 2$).

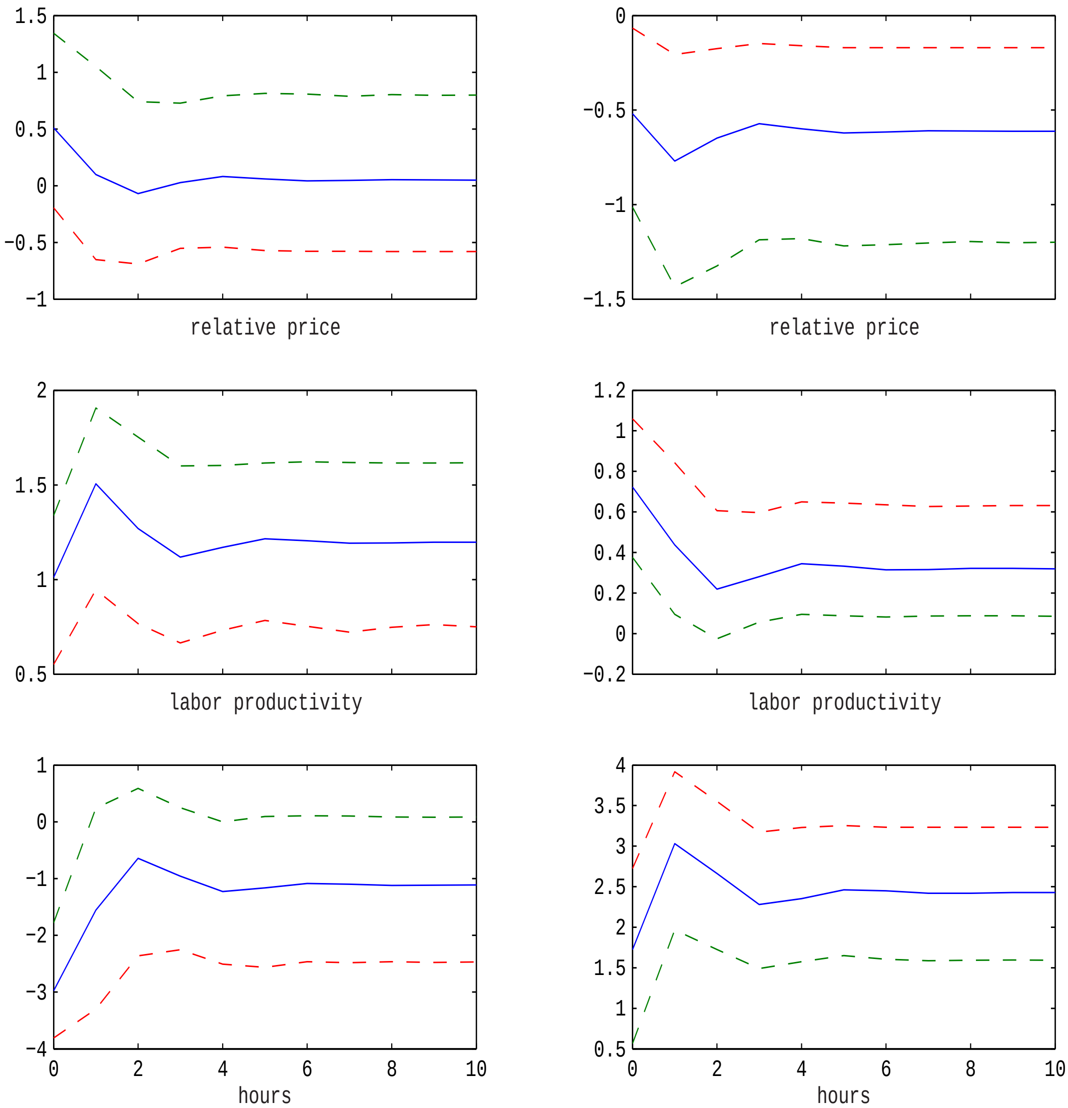

Figure 7: Response functions of relative price, aggregate labor productivity, and aggregate hours. On the right-hand side we report the effects of an investment-specific shock while on the left-hand side those of a sector-neutral shock.

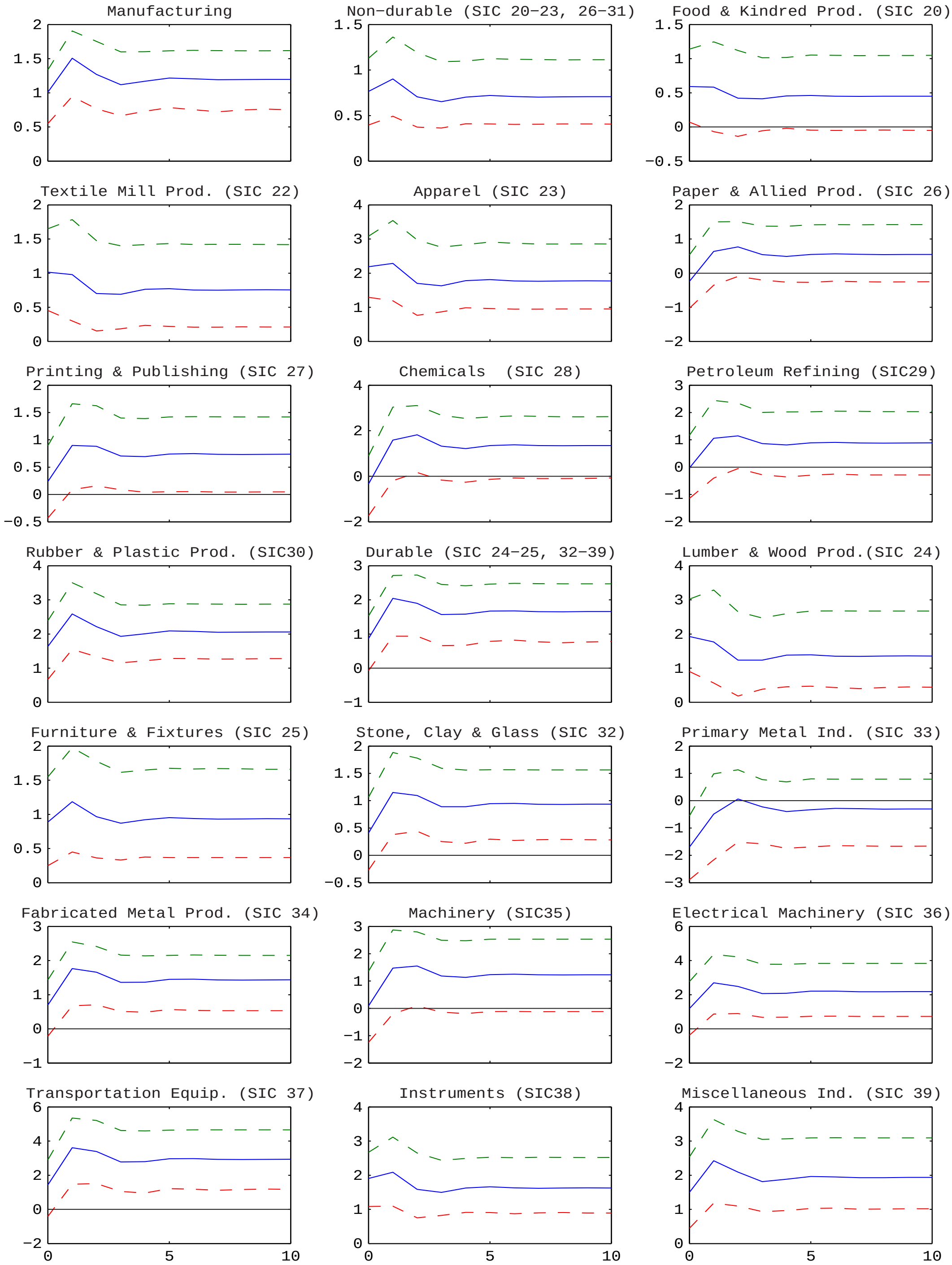

Figure 8: Response functions of the labor productivity across sectors to a sector-neutral shock ($r = 2$).

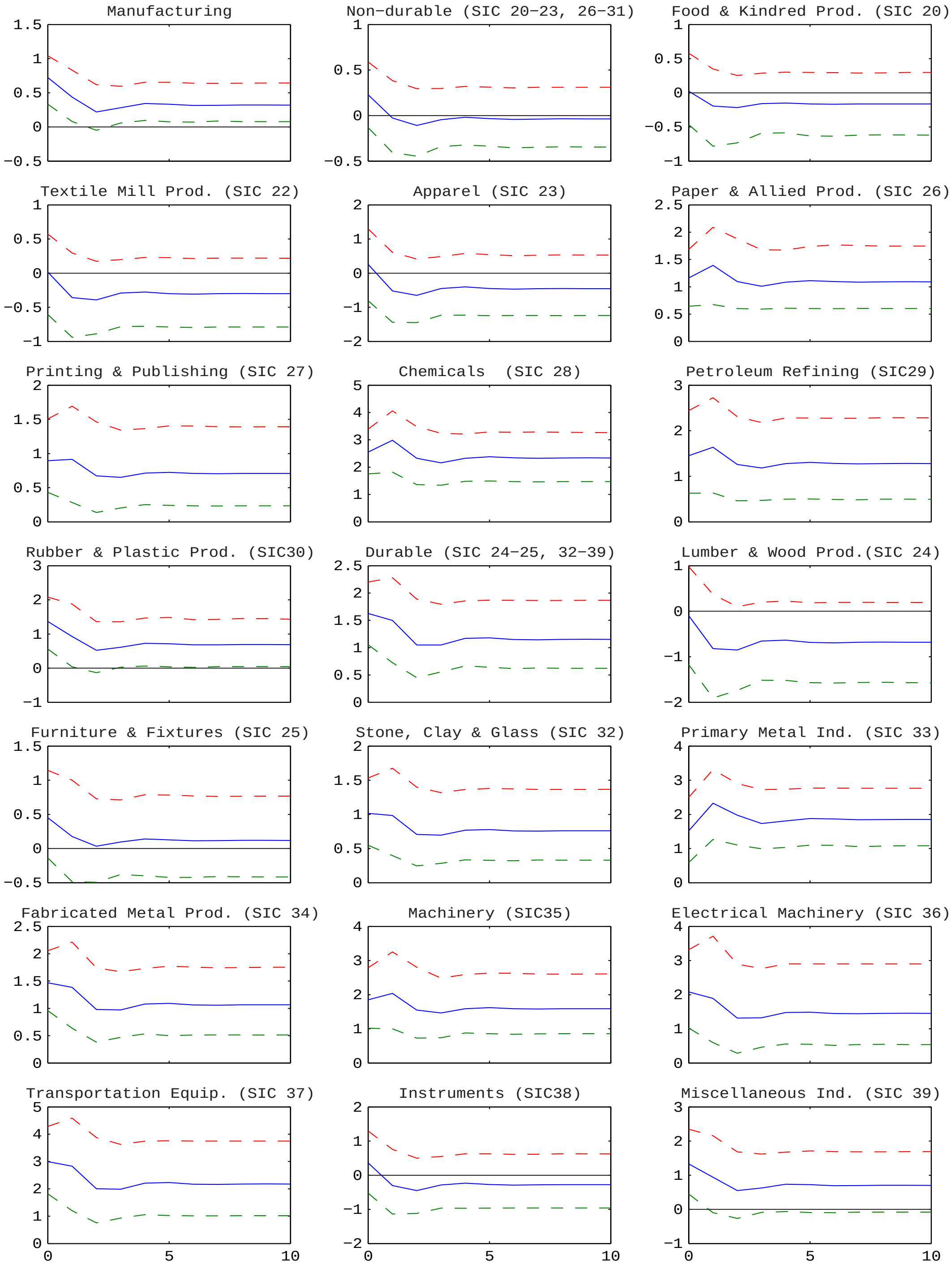

Figure 9: Response functions of the labor productivity across sectors to an investment-specific shock ($r = 2$).