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WORKING PAPER

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Working Paper No. 2005-11

DEPARTMENT OF ECONOMICS

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Technology and non-technology shocks in a two-sector economy[1]

Francesco Busato[2], Alessandro Girardi[3], Amedeo Argentiero[4]

Abstract

This paper presents an empirically testable two-sector dynamic general equilibrium model for the United States economy that admits technology and non-technology shocks. Long-run identification restrictions further distinguish the impact of each shocks over the originating sector (i.e. as a sector-specific), and over other sectors different from the originating one (i.e. as a cross-sector shock), also exploring the shocks transmission mechanism across sectors.

There are **three** main results. **First**, business cycle are mainly generated, in each sector, by technology shocks (mainly described by sector-specific shocks), but they are transmitted across sectors along the sectors' demand side, i.e. passing through non-technology shocks. **Second**, technology and non-technology shocks almost equally share the responsibility of fluctuations in the aggregate manufacturing sector. **Third**, the dynamic behavior of the durable good sector may be well represented by a standard Real Business Model; the non-durable good sector, on the other hand, would not be consistent with that predictions. Overall, due to a size effect, the aggregate dynamics is driven by the relatively larger sector, which is the non-durable good one.

Keywords: Long-run restrictions, sector-specific shocks, cross sector shocks, real business cycle, United States economy.

JEL Classification: E2, E3, E32.

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[1] We are grateful to John Donaldson, Niels Haldrup, Marc Giannoni, Marco Lippi, Enrico Marchetti and Paolo Paesani for many conversation, and the participants to seminars at the University of Aarhus, University of Rome "Tor Vergata", and to the Halle Institute for Economic Research 6th Macroeconometric Workshop, XIV International Tor Vergata Conference on Banking and Finance for comments on previous versions of the paper. Of course, all errors are ours. Francesco Busato gratefully acknowledges financial support from Aarhus University FORSKNINGSFOND, Grant # 298.

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1 – Introduction

Over the last two decades, macroeconomists explained aggregate fluctuations as mainly driven by technology shocks. This is the standard Real Business Cycle (RBC) model (e.g. Kydland and Prescott, 1982; Long and Plosser, 1983).

A recent body of literature questions the very foundations of RBC theory, suggesting that positive technological shocks lead to declines in input use, that selected productivity measures are essentially uncorrelated with output, and negatively correlated with input growth (e.g. Basu et al. 2004; Francis and Ramey, 2005; Busato, 2004; Gali, 1999 and 2004; Shea, 1998). A growing number of works originated from this debate, mainly addressing four key issues: the role of aggregate technology shocks in explaining output fluctuations (Gali, 1999; Francis and Ramey, 2005); the sign of the correlation between technology shock and labor inputs (Gali, 1999; Francis and Ramey, 2005; Christiano et al. 2003); the nature of the stochastic process driving labor inputs series (Christiano et al. 2003); and the adequateness of the Vector AutoRegression (VAR) methodology as a statistical tool for the analysis of the predictions of RBC models (Chari et al., 2004).

These studies, the results of which have relevant normative and positive implications, have been conducted exclusively within the context of the aggregate manufacturing sector. Only recently Chang and Hong (2005) studied the role of total factor productivity in explaining employment movements at an industry level. Yet, their investigation is limited to a sector-specific level and does not analyze, for example, the transmission of shocks across sectors, which is, anticipating a result, an interesting part of the story. In addition, we are not aware, to the best of our knowledge, of other studies that explain aggregate United States business cycle regularities by using a structural VAR approach specifically focusing on interdependencies across sectors. This paper is an attempt to fill this gap.

Our analysis contributes to this debate by suggesting a disaggregate perspective over the relationships between technology/non-technology shocks and productivity/employment, looking at a multi-sector economy. The theoretical model underlining our estimates is a general one; it allows resources transfer across sectors without any restrictions, and it does not impose, *a priori*, any restriction on price behavior. Testable restrictions are, then, applied and tested relying on the data to precisely identify the relative contributions of these shocks and their interaction. In our setup, the two sectors represent the durable and the non-durable sectors for the United States economy over the period 1953-1996.

Here is an overview of our methodology and of the main results.

We estimate our theoretical model by employing a multi-equation autoregression model with long-run restriction that allows for sector-specific and cross-sector shocks in our two-sector economy. Following Gali (1999) and Chang and Hong (2005), for the identification of the sources of macroeconomic fluctuations we use long-run restrictions, according to the approach proposed by Blanchard and Quah (1989). We define sector-specific shocks as disturbances that originate in one sector and affect labor productivity and employment of that sector; cross-sector shocks are disturbances that originate in one sector, but that eventually affect labor productivity and employment of the other sector.

Focusing on the **sources of macroeconomic fluctuations**, we find that sector-specific technology shocks are the most relevant source of productivity volatility on a sector-by-sector basis, while sector-specific non-technology shocks are the main driving factor for employment volatility in each sector.

However, this is only a part of the whole story. For properly understanding the **resource transmission mechanism across sectors**, we show that while cross-sector technology shocks have a negligible role in capturing productivity and employment fluctuations, cross-sector non-technology shocks explain more than a half of employment reallocated across sector, putting forward a shock transmission mechanism across sectors along the “demand side” of the economy.

Concerning then the **theoretical implications of our analysis**, this paper suggests that the dynamic behavior of the durable good sector may be well represented by a standard Real Business Model; the non-durable good sector, on the other hand, would not be consistent with that predictions.

In summary, we find that the aggregate United States business cycle is driven by both cross-sector disturbances and sector-specific shocks hitting the non-durable sector. These findings hold across several alternative empirical specifications.

To conclude, estimations results as well as dynamic simulation exercises suggest that the dynamical behavior of the aggregate economy documented in previous studies is driven by the relatively larger-in-size sector (i.e. the non-durable goods sector). Hence, looking at the sole aggregate economy might produce misleading results due to the presence of strong heterogeneities across sectors, leading to an *aggregation bias*. We argue that a more satisfactory characterization of the United States (US in the sequel) economy requires a multi-sector perspective. In this respect, a disaggregate analysis may shed light on the mechanisms behind the propagation of shocks across sectors and over time.

The paper is structured as follows. After this introduction we discuss the theoretical and methodological framework in Section 2. Next, we illustrate selected stylized facts on the durable and non-durable sectors of the US manufacturing in Section 3. Estimates and dynamic simulations are presented in Section 4 and 5. Robustness checks and extensions are discussed in Section 6. Final remarks and bibliographical notes conclude.

2 – Methodological outline

We study the dynamic effects of technology and non-technology shocks in a two-sector dynamic general equilibrium model in which the identification of the sources of macroeconomic fluctuations relies on the assumption that labor productivity is driven by productivity shocks, while labor services are driven by preference shocks.

2.1 – Theoretical model

Assume that there are no restrictions to trade, and that a Planner equilibrium is solved. This implies that the dynamic equilibrium of the theoretical model is characterized from the sequence of quantities representing the optimal choice of the representative consumer given feasibility constraints. This characterization does not impose any restriction on underlining price behavior. If underlining prices were fully competitive the resulting planner allocation could be decentralized as a competitive equilibrium along the lines of the Second Welfare Theorem; in this case the allocation would be Pareto-efficient. If prices were not competitive (e.g. consider for example the case of "*sticky prices*"), the resulting allocation would be interpreted as a sub-optimal one.

The representative households' intertemporal preferences are specified over two consumption goods and leisure:

(1) $$U\left(\left(C_{1,t}\right)_{t=0}^{\infty},\left(C_{2,t}\right)_{t=0}^{\infty}\right)=E_0\sum\nolimits_{t=0}^{\infty}\beta^t\left[u\left(C_{1,t};\tilde{\theta}_{1,t}\right)+v\left(C_{2,t};\tilde{\theta}_{2,t}\right)+B\left(N_t\right)\right],$$

where $u\left(C_{1,t};\tilde{\theta}_{1,t}\right)$ and $v\left(C_{2,t};\tilde{\theta}_{2,t}\right)$ are two instantaneous utility function measuring utility from consuming $C_{1,t}$ and $C_{2,t}$, respectively; $\tilde{\theta}_{i,t}$, $i=1,2$, denote idiosyncratic preference (i.e. non-technology) shocks affecting each consumption flow, and following AR(1) processes $\tilde{\theta}_{i,t}=\rho\tilde{\theta}_{i,t-1}+\tilde{u}_{i,t}$, $\tilde{u}_{i,t}$ being white noise innovations; $0<\beta<1$ is the subjective discount factor, and E_0 denotes expectation conditional on time zero available information. The parameter $B<0$ denotes the disutility of working, and N_t denotes aggregate employment supply, which satisfies the following feasibility constraint:

(2) $N_{1,t}+N_{2,t}=N_t$,

where $N_{i,t}$ denotes labor input in i-th sector.

In addition, the sum of consumption and investment (next period capital stock) in each sector should not exceed produced resources:

(3) $C_{i,t}+K_{i,t+1}=\tilde{\lambda}_{i,t}\cdot F\left(K_{i,t},N_{i,t}\right)+\left(1-\Omega_i\right)\cdot K_{i,t}$ for $i=1,2$,

where $\tilde{\lambda}_{i,t}$ denote idiosyncratic technology shocks, $K_{i,t}$ is the capital stock, $F\left(K_{i,t},N_{i,t}\right)$ is the production function and Ω_i is the quarterly depreciation rate of capital. Productivity shocks follow AR(1) process as well. Production functions satisfy neoclassical hypothesis and are well behaved.

The Planner maximizes representative consumer's intertemporal utility function (1) subject to the labor allocation constraint (2), to the feasibility constraint (3), to the technological constraints (4) and to the autoregressive structure of the preference and the technology shocks. Technically speaking, define with $s_t=\left\{K^*_{1,t},K^*_{2,t},\tilde{\theta}_{1,t},\tilde{\theta}_{2,t},\tilde{\lambda}_{1,t},\tilde{\lambda}_{2,t}\right\}$ the "state" of the economy at time t; it depends on the predetermined values of capital stocks in each sector, and on the actual realization of technology and non-technology shocks. An optimal Planner allocation is a vector

(5) $\Theta^*_t(s_t)=\left\{C^*_{1,t}(s_t),C^*_{2,t}(s_t),N^*_{1,t}(s_t),N^*_{2,t}(s_t),K^*_{1,t+1}(s_t),K^*_{2,t+1}(s_t)\right\}$

that maximizes

$$
\begin{aligned}
maxU\left(\left(C_{1,t}\right)_{t=0}^{\infty},\left(C_{2,t}\right)_{t=0}^{\infty}\right) &= E_0\sum_{t=0}^{\infty}\beta^t\left[u\left(C_{1,t};\tilde{\theta}_{1,t}\right)+v\left(C_{2,t};\tilde{\theta}_{2,t}\right)-B\left(N_t\right)\right]\\
s.t.N_{1,t}+N_{2,t} &= N_t\\
s.t.C_{i,t}+K_{i,t+1}-\left(1-\delta_i\right)K_{i,t} &= \tilde{\lambda}_{i,t}F(K_{i,t},N_{i,t}) \quad i=1,2\\
\tilde{\lambda}_{i,t}F(K_{i,t},N_{i,t}) &= \tilde{\lambda}_{i,t}K_{i,t}^{\alpha_i}N_{i,t}^{1-\alpha_i} \qquad i=1,2\\
\tilde{\theta}_{i,t} &= \rho\tilde{\theta}_{i,t-1}+\tilde{u}_{i,t} \quad \tilde{u}_{i,t}\sim N\left(0,\sigma^2_{u,i}\right) \quad i=1,2\\
\tilde{\lambda}_{i,t} &= \psi\tilde{\lambda}_{i,t-1}+\tilde{e}_{i,t} \quad \tilde{e}_{i,t}\sim N\left(0,\sigma^2_{e,i}\right) \quad i=1,2
\end{aligned}
$$

Now, the optimal planner allocation $\Theta^*_t(s_t)$ can be characterized (i.e. rearranged) as a sequence of labor productivities (the Π^*'s) and employment flows in each sector (the N's):

(6) $Z^*_t(s_t)=\left\{\Pi^*_{1,t}(s_t),\Pi^*_{2,t}(s_t),N^*_{1,t}(s_t),N^*_{2,t}(s_t)\right\},t=0,1,2,...$

The sequence $Z_t^*(s_t)$ expresses the dynamic optimal planner allocation of the model relating the labor productivities and the employment flows in each sector to the technology and the non-technology shocks included in state vector s_t.[1]

In order to more clearly explain the connection among labor productivities, employment flows with technology and non-technology shocks, we specify functional forms for preference and technology, and we present an example focusing, for the sake of simplicity, on the deterministic stationary state.

Example. *Assume that* $u() = \ln(c_1)$, $v() = \ln(c_2)$, $B(n) = Bn$, *that the production functions are Cobb-Douglas with capital shares* $0 < \alpha_i < 1$, *and solve the Social Planner problem previously defined, deriving the necessary and sufficient first order conditions. Imposing certainty equivalence it can be shown, after a fair amount of algebra (see the Appendix for details), that there exists a unique deterministic stationary state for capital stock and labor services ratio, such that:*

$$K_i^* = \frac{(1-\alpha_i)\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}(\theta_i)}{B\left[\lambda_i\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]}$$

$$N_i^* = \frac{(1-\alpha_i)\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right](\theta_i)}{B\left[\lambda_i\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]}$$

Combining them, we obtain the following expressions for labor productivity and for labor input in each sector:

$$\Pi_i = \tilde{\lambda}_i * \left[\frac{K_i^*}{N_i^*}\right]^{\alpha_i} = \tilde{\lambda}_i * \left[\frac{\dfrac{(1-\alpha_i)\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}(\theta_i)}{B\left[\lambda_i\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]}}{\dfrac{(1-\alpha_i)\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right](\theta_i)}{B\left[\lambda_i\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]}}\right]^{\alpha_i} = \tilde{\lambda}_i * \left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}$$

[1] If technology shocks represent innovations in the "supply side" of the economy, the non-technology shocks can be thought as representing innovations in the "demand side". Given this interpretation, equation (6) suggests that employment and labor productivities are driven by shocks originating from the demand side and/or from the supply side of the economy, and on their dynamic interaction. This sequence represents the starting point of our estimation procedure (more details in the following section).

$$N_i^* = \frac{(1-\alpha_i)\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right]\ \tilde{\theta}_i}{B\left[\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]}$$

Applying a logarithmic transformation to these equations yields the baseline structure of the empirical analysis:

$$\text{(7)}\quad \begin{aligned} \pi_i &= \ln \Pi_i = \gamma_i + \lambda_i \\ n_i &= \ln N_i^* = \varphi_i + \theta_i \end{aligned}$$

where π_i *(* n_i *) is the logarithm of the labor productivity (employment supply) in the i-th sector,* $\lambda_i = \ln \tilde{\lambda}_i$, $\theta_i = \ln \tilde{\theta}_i$ *are stochastic disturbances, and the quantities*

$$\gamma_i = \frac{\alpha_i}{\alpha_i - 1} \ln\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right]$$

$$\varphi_i = \ln\left[\frac{(1-\alpha_i)}{B}\right] + \ln\left[\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right] - \ln\left[\left(\frac{(\beta^{-1}-1+\delta_i)}{\alpha_i}\right)-\delta_i\right]$$

depend on the stationary value of capital stocks, as predicted by equation (6).

Equation (7) shows that in a stationary equilibrium, employment productivity depends on the stationary level of capital stock in its sector and the productivity level in its sector as well. Stationary level for employment flow depends on the stationary level of capital stock in its sector and the non-technology shock in its sector as well.

Notice, however, that by construction in the stationary state we cannot discuss the dynamic correlation structure of different types of shocks (technology and non-technology) across sectors, and therefore the stationary state analysis can be only considered as an illustrative, simplified, example.

2.2 – Econometric implementation

According to equation (6), the baseline model describes the dynamic equilibrium of the two-sector economy by means four variables: labor productivity and employment levels for each sector. We collect them in the vector $\mathbf{y}_t = \left[\mathbf{y}_{1,t} \mid \mathbf{y}_{2,t}\right]' = \left[\pi_{1,t} \quad n_{1,t} \mid \pi_{2,t} \quad n_{2,t}\right]'$. In order to investigate the dynamic interactions among these variables we employ a reduced-form vector time series method. Let $\mathbf{x}_t$ be a (4x1) covariance stationary vector containing appropriate transformations of the elements in $\mathbf{y}_t$. We assume that the DGP of $\mathbf{x}_t$ obeys a finite autoregressive process

(8) $\mathbf{D}(L)\cdot\mathbf{x}_t = \boldsymbol{\varepsilon}_t$

where $\mathbf{D}(L) = \mathbf{I}_4 + \sum_{l=1}^{p}\mathbf{D}_l$, L is the lag operator and the reduced form covariance matrix $E(\boldsymbol{\varepsilon}_t \cdot \boldsymbol{\varepsilon}_t') = \boldsymbol{\Omega}$ is, in general, non-diagonal. If model (8) is invertible, then it admits an isomorphic infinite order moving average representation

(9) $\mathbf{x}_t = \mathbf{C}(L)\cdot\boldsymbol{\varepsilon}_t$

with $\mathbf{C}(L) = \mathbf{D}(L)^{-1}$. The structural moving average representation associated to model (9) constitutes the empirically tractable representation of the rearranged optimal Planner allocation (6) and has the following form:

(10) $\mathbf{x}_t = \mathbf{A}(L)\cdot\mathbf{u}_t$

where $\mathbf{u}_t = \left[\lambda_{1,t}, \theta_{1,t}, \lambda_{2,t}, \theta_{2,t}\right]'$ and $E(\mathbf{u}_t \cdot \mathbf{u}_t') = \mathbf{I}_4$.[2] Under these assumptions, the relationships between model (9) and (10) are:

(11) $\mathbf{A}(L)\cdot\mathbf{u}_t = \mathbf{C}(L)\cdot\boldsymbol{\varepsilon}_t$; $\mathbf{A}_0\cdot\mathbf{u}_t = \boldsymbol{\varepsilon}_t$; $\mathbf{A}_0\cdot\mathbf{A}_0' = \boldsymbol{\Omega}$ and $\mathbf{A}_i = \mathbf{C}_i\cdot\mathbf{A}_0$

The matrix $\mathbf{A}_0\cdot\mathbf{A}_0'$ has sixteen elements, but the estimated variance-covariance matrix $\boldsymbol{\Omega}$ has only ten distinct elements. Hence, the estimation of model (10) requires (at least) six more identifying restrictions.

3 – Selected stylized facts

Prior to the discussion on route we follow to retrieve the structural representation (10) from the reduced form model (8), we briefly discuss selected stylized facts relative to the US manufacturing sectors involved in the empirical analysis.

3.1 –Data description

We assume that the sectors $i = 1, 2$ represent non-durable consumption flow (*ND*) and services from durable goods (*D*), respectively. Their sum represents the aggregate

[2] The state vector of the economy in equation (6) includes also the stationary values of capital stock in each sector. These are, however, predetermined variables at time *t* which value is not affected by realization of next period shocks.

manufacturing sector.[3] Our data set consists of $T = 176$ quarterly observations, ranging from 1953q1 to 1996q4. All seasonally adjusted data are taken from Bureau of Economic Analysis-National Economic Accounts (BEA-NEA, Table 1.2.5) and Bureau of Labor Statistics (BLS, Table 1.2.6). Quarterly employment data are constructed as an arithmetic average of monthly observations.[4]

We test for unit root behavior of each of the (log-) labor productivity and employment time series by calculating standard ADF test statistics (Table 1), where the number of lags is chosen such that no residual autocorrelation was evident in the auxiliary regressions. Also, note that a deterministic trend is found to be statistically significantly different from zero at conventional nominal levels of significance. In each case, we are unable to reject the unit root-null hypothesis at conventional nominal levels of significance. On the other hand, differencing the series appears to induce stationarity in each case.[5]

Table 1 about here

3.2 – Measuring the co-movement of cyclical components

As a preliminary analysis, we study the joint dynamics of labor productivity and employment within sectors by means of univariate techniques at a quarterly frequency. We extract the cyclical component of each series by applying three filters: the Band Pass, BP (Baxter and King, 1995), the HP (Hodrick and Prescott, 1997) and the first-differencing method. Table 2 presents the cross-correlations between the variables under investigation for both sectors). The numerical columns show the cross-correlations at the indicated leads and lags (h), where standard errors are computed using a procedure suggested in Den Haan and Levin (1997).[6]

Table 2 about here

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[3] Real consumption for durable goods and for non-durable goods accounts for 5% and 23% of the aggregate GDP, respectively. Relative to total consumption expenditure, the share of real consumption for durable goods and for non-durable goods account rises to 8% and 36%, respectively.

[4] To better focus our attention on the effects of a resource reallocation among the sectors, subsequent to the shocks, we have chosen an extensive measure of labor input, i.e. the number of employees, instead of an intensive measure of it, i.e. the hours worked. Moreover, Alesina and Giavazzi (2007) underline a substantial positive correlation between the hours worked and the number of employees for the US data.

[5] In addition to the ADF tests, we also execute stationarity tests of the type proposed by Kwiatkowski et al. (1992). The results are consistent with the ADF tests results, indicating that the series are $I(1)$ processes. Results are available on request.

[6] A maximum correlation at h>0 (h<0) indicates that the cyclical component of employment lags (leads) the cyclical component of labor productivity by h quarters. Standard errors computed using the Newey and West (1987) optimal bandwidth produces almost identical results.

The correlation coefficients between non-durable labor productivity and employment growth rates are typically negative (at all leads and lags) and also large and significant; this conclusion holds for the aggregate manufacturing sector too (not reported). By contrast, the sign of the correlation in the durable sector is positive at leads and negative or not statistically significant at lags. The correlation coefficients computed using HP-filtered and BP-filtered labor productivity and employment lead to similar conclusions, and turn to be substantially larger (in absolute value) compared to first differencing.

Den Haan (2000) and Den Haan and Sumner (2004) provide an alternative framework based upon correlations from VAR forecast errors at different horizons, which can accommodate both stationary and integrated variables and thus does not require pre-filtering.[7] The most convenient way to estimate covariances and correlation coefficients is to construct time series for the forecast errors using the difference between subsequent realizations and their forecasts.[8] Table 3 summarizes the results from VAR models estimated in first differences by imposing the unit-root restriction, with the i-step ahead within sample forecast errors are calculated for the levels.[9]

Table 3 about here

The negative and statistically significant correlations of the forecast errors at time horizons from 1 to 5 years for the non-durable sector are consistent with previous results. For the durable sector, the correlations turn to be positive and statistically significant.

4 – The empirical model: specification and identification issues

Data clearly show that there is a significant positive (negative) co-movement between (non-) durable labor productivity and employment forecast errors for long-term forecast horizons. Such a strong heterogeneity across sector is the most interesting piece of

[7] The BP filter, the HP filter and the first-differencing method have known distortions. The HP filter improves on first-differencing by attenuating less of the cyclical component and not amplifying the high frequency component. Nonetheless, it still passes much of the high frequencies that are outside the business-cycle frequency band. The BP filter performs similarly to the HP filter at low and middle frequencies but is more successful in blocking high frequencies that are outside the specified frequency band. See Canova (1998) and Koustas (2003) for a detailed discussion.

[8] An alternative method to construct measures of co-movement at different forecast horizons by means of the VAR methodology is based on the computation of impulse response functions. Estimating impulse response functions, however, requires making identifying assumptions, and the assumptions are often *ad hoc*. See Den Haan (2000, p. 8).

[9] Bootstrapped standard errors based on 1000 replications are used to construct 95 percent confidence bands. The lag length, as well as the deterministic part, is chosen according to the BIC. For a check of robustness, we also estimated VAR models whose lag length and deterministic part were optimally chosen by the AIC. Moreover, we also controlled our finding by avoiding the imposition of unit-root restriction in models specified according both the AIC and the BIC. In all specifications considered, the results are qualitatively identical to those reported in Table 3.

information in relation to the literature, which typically focuses on the aggregate economy.

The set of descriptive statistics illustrated in Section 3 provides the "natural" benchmark against which a (multi-sector) structural model has to be judged.

A structural perspective allows to estimate how the non-technology and the technology shocks are correlated between sectors and to compute how much volatility of productivity and of employment each type of structural disturbances explains. In other words, we would be able to investigate the source of business cycle fluctuations (i.e. whether fluctuations in labor productivity and/or employment in the two sectors are driven by technology or by non-technology shocks), and to study the shocks' transmission mechanism across sectors.

<u>4.1 – Model specification</u>

Our baseline model is defined as a multivariate specification of equation (6) augmented by an intercept and a linear trend as deterministic part, in a way consistent with the specification of the deterministic component in unit root/stationary tests. The model is reported below for reader's convenience.

$$\mathbf{y}_t = \mathbf{c} + \boldsymbol{\gamma} \cdot t + \sum_{l=1}^{p} \mathbf{D}_l \cdot \mathbf{y}_{t-l} + \boldsymbol{\varepsilon}_t$$

Since the theoretical model of reference describes the optimal Planner allocation as an infinite sequence of primitive disturbances (equation 6), it does not provide any guidance on the appropriate lag length in our empirical model in its autoregressive representation. We have chosen the order of autoregression using the AIC, which takes its minimum at p equal to 3.[10,11] With both sector labor productivity and employment levels found to be realizations from stochastic processes integrated of order one, testing for cointegration among these series is the logical next step. Both maximum eigenvalue and trace tests (Johansen, 1995) suggest choosing rank 0 for matrix $\boldsymbol{\Gamma} = \sum_{l=1}^{p} \mathbf{D}_l - \mathbf{I}_4$ (Table 4).[12]

[10] We were very careful in selecting the number of lags in the VAR, being aware of the sensitivity of VAR autoregression analysis to the lag length in this context. To this aim we use the AIC, BIC and the Hannan and Quinn criteria as well as the conventional general-to-specific procedure. The AIC has been preferred when discordant results occur, in order to ensure a richer dynamics, given the well known property of that criterion to favor non parsimonious models. Notwithstanding, the order of autoregression seems to be quite limited in all cases, suggesting that they are pure-vector-autoregressive processes.

[11] In order to detect possible structural changes, multivariate Chow tests are iteratively run, starting from a sample of 88 observations (i.e. the first half of our estimation horizon) and extending it by one observation in each iteration. Forecasts are one step ahead (1-step), *N* steps ahead (*N*-up) and break-point (*N*-down) *F*-tests. The system appears stable, thus confirming a good specification of the statistical model.

[12] A null cointegration rank suggests a two-fold remark. *First*, there is evidence neither of common technology nor of non-technology shocks between durable and non-durable sectors for the US economy. *Second*, the cointegration analysis corroborates the conclusions of the unit root/stationarity tests analysis, providing further evidence on the $I(1)$-ness of the series involved in the analysis.

Table 4 about here

To conclude, the differenced specification (i.e. $\mathbf{x}_t = \Delta \mathbf{y}_t$) of the baseline VAR model appears to be appropriate, since it does not produce losses of useful information.

4.2 – Identification of technology and non-technology shocks

In our econometric setup, fluctuations in sector labor productivity and employment are driven by two fundamental disturbances: technology shocks (λ_i, $i = D, ND$) and non-technology shocks (θ_i, $i = D, ND$), which are orthogonal to each other.

Following Blanchard and Quah (1989), we impose long-run restrictions on the coefficients of model (10) by means the following relationship:

(12) $\mathbf{C}(1) \cdot \mathbf{A}_0 = \mathbf{A}(1)$

where $\mathbf{C}(1)$ and $\mathbf{A}(1)$ collect the cumulated effects of reduced form and structural innovations, and have

$$C^{rc}(1) = \sum_{m=0}^{\infty} c_m^{rc} \text{ and } A^{rc}(1) = \sum_{m=0}^{\infty} a_m^{rc}$$

as generic element of row r and column c, respectively.

As discussed in Section 2.2, the identification of the system implies the imposition of **six** constraints to retrieve the structural disturbances from the estimated residuals.

A **first** assumption is that only technology shocks have a permanent effect on the level of labor productivity. This is a quite standard statement in the literature, and represents a fixed point for our simulation exercises.[13] A **second** set of restrictions assumes that technology and non-technology shocks can have a permanent effect on employment. These two assumptions combined place on matrix $\mathbf{A}(1)$ four restrictions, which correspond to:

(13) $\sum_{m=0}^{\infty} a_m^{1,2} = 0$, $\sum_{m=0}^{\infty} a_m^{1,4} = 0$, $\sum_{m=0}^{\infty} a_m^{3,2} = 0$, and $\sum_{m=0}^{\infty} a_m^{3,4} = 0$.

In particular, the first two restrictions indicate that non-technology shocks (originating from the durable and non-durable sector, respectively) have no long-run impact on durable labor productivity; the last two constraints have the same interpretation but refer to the effects of non-technology shocks on non-durable productivity.

[13] In a number of studies the validity of such an assumption is questioned, even though the debate is still open. Two recent contributions on this issue are those of Chang and Hong (2005) and Feve and Guay (2006). The former focuses on total factor productivity as a more natural measure of technology because labor productivity may reflect input mix as well as technology. In the latter, technology shocks are identified by means of a two-step modeling strategy, which circumvents the problems related to the order of integration of labor input.

4.3 – Identification of the transmission mechanism across sectors

Since the estimation of our model requires six identification restrictions, there are, at this stage, two left. These originate from the definition of the spillovers across sectors. To this aim, define *sector-specific shocks* as disturbances that originate in one sector and affect labor productivity and/or employment of the originating sector (for example, a technology shock that originates in the non-durable good sector and affect productivity in the same sector). *Cross-sector shocks* are disturbances that originate in one sector, but that eventually affect labor productivity and/or employment of the other sectors (for example, a technology shock that originates in the non-durable good sector but affects productivity in the durable good sector).

In this context, we distinguish between two classes of shocks' propagation mechanisms, which depend on whether the direction of these linkages goes from the non-durable to the durable block of the system (i.e. the **"non-durable good regime"**), or viceversa (i.e. the **"durable good regime"**).

Under the non-durable good regime, a technology shock originating in the non-durable sector impacts over labor productivities in the non-durable and in the durable good sectors; non-technology shocks originating within the non-durable good sector affect employment in both sectors. The story would be different when we consider shocks originating in the durable good sector. These shocks do not have, by construction, any permanent effect over employment and productivity in the non-durable good sector. The durable-good regime implies a symmetric interpretation, *mutatis mutandis*.

In terms of the elements of $\mathbf{A}(1)$, the non-durable good regime implies imposing:

(14) $$\sum_{m=0}^{\infty} a_m^{3,1} = 0 \text{ and } \sum_{m=0}^{\infty} a_m^{4,2} = 0 .$$

These restrictions imply that technology and non-technology shocks from the durable sector have no long-run effects on non-durable productivity and labor input, respectively.

Conversely, the durable good regime translates into the two following restrictions on $\mathbf{A}(1)$:

(14') $$\sum_{i=0}^{\infty} a_i^{1,3} = 0 \text{ and } \sum_{i=0}^{\infty} a_i^{2,4} = 0 ,$$

where the first constraint does not allow technology shocks originated in the non-durable sector to have long-run effects on durable productivity; according to the second restriction, non-technology shocks from the non-durable block do not exert permanent effects on durable employment.

In order to discriminate between these two mutually exclusive regimes, Granger- and instantaneous-causality tests are used to retrieve indications on the interdependencies among variables and between the two sectors (Table 5 below).

Table 5 about here

The table suggests that none of labor inputs turns out to be exogenous, while traces of exogeneity can be detected for both labor productivity series. At the sector level, the durable block does not Granger-cause the non-durable sub-system, with no evidence of instantaneous causality. Result I follows.

<u>Result I</u>: the *non-durable good regime* (i.e. the identification scheme in which the non-durable good sector drives the business cycle for manufacturing sector) appears to be the correct (data-consistent) identification scheme for the fully-fledged multi-sector economy. Such a structure will be our working assumption from now onward.

The estimate of the long-run multipliers matrix $\mathbf{A}(1)$ is reported below:

$$\begin{bmatrix} \Delta\pi_{D,t} \\ \Delta n_{D,t} \\ \hdashline \Delta\pi_{ND,t} \\ \Delta n_{ND,t} \end{bmatrix} = \begin{bmatrix} \underset{(0.11)}{2.05} & 0 & \underset{(0.16)}{-0.15} & 0 \\ \underset{(0.18)}{0.59} & \underset{(0.06)}{1.15} & \underset{(0.19)}{-0.70} & \underset{(0.14)}{2.08} \\ 0 & 0 & \underset{(0.05)}{0.97} & 0 \\ \underset{(0.07)}{0.07} & 0 & \underset{(0.07)}{-0.35} & \underset{(0.05)}{0.94} \end{bmatrix} \begin{bmatrix} \lambda_{D,t} \\ \theta_{D,t} \\ \hdashline \lambda_{ND,t} \\ \theta_{ND,t} \end{bmatrix},$$

where asymptotic standard errors for each point estimator are reported in parenthesis. There are several interesting features of these results. *First*, the estimated coefficients reveal the existence of statistically significant interconnections among the variables of the model, with two exceptions: the effect of a cross-sector technology shock on durable productivity (-0.15) and on non-durable employment (0.07). *Second*, note the quantitatively different response of the durable and non-durable labor productivity to a sector-specific technology shock: the response of the former (2.05) is more than twice the latter (0.97), depicting the durable sector as the more technology-driven segment of the US manufacturing. *Third*, sector-specific non-technology shocks produce roughly the same response on both sector employment rates of growth (1.15 and 0.94, respectively).

Given these results, two issues with respect to them merit further consideration: *i*) the opposite sign in the response of employment to sector-specific technology shocks (0.59 and -

0.35 for the durable and the non-durable block, respectively); *ii*) the effect of cross-sector shocks on durable employment (i.e. the remaining two numerical values in the matrix).

The following Section is devoted to illustrate explicitly these linkages.

5 – Structural Vector Autoregression Results

Once a structural and data-consistent identification of the model is provided, dynamic simulations as well as conditional correlations on structural shocks can be performed. The simulation horizon is set equal to 20 quarters. We employ these tools in order to address three main issues: *first*, the assessment of the role played by the primitive (structural) sources in explaining the variability in sector employment and labor productivity, with a particular attention paid at discriminating between sector-specific and cross-sector disturbances (Section 5.1); *second*, the analysis of the correlation sign between corresponding sectoral quantities induced by all kinds of technology and non-technology sector-specific shocks (Section 5.2); *third*, the ability of sector-specific and cross-sector shocks in matching post-war recession periods for the aggregate US economy (Section 5.3).

5.1 – Forecast error variance decomposition

The rows in Table 6 show how much volatility of the variables of the system, in percentages, can be attributed to a specific structural disturbances, while the μ-column indicates the average contribution of each shock across different variables (employment and productivity).

Table 6 about here

Decomposing the shocks along their "**origin**", the table suggests that *sector-specific shocks* explain about the 80 percent of volatility in the manufacturing sector, and that the remaining 20 percent is explained by cross-sector shocks. On the other hand, *cross-sector shocks* are mainly represented by non-technology shocks.

Concerning, next, the shock "**nature**", *technology shocks* (sector-specific and cross-sector) explain 48 percent of fluctuations, while *non-technology shocks* (sector-specific and cross-sector) account for 52 percent.[14] Notice that this result has important positive and

[14] Our findings are broadly consistent with the empirical evidence for the aggregate US economy over the last decade. Bergman (1996) shows that more than one half of the macroeconomic fluctuations are due to supply shocks at the typical business cycle frequency (the twenty quarters horizon), using a bivariate VAR model for output and inflation. More recently, by distinguishing the source of technical changes into "neutral" shocks (which affects homogeneously all goods) and an "investment-specific" shock (in the spirit of Greenwood et al., 1997), Fisher (2002) indicates that investment-specific shocks

normative implications, related to the actual debate in the literature. Consider, for example, the standard RBC model, which relies uniquely on technology shocks. The presented evidence suggests that this would be only half of the story; it should be no surprise that the RBC model falls short along selected empirical dimensions. That happens because it relies, by its very construction, only on technology shocks, ignoring the non-technology (i.e. demand) side of the economy that needs to be explored as well.[15] We are now able to add another piece of evidence on the interactions between the two blocks of the US manufacturing sector; denote it as Result II.

Result II: Business cycle are mainly generated, in each sector, by the class of *technology shocks* (which are mainly described by the sector-specific shocks), but they are transmitted across sectors along the sectors' demand side, i.e. passing through non-technology shocks; in addition, technology and non-technology shocks almost equally share the responsibility of fluctuations in the two-sector economy as a whole.

5.2 – Labor productivity and employment

5.2.1 – Conditional correlations

The sign of the correlation between labor productivity and employment turns out to be an important statistics for many macroeconomists, since it may help understanding whether baseline versions of traditional neoclassical growth models (predicting a strong and positive correlation between employment and labor productivity) represent a sufficiently good model for studying aggregate dynamics for the US economy.

The largest part of the above-reported evidence does not provide, however, an explanation of the sector heterogeneity relative to the unconditional correlations between labor productivity and employment.[16] To shed light on this point, we adapt the approach proposed in Gali (1999) by computing correlation coefficients for the technology- and non-

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account for the 48 percent of the United States business cycle variation. Finally, Christiano et al. (2003) estimate that permanent technology shocks play an even more important role (70 percent) for explaining aggregate fluctuations in a bivariate VAR system for output and labor inputs. Their results show that the share of aggregate volatility explained by this type of shock drops to 35 percent in a six-variable system when consumption, fed funds, inflation and investment are included as additional variables.

[15]The forecast error variance decomposition exercise provides similar results even when the fluctuations of the variables in the levels are considered. More in details, cross-sector shocks account for one-fifth of overall variability, while cross sector non-technology shocks act as the most important channel of transmission between sectors, explaining more than one-half of employment fluctuations and around 6 percent of productivity variability in the durable sector. Results are available on request.

[16] In particular, the durable sector presents a positive unconditional correlation between employment and productivity (Table 2 and 3) coupled by a dominant role of technology shocks (Table 6) in a way coherent with the RBC predictions; conversely, what emerges from the non-durable sector deserves a more accurate investigation, since the negative unconditional correlation between employment and labor productivity cannot be directly rationalized within that theoretical paradigm.

technology-driven components of each series relative to sector-specific and cross-sector shocks. Defining $k = \lambda_D, \theta_D, \lambda_{ND}, \theta_{ND}$, the conditional correlation coefficients for the durable and non-durable blocks respectively read:

$$\rho\left(\Delta\pi_D, \Delta n_D \middle| k\right) = \left(\frac{\sum_{m=0}^{\infty} A_m^{1k} \cdot A_m^{2k}}{\sqrt{\sum_{m=0}^{\infty} \left(A_m^{1k}\right)^2 \cdot \sum_{m=0}^{\infty} \left(A_m^{2k}\right)^2}} \right), \; \rho\left(\Delta\pi_{ND}, \Delta n_{ND} \middle| k\right) = \left(\frac{\sum_{m=0}^{\infty} A_m^{3k} \cdot A_m^{4k}}{\sqrt{\sum_{m=0}^{\infty} \left(A_m^{3k}\right)^2 \cdot \sum_{m=0}^{\infty} \left(A_m^{4k}\right)^2}} \right).$$

Table 7 reports the estimated figures, distinguishing between sector-specific shocks and cross-sector shocks.

Table 7 about here

As far as the **sector-specific shocks** are considered, the estimated correlation coefficients corroborates a standard RBC theory-based perspective of business cycle fluctuations (Kydland and Prescott, 1982; Long and Plosser, 1983) for the durable block: sector-specific technology and non-technology shocks produce a positive and statistically significant correlation between labor productivity and employment. The non-durable sector presents a different picture, in which the conditional correlation between employment and labor productivity is negative, following a positive sector-specific technology shock.[17] In this sense, the prediction of a standard RBC model would not be consistent with this sectoral behavior.

Focusing, next, on the **cross-sector shocks**, both correlations estimated for the durable sector are positive and statistically significant, even though the co-movement induced by a cross-sector technology shock turns to be scarcely significant from an economic perspective (as also suggested by the results in Table 6). In the non-durable sector the co-movement are positive, even though weak, and statistically significant: from an economic point of view they can be explained as a standard RBC response of the relatively smaller sector to the shocks coming from the relatively larger sector. Notice that this last response is the same as the one of sector specific shocks in the durable block: this means that the non durable sector is “captured” by the durable sector when the latter is hit by any kind of perturbation.

[17] Technically speaking, the unconditional negative correlation estimated for the non-durable sector is induced mainly by the negative conditional correlation for the technology-driven components of the two series, partially offset by the positive co-movement of their non-technology-driven parts.

5.2.2 – Impulse-response functions

The analysis of impulse-response functions follows two dimensions: one investigates the impact that each shock has in the originating sector (i.e. we first study the role of that shock as a sector-specific one), and the second refers to the impact that the same shocks has, or might have, over other sectors, different from the originating one (i.e. we next study the role of that shock as a cross-sector shock).[18]

Figure 1 reports the impulse response functions to **technology shocks**, explicitly distinguishing between sector-specific and cross-sector types. The panels on the left refer to responses to sector-specific positive technology shocks, while those on the right are relative to cross-sector positive technology impulses.

Figure 1: Impulse response functions to a positive technology shock

The following taxonomies qualitatively summarize the impact response of variables under investigation, to positive technology shocks originating either in the non-durable good sector or in the durable good sector. While casually inspecting the figure, it is important to keep in mind that each shock acts, in this context, both as sector-specific shocks and as cross-sector shocks, and that both dimensions need to be explored.

Table 8 about here

Table 9 about here

Consider, first, the **employment response**. Technology shocks originating in the non-durable sector have a negative impact over employment, in both sectors;[19] on the contrary, technology shocks "born" in the durable sector produce an expansion in employment in both sectors.

It seems that the latter kind of innovation is perceived "stronger" by the economy, and does not crowd out labor services. As argued in Gali (1999), the positive correlation between employment and labor productivity reflects the shift in labor demand (triggered by a positive technology shocks), along an upward sloping labor supply schedule. In this sense, we could claim that "productivity shocks" typically driving business cycle within neoclassical growth

[18] In the impulse response analysis, relatively wide probability bands (80%) are considered. Confidence intervals are computed by means of bootstrap techniques with 5000 replications. It is advisable to stress some caveats that should be taken into account in performing these simulation exercises. First, as argued by Faust and Leeper (1997), identification procedures which involve long-run restrictions may imply that type II errors are more likely in confidence intervals because of the imprecision of the long-run parameter estimates. Second, the usefulness of confidence bounds does not appear undisputedly shared among scholars (see, among others, Benkwitz et al., 2000).

[19] Non-durable employment falls after a sector-specific technology shock, consistently with the empirical findings for the US aggregate manufacturing documented in the relevant literature. Vigfusson, (2002) argues that adjustment costs (in the aggregate economy) may lead a negative response of labor inputs to a technology shock. However, such an explanation stands out against the evidence reported here, since these costs are expected to be stronger in the durable sector.

models precisely captures technology shocks originating from the durable good and spreading out over the economy. Technology shocks born in the non-durable sector seem, on the contrary, perceived in a different manner, reflecting a relatively minor innovation.

Concerning the **labor productivity response**, technology shocks originating in the non-durables have a negative impact over durables' productivity (i.e. when acting as a cross-sector shock) and positive over the non-durable counterpart (i.e. when acting as a sector-specific sector shock). Technology shocks from the durable sector have, on the other hand, a positive impact over idiosyncratic productivity, and leave almost unaffected productivity in the non-durable sector, as a consequence of the identification scheme in which we are working (the non-durable good regime).

Figure 2 has the same structure as Figure 1 and reports the impulse response functions to **non-technology shocks**, also in this case distinguishing between sector-specific and non-cross-sector types.

Figure 2: Impulse response functions to a positive non-technology shock

As before, we start from the **employment response**. We assist to a positive response of employment regardless to the origin and the destination of the shocks, even though the non-durable positive employment response falls rapidly after six quarters. These results are consistent with Gali' (1999), who finds positive correlation between non-technology shocks and both employment and hours worked for the aggregate economy. In this sense, a positive non-technology shock, that hits one sector generates an increase in its own employment, but also in the other sector employment through the economic interdependence well described by the identification scheme.

Concerning the **productivity response**, non-technology shocks originating in the non-durables have a positive impact both over durables' productivity and the non-durable counterpart, leading to a positive correlation between employment and labor productivity. Non-technology shocks originating in the durable sector have, on the other hand, a positive impact over sector-specific productivity, and a negative impact over cross-sector productivity (i.e. non-durable sector productivity). This evidence, coupled by the results of the productivity response to a technology shock in the durable sector, support a RBC theory, giving the chance of modeling the durable sector as a standard neoclassical economy.[20] Yet, the non-durable sector response depends crucially on where the shock comes from: if the shock is sector-

[20] The standard empirical evidence of RBC models predicts a positive response of labor productivity to a technology shock and explains the possible absence of correlation between these two variables by the presence of other kinds of shocks (i.e. non-technology shocks), which would lead to a decline in labor productivity.

specific, we assist to an increase in labor productivity as in standard RBC models, whereas if the sector is hit by a cross-sector shock (i.e. which comes from the durable sector), labor productivity decreases. This result, together with the correspondent one of employment response to a non-technology shock (i.e. a short increase in employment) suggests that real income is unaffected, as labor productivity decreases and employment increases. A possible economic interpretation of this empirical finding could be a persistence in consumption habits (habit formation), which generates stickiness in the shock transmission mechanism across the sectors.[21]

Result III: the dynamic behavior of the durable good sector may be well represented by a standard Real Business Model; the non-durable good sector, on the other hand, would not be consistent with that predictions. Due to a size effect, the aggregate dynamics is likely to be driven by the relatively larger sector, which is the non-durable good one.

5.3 – Sector-specific vs cross-sector: an explanation of aggregate fluctuations

Our two-sector framework can be employed to analyze selected key features of the aggregate US economy business cycle. To do this, we retrieve the aggregate real manufacturing GDP following a four-steps procedure: *i*) start from the decomposition of the four variables of the baseline system (i.e. employment and labor productivity in both sectors) into their structural driven parts; *ii*) for each variable, cumulate the growth rates of the logged quantities to get the implied value of the levels; *iii*) take the anti-log of these series and, then, multiply the labor productivity by employment to obtain the levels of the aggregate manufacturing real output as the sum of the two sector real GDP; *iv*) as in Gali (1999), apply the HP-filter to the logarithm transformation of this series in order to compare its cyclical pattern to the post-war recession chronology dated by the National Bureau of Economic Research (NBER). Finally, we replicate the stages *i*) - *iv*) disentangling the part of the series driven by cross-sector and sector-specific shocks.

Given these preliminaries, we posit the following two questions: "*do cross-sector shocks matter in explaining the cyclical fluctuations of the aggregate manufacturing real output?*";

[21] Notice that this friction could be interpreted also as a rigidity in prices (price stickiness) as in Gali'(1999), anyway to be consistent with our theoretical model, presented at the beginning of the paper, where all the variables are expressed in real terms with a Constrained Pareto Problem Solution, we think that the habit formation hypothesis is more suitable within this framework. For instance, Francis and Ramey (2005) document that the negative effect of a technology shock on labor input can be captured by dynamic general equilibrium models when non-standard additional factors - such as habit formation - are taken into account. In the context of the present work, this is interesting especially because non-durable consumption is mainly represented by basic consumption goods (i.e. food and clothing), and an external habit on non-durable consumption might be more easily rationalized.

and if the answer to the previous question is positive, "*what is the relevance of cross-sector shocks compared with sector-specific disturbances?*".

Figure 3 provides an overall picture of the properties of the sector-specific and cross-sector shocks at business-cycle frequencies. The upper panel shows that the cyclical component of the aggregate manufacturing output, implied by the estimated structural shocks, closely matches the recessions for the US economy identified by the NBER (the gray regions).

Figure 3: cyclical component of sector-specific shocks and of cross-sector shocks

Focusing, next, on the disturbances relative to the durable sector (panel on the center), cross-sector shocks display an evolution over time that resembles the behavior of the aggregate real manufacturing GDP, while sector-specific disturbances driven fluctuations fail in capturing the recession periods occurred in the early seventies and eighties.

Finally, both sector-specific and cross-sector shocks hitting the non-durable sector (lower panel) exhibit an erratic pattern, so it is hard to discover any interesting regularities: most importantly, they appear uncorrelated with episodes of economic downturn in the US economy over the most recent decades.

A possible economic interpretation for this evidence is that the aggregate US economy is driven by innovations specific to the non-durable sector (the relatively larger sector in GDP percentage terms), and it is transmitted to the other sectors (durable goods' one) driven by a demand push (i.e. through a non-technology shock).

In summary, the answer to the first question would be positive. Concerning on the related issue, which is "what is the true source of aggregate business cycle?", the evidence suggests that the answer to this may-be-too-ambitious question is that sector-specific and cross-sector shocks fairly share the responsibility of generating the aggregate business cycles. This results is a further confirmation of what the variance decomposition analysis suggests.

6 – Further discussions and robustness of the results

Several studies have questioned the conclusions in Gali (1999) on the grounds of problems related to the possible inconsistency of long-run identification schemes in a structural VAR with respect to the data generating process of a standard dynamic stochastic general equilibrium model (see, among others, Chari et al., 2004). Sharing the same econometric framework as in Gali (1999), we were aware of this possible weakness. However, there are a number of motivations supporting our choice. A *first*, general argumentation is that since most theoretical disputes focus on short-run issues, such a choice allows us to use less debatable assumptions than would be the case if we had to impose short-run restrictions as well. *Second*, from an economic point of view, a relatively small order of autoregression is consistent with the argumentations in Faust and Leeper (1997) on the conditions have to be met in order to get reliable results from long-run identification schemes. *Third*, a number of empirical works have confirmed that VAR models identify productivity shocks that closely resemble classic and refined Solow residuals (Kiley, 1998; Alexius and Carlsson, 2005). *Fourth*, using different data frequency and specification of variables, Chang and Hong (2005) obtain empirical results that are substantially similar to the evidence here reported: the durable sector clearly exhibits RBC-like features, while in the non-durable sector a technology shock produces no effect on the co-movement between labor input and efficiency growth rates.

Nonetheless, a potential drawback of the structural VAR models with long-run restrictions relies on the sensitivity of the outcomes with respect to the exact specification of the empirical model. We analyze the robustness of our results along two dimensions. *i*) we provide further evidence on the relevance of inter-sector forces working in the US economy in order to corroborate the soundness of our preferred shocks' propagation mechanism with respect to changes in identifying assumptions (Section 6.1); *ii*) finally, we compare the above-discussed empirical findings to those obtained from a number of alternative specifications (section 6.2).

6.1 – The role of cross-sector shocks: a reassessment

We start with the analysis of the dynamic relationships between productivity and employment after a technology shock using bivariate VAR models for the two sectors and for the aggregate manufacturing.[22] Impulse response functions (not reported) show that, on impact, the positive technology impulse translates into a rise in durable employment and productivity levels. In the non-durable sector, a technology shock generates a negative response in employment both on impact and in the medium-run. The same holds for the aggregate manufacturing sector. These results are consistent with the evidence reported on the left part of Figure 2 and suggest that the evidence from aggregate data (e.g. Basu et al. 2004;

[22] In each case, the AIC indicates p=3 as the optimal lag length of VAR models. Trace and maximum eigenvalue tests suggest choosing rank zero for all the models; hence, we estimated the three models in first differences. Results are available on request.

Francis and Ramey, 2005; Busato, 2004; Gali, 1999 and 2004; Shea, 1998) may be due to a "sector size-effect".

The outcome from sector bivariate models may be biased or, at least, partial in the presence of possible interactions across sectors. In order to test the significance of these forces, we consider a scheme that does not identify any shock transmission mechanism between sectors. We refer to this as to an "autarky" identification scheme. This structure implicitly assumes that all shocks generating fluctuations within each sector originate in the corresponding sector, and do not transmit to the other sector. In terms of the elements of the structural long-run impact matrix $\mathbf{A}(1)$, it implies imposing the following four restrictions

$$\sum_{i=0}^{\infty} a_i^{1,3} = 0, \ \sum_{i=0}^{\infty} a_i^{2,3} = 0, \ \sum_{i=0}^{\infty} a_i^{2,4} = 0 \text{ and } \sum_{i=0}^{\infty} a_i^{4,1} = 0.$$

in place of (14) or (14'). The (over-identified) "autarky" identification scheme is strongly rejected by the data [$\chi^2(4)$ =266.42 with a p-value of 0.00], giving support for a multi-sector investigation accommodating resource allocation across sectors.

A second issue is related to the criterion (the notion of Granger-causality) on the basis of which we discriminate between the two propagation mechanisms. Using in Table 10 the same structure as the one in Table 6, we present the contributions of sector-specific and cross-sector shocks for sector labor productivity and employment fluctuations under the propagation mechanism going from the durable to the non-durable part of the system.

Table 10 about here

The evidence seems to be at odds with the underlying identification scheme. Indeed, the contribution of cross sector technology shocks in explaining both labor productivity and employment is more relevant for variables belonging to the durable sector rather than for their non-durable counterparts.

The last point is the following. Even though the data contradicts the hypothesis behind the durable regime, the results in Section 5 are based on an exactly identified scheme, so no formal test can be performed. However, non-contradiction (i.e. being data-consistent) is not the same as confirmation. In order to put the non-durable regime into a test, we set to zero the long-run coefficients not statistically significant in matrix $\mathbf{A}(1)$. This implies using (14) together with

$$\sum_{i=0}^{\infty} a_i^{1,3} = 0 \text{ and } \sum_{i=0}^{\infty} a_i^{4,1} = 0$$

where the two restrictions implies no technology spillover between sector and the long-run "exogeneity" of the non-durable block, respectively. The over-identified structure is not rejected by the data: the χ^2-distributed LR test for the two additional constraints produces a statistics equals to 2.00 with a p-value of 0.37. Moreover, dynamic simulations provides results almost identical to those reported previously (not reported to save space), corroborating the conclusions that the mechanisms going from the non-durable to the durable block is actually in place for the US economy.

6.2 – Alternative specifications of the empirical model

A possible source of misspecification of our empirical analysis refers to the statistical treatment of sector labor input series. If they are in fact trend stationary and we difference them, then we create a moving average component, which may bias the results. Thus, their (log) levels should be considered in the empirical analysis rather than their first difference or a detrended series.[23] Whether such variables contains a unit root or constitutes a trend stationary process and whether the bias induced by possible over-differencing is substantial or negligible remain controversial issues in the literature, with formal tests giving borderline results depending on the choice of sample period. Particularly, while Shapiro and Watson (1988) find similar results when the growth rate of hours are replaced by detrended hours, Christiano et al. (2003) documents that the contractionary effect of productivity on hours crucially depends on the specification in first differences of labor input series.

The ongoing debate has mainly focused on intensive measures of labor input series (namely, hours worked) and on the aggregate economy. As pointed out in Chang and Hong (2005), the stationarity of labor input is often motivated by the so-called balanced growth path at the aggregate level. At the sector level, however, a permanent change in labor productivity may imply a permanent change in labor services through a reallocation of labor across sectors, as we have shown in the previous Section. Furthermore, in our empirical framework we use and extensive measure of labor input (employment).

However, in the light of the relevance of this intense discussion in the profession, we also examine the issue of the stationarity of sector labor input series in our analysis. In particular, we alternatively assume that employment and hours worked are difference stationary, stationary around a linear trend and stationary around a quadratic trend, using both quarterly

[23] In the absence of cointegration among a set of variables, the literature on integrated processes indicates several ways to achieve stationarity. Simulation results obtained from the models with HP-filtered series (not reported) are qualitatively similar to those discussed in Section 5.

and annual observations. Under these (eleven) alternative specifications, we focus on our preferred identification scheme (the non-durable regime), so that sector-specific, cross-sector, λ's and θ's disturbances have the same interpretation as before.

Overall, the empirical finding from the baseline model appear to be reasonably robust, with estimated values generally falling into the ranges of values computed for the alternative specifications. More in details, the most salient results from our check of robustness are as follows: over the simulation horizon (20 quarters or five years, depending on the frequency of data we use), *i*) the non-durable regime is consistent with the data in nine out of eleven alternatives, with the two exceptions arising when annual employment levels are treated as stationary process around a linear or a quadratic trend; *ii*) as far as the "origin" of the structural disturbances is considered, the relative contribution of cross-sector shocks on the variability of the system as a whole, ranges from 25 percent (in the case of quarterly first differenced hours worked) to around 42 percent (when annual detrended hours worked enter in the system as variables), *iii*) concerning on the "nature" of orthogonal impulses, non-technology shocks account for 62 percent across specifications involving (both quarterly and annual) employment, while such a share goes down to 35 percent, but is still large, when specifications with hours worked are taken into account; *iv*) in six of nine specifications consistent with the non-durable regime, at least one of the two over-identifying restriction imposed on our baseline model are not rejected by the data at the 5% nominal level of significance; *v*) the analysis of impulse response functions gives qualitatively the same results as those discussed in Section 5 only when we make use of first differenced labor input series (employment or hours worked, both at quarterly and annual frequency).

In a nutshell, the estimation of these alternative specifications suggests a twofold conclusion. On the one hand, the exercise of robustness check of our baseline model seems to provide further evidence on the non-durable regime as the most likely channel of interconnection between the durable and non-durable block of the US manufacturing sector. On the other hand, the effects of technology shocks on labor input appear to be dependent on the statistical specification of that variable, in a way consistent with the argumentation in Christiano et al. (2003).

7 – Conclusions

The growing literature stimulated by the influential work by Gali (1999) has followed several routes of research in explaining the decline in labor input induced by a positive technology shock. This paper aims at extending this debate looking at a multi-sector economy.

Following Busato (2004), we analyze the interdependencies across sectors through a transmission mechanism driven by cross-sector shocks, not previously explored in the empirical literature. More in details, we develop and estimate a two-sector dynamic general equilibrium model that allows for sector-specific disturbances (i.e. they originate in one sector and affect only the variables within that sector) and cross-sector disturbances (i.e. they may originate in one sector, but affect the variables of the other sectors) of two different types: technology and non-technology shocks. We first develop and present a simple two-sector theoretical model (solved as a Central Planner problem in order to keep a general approach concerning the price structure), which can be directly taken to the data.

In keeping with the very large number of studies of the effects of technology shocks on labor input we are unable to support an orthodox RBC view for the explanation of the fluctuations of the United State economy. However, we suggest an alternative explanation of the failure of the standard RBC theory, at least in its simplest formulation, in matching actual data. The "puzzling" evidence for aggregate data (e.g. Basu et al. 2004; Francis and Ramey, 2005; Busato, 2004; Gali, 1999 and 2004; Shea, 1998) may be reconciled on the basis of a sort of sector size-effect, where the relatively larger sector (the non-durable goods sector) drives the dynamical behavior of the aggregate economy, while only the evidence from the durable sector can be reconciled with the RBC paradigm. We also find that cross-sector non-technology shocks explain more than a half of employment reallocated across sector, establishing a shock transmission mechanism across sectors along the demand side of the economy. Finally, cross-sector disturbances hitting the durable sector and durable sector-specific shocks are responsible of the aggregate manufacturing real output fluctuations.

Overall, the data suggests that a framework which does not allow for sector heterogeneity is, at best, missing a part of the explanation of the United States business cycle. We argue that an appropriate modeling strategy requires at least two sectors, representing, for example, durable and non-durable goods.

We think that these are important results that deserved further theoretical research for properly modeling exogenous fluctuations within multi-sector dynamic general equilibrium models, and that has relevant policy implications as well. We leave these issues to future research.

8 – References

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9 – Appendix

Assume the following two-sector neoclassical model, where the utility functions for each sector $u(.)$ and $v(.)$ are increasing in the consumption logs of both the commodities c_1 and c_1 and decreasing in the total labor services BN_1 and BN_2:

(A.1) $u = \theta_1 \log\left(C_{1,\,t}\right) - BN_{1,\,t}$

(A.2) $v = \theta_2 \log\left(C_{2,\,t}\right) - BN_{2,\,t}$

The production functions in both the sectors are Cobb-Douglas with capital shares α and labor shares $1-\alpha$:

(A.3) $Y_{i,\,t} = \lambda_i K_{i,\,t}^{\alpha_i} N_{i,\,t}^{1-\alpha_i} \quad i = 1, 2$

with the feasibility constraint:

(A.4) $N_t = N_{1,\,t} + N_{2,\,t}$

Capital stocks depreciates for each sector according the rate δ and $X_{i,t}$ are the investment flows:

(A.5) $K_{i,\,t+1} = \left(1-\delta_i\right) \quad K_{i,\,t} + X_{i,\,t} \;\; i = 1, 2$

We aim to solve the Social Planner's problem along two steps:

- Writing down the necessary first order conditions;
- By imposing certainty equivalence, it can be shown that there exists a unique deterministic stationary state for capital stock and labor services ratio.

9.1 –The Social Planner's Problem

The objective of the social planner is to maximize the expected discounted "social utility" U_t, as the sum of the utility functions of both the sectors, subject to the feasibility constraint, i.e.:

(A.6) $\underset{\{c_i(t),\, n_i(t),\, k_i(t+1)\}_{t=0}^{\infty}}{Max} \quad E_0\left[\sum_{t=0}^{\infty} \beta^t U_t\right]$

(A.7) $U_t = \theta_1 \log\left(C_{1,\,t}\right) + \theta_2 \log\left(C_{2,\,t}\right) - BN_t$

(A.8) $N_t = N_{1,\,t} + N_{2,\,t}$

(A.9) $s.t. C_{i,\,t} + K_{i,\,t+1} - \left(1-\delta_i\right) \quad K_{i,\,t} = \lambda_i K_{i,\,t}^{\alpha_i} N_{i,\,t}^{1-\alpha_i} i = 1, 2$

To calculate the necessary first order conditions (FOCS), we have to maximize the Lagrangian function L:

(A.10) $$\underset{\{C_i(t),\ N_i(t),\ K_i(t+1)\}_{t=0}^{\infty}}{Max} L = E_0\left[\sum_{t=0}^{\infty}\beta^t \begin{pmatrix} \theta_1 \log\left(C_{1,\,t}\right)+\theta_2 \log\left(C_{2,\,t}\right)-BN_t + \\ -\phi_{i,\,t}\begin{pmatrix} \lambda_i K_{i,\,t}^{\alpha_i} N_{i,\,t}^{1-\alpha_i} - C_{i,\,t} - K_{i,\,t+1} + \\ +\left(1-\delta_i\right)\ K_{i,\,t} \end{pmatrix}\end{pmatrix}\right]$$

where $\phi_{i,t}$ is the dynamic Lagrange multiplier.

9.2 –The first order conditions

The first order conditions are:

(A.11) $C_{i,\,t} : \dfrac{\theta_i}{C_{i,\,t}} = \phi_{i,\,t}$

(A.12) $N_{\ i,\,t} : B = \phi_t\left(1-\alpha_i\right)\ \lambda_i K_{i,\,t}^{\alpha_i} N_{i,\,t}^{-\alpha_i}$

(A.13) $K_i\left(t+1\right) : \beta^t E_t\left[\phi_{i,\,t+1}\left(\alpha_i\lambda_i K_{i,\,t+1}^{\alpha_i-1} N_{i,\,t+1}^{1-\alpha_i} + \left(1-\delta_i\right)\right)\right] = \phi_{i,\,t}$

(A.14) $\phi_{i,\,t} : C_{i,\,t} + K_{i,\,t+1} - \left(1-\delta_i\right)\ K_{i,\,t} = \lambda_i K_{i,\,t}^{\alpha_i} N_{i,\,t}^{1-\alpha_i}$

9.3 –The steady state

To solve for the steady state, we rewrite the necessary conditions by dropping the time indices and by imposing the certainty equivalence:

(A.15) $\dfrac{\theta_i}{C_i} = \phi_i$

(A.16) $B = \phi_i\left(1-\alpha_i\right)\ \lambda_i K_i^{\alpha_i} N_i^{-\alpha_i}$

(A.17) $1 = \beta\left(\lambda_i\alpha_i K_i^{\alpha_i-1} N_i^{1-\alpha_i} + 1 - \delta_i\right)$

(A.18) $\lambda_i K_i^{\alpha_i} N_i^{1-\alpha_i} = C_i + \delta_i K_i$

From equation (A.17) we can easily derive the steady state capital stock K_i as a function of labor services N_i:

(A.19) $$\left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\lambda_i\alpha_i}\right]^{\frac{1}{\alpha_i-1}} N_i = K_i$$

From the equation (A.16), instead, we derive the value of the Lagrange multiplier ϕ_i, by substituting to K_i the equation (A.19):

(A.20) $$B = \phi_i\lambda_i\left(1-\alpha_i\right)\ \left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}$$

(A.21) $$\phi_i = \frac{B}{\left(1-\alpha_i\right)\ \lambda_i\left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}}$$

By substituting the value of ϕ_i of the previous expression and the value of capital stock of equation (A.19) in the feasibility constraint (A.18), we can derive the steady state labor services N_i (A.24):

$$\text{(A.22)} \quad \lambda_i \left[\frac{\left(\beta^{-1} - 1 + \delta_i\right)}{\alpha_i} \right]^{\frac{\alpha_i}{\alpha_i - 1}} N_i = \frac{\theta_i}{\phi_i} + \delta_i \left[\frac{\left(\beta^{-1} - 1 + \delta_i\right)}{\alpha_i} \right]^{\frac{1}{\alpha_i - 1}} N_i$$

$$\text{(A.23)} \quad \left[\lambda_i \left(\frac{\left(\beta^{-1} - 1 + \delta_i\right)}{\alpha_i} \right)^{\frac{\alpha_i}{\alpha_i - 1}} - \delta_i \left(\frac{\left(\beta^{-1} - 1 + \delta_i\right)}{\alpha_i} \right)^{\frac{1}{\alpha_i - 1}} \right] N_i = \frac{\theta_i}{\dfrac{B}{(1-\alpha_i)\left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}}}$$

$$\text{(A.24)} \quad N_i^* = \frac{(1-\alpha_i) \left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right] (\theta_i)}{B\left[\lambda_i \left(\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right) - \delta_i \right]}$$

Once we have found the steady-state labor services N^*, we can easily derive the steady state capital stock by substituting the expression (A.24) in expression (A.19):

$$\text{(A.25)} \quad \frac{(1-\alpha_i) \left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right]^{\frac{\alpha_i}{\alpha_i-1}} (\theta_i)}{B\left[\lambda_i \left(\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right) - \delta_i \right]} = K_i^*$$

Combining the expression (A.24) and (A.25), we obtain the following expressions for labor productivity and for labor input in each sector:

$$\text{(A.26)} \quad \Pi_i = \tilde{\lambda}_i * \left[\frac{K_i^*}{N_i^*} \right]^{\alpha_i} = \tilde{\lambda}_i * \left[\frac{\dfrac{(1-\alpha_i)\left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right]^{\frac{\alpha_i}{\alpha_i-1}}(\theta_i)}{B\left[\lambda_i\left(\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right)-\delta_i\right]}}{\dfrac{(1-\alpha_i)\left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right](\theta_i)}{B\left[\lambda_i\left(\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i}\right)-\delta_i\right]}} \right]^{\alpha_i} = \tilde{\lambda}_i * \left[\frac{\left(\beta^{-1} - 1 + \delta_i\right)}{\alpha_i} \right]^{\frac{\alpha_i}{\alpha_i - 1}}$$

$$\text{(A.27)} \quad N_i^* = \frac{(1-\alpha_i) \left[\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right] \tilde{\theta}_i}{B\left[\left(\frac{\left(\beta^{-1}-1+\delta_i\right)}{\alpha_i} \right) - \delta_i \right]}$$

where $\tilde{\lambda}_i$ is the stochastic total factor productivity and $\tilde{\theta}_i$ is a stochastic non- technology shock.

Applying a logarithmic transformation to the equations (A.26) and (A.27) yields the baseline structure of the empirical analysis (7) in the main text.

Tables and Figures

Table 1 – Unit Root Tests

	π_D	n_D	π_{ND}	n_{ND}
Deterministic part	c,t	c,t	c,t	c,t
Test statistics	-2.48	-3.10	-2.95	-2.01
	$\Delta\pi_D$	Δn_D	$\Delta\pi_{ND}$	Δn_{ND}
Deterministic part	c	c	c	c
Test statistics	-6.97	-7.27	-10.25	-7.73

Note. Statistics are augmented Dickey–Fuller test statistics for the null hypothesis of a unit root process; π and n denote the log level of the labor productivity and the log level of employment, respectively. Δ is the first-difference operator. The critical value at the 5% level of significance is -2.86 to two decimal places if a constant (c) in the regression, and -3.41 if a linear trend (t) also is included in the regression (MacKinnon, 1991).

Table 2 – Business Cycle Statistics: Univariate Methods

Cross-correlation of cyclical components of labor productivity at t and employment at $t+h$

	$\rho(\Delta\pi_{D,t}, \Delta n_{D,t+h})$	$\rho(\Delta\pi_{ND,t}, \Delta n_{ND,t+h})$
	First-differenced data (1953q2-1996q4)	
$h = -1$	-0.12*	-0.14*
$h = 0$	0.42*	-0.27*
$h = 1$	0.30*	-0.06
	HP-filtered data (1953q1-1996q4)	
$h = -1$	0.02	-0.43*
$h = 0$	0.37*	-0.42*
$h = 1$	0.54*	-0.28*
	BP-filtered data (1956q1-1993q4)	
$h = -1$	0.08	-0.41*
$h = 0$	0.42*	-0.41*
$h = 1$	0.56*	-0.28*

Note. An asterisk indicates coefficients are significantly different from zero using a 5% one-side test based on the VARHAC procedure. The smoothing parameter of the HP filter is set equal to 1600. For the BP filter, only the part of the series with cycles less than or equal to 32 periods (8 years) is included.

Table 3 – Business Cycle Statistics: Multivariate Method

Cross-correlation of cyclical components of labor productivity and employment at horizon h

	$\rho(\pi_D, n_D)$	$\rho(\pi_{ND}, n_{ND})$
$h = 4$	0.55*	-0.28*
$h = 8$	0.40*	-0.35*
$h = 16$	0.32*	-0.38*
$h = 20$	0.31	-0.38*

Note. An asterisk indicates coefficients are significantly different from zero using 95% confidence bands based on bootstrap with 1000 replications. The baseline model includes an intercept as well as a linear and a quadratic trend. The optimal lag is chosen according to the BIC. Unit roots are imposed.

Table 4 – Cointegration Tests

	Eigenvalues			
	0.147	0.130	0.023	0.020
	Trace Test		Maximum Eigenvalue Test	
Rank	No DFC	DFC	No DFC	DFC
0	58.77 [0.12]	54.70 [0.23]	27.44 [0.17]	25.54 [0.27]
1	31.34 [0.43]	29.16 [0.56]	24.05 [0.08]	22.38 [0.14]
2	7.29 [0.99]	6.78 [0.99]	3.85 [0.99]	3.59 [0.99]
3	3.44 [0.81]	3.20 [0.84]	3.44 [0.81]	3.20 [0.84]

Note. Under the null hypothesis there are r cointegration vectors against the alternative one of exactly (at most) $r+1$ cointegration vectors for the maximum eigenvalue (trace) test. The rank r is selected as the first non-significant statistics, starting from $r = 0$. p-values are reported in square brackets. No DFC (DFC) indicates the version of the test without (with) correction for degrees of freedom.

Table 5 – Causality Tests

		Granger causality		Instantaneous causality	
		F(6,656)		$\chi^2(3)$	
Durable Sector	$\Delta\pi_D$	**0.73**	[0.62]	59.57	[0.00]
	Δn_D	3.49	[0.00]	84.41	[0.00]
Non-Durable Sector	$\Delta\pi_{ND}$	*2.61*	[0.02]	*10.50*	[0.01]
	Δn_{ND}	4.83	[0.00]	65.11	[0.00]
		F(8,656)		$\chi^2(4)$	
Durable Sector Block		**1.29**	[0.24]	72.42	[0.00]
Non-Durable Block		**3.69**	[0.00]	72.42	[0.00]

Note. Statistics in bold (italics) indicates the rejection of the null hypothesis of non-causality at the 5% (1%) for each variable (upper part) and for each sector (lower part). p-values are reported in square brackets.

*Table 6 – Variance Decomposition: the **non-durable good regime***

	$\Delta\pi_D$	Δn_D	$\Delta\pi_{ND}$	Δn_{ND}	μ	Origin	Nature
Sector-specific Shocks							
Technology Shocks (*D*, *ND*)	73.18	4.71	75.98	21.08	43.74	79.74	48.46
Non-technology Shocks (*D*, *ND*)	10.40	34.76	22.46	76.39	35.93		
Cross Sector Shocks							
Technology Shocks (*D*, *ND*)	7.91	9.74	0.62	0.63	4.72	20.26	51.54
Non-technology Shocks (*D*, *ND*)	8.51	50.79	0.94	1.90	15.54		

Note. Average contribution of sector-specific and relative technology and non-technology shocks for each variable of the system and for the model as a whole (μ-column) over the entire simulation horizon. “Origin” indicates the share of variability due to sector-specific and to cross-sector shocks. “Nature” specifies the relative contribution of technology and non-technology shocks in explaining the variability of the system as a whole.

Table 7 – Conditional Correlations

	Column A - Durable Sector		Column B – Non-Durable Sector	
	Sector-Specific Shocks			
	$\rho(\Delta\pi_D, \Delta n_D \mid u_D^T)$	$\rho(\Delta\pi_D, \Delta n_D \mid u_D^{NT})$	$\rho(\Delta\pi_{ND}, \Delta n_{ND} \mid u_{ND}^T)$	$\rho(\Delta\pi_{ND}, \Delta n_{ND} \mid u_{ND}^{NT})$
	0.78*	0.69*	-0.69*	-0.01
	Cross-Sector Shocks			
	$\rho(\Delta\pi_D, \Delta n_D \mid u_{ND}^T)$	$\rho(\Delta\pi_D, \Delta n_D \mid u_{ND}^{NT})$	$\rho(\Delta\pi_{ND}, \Delta n_{ND} \mid u_D^T)$	$\rho(\Delta\pi_{ND}, \Delta n_{ND} \mid u_D^{NT})$
	0.60*	0.50*	0.15*	0.25*

Note. An asterisk indicates coefficients are significantly different from zero using a 5% one-side test based on the VARHAC procedure.

Table 8 – Consequences of a Positive Technology Shock Originating in the Non-durable Good Sector

	Impact over non-durable good sector (i.e. $\uparrow\lambda_{ND}$ as a *sector-specific* shock)	Impact over durable good sector (i.e. $\uparrow\lambda_{ND}$ as a *cross-sector* shock)
$\uparrow\lambda_{ND}$	$\downarrow n_{ND}$	$\downarrow n_{D}$
	$\uparrow\pi_{ND}$	$\downarrow\pi_{D}$

Note. λ_{ND} denotes a technology shock originating into the non-durable sector; n_{ND}, n_D : employment in the non-durable and in the durable sectors, respectively; π_{ND}, π_D : labor productivity in the non-durable and in the durable sectors, respectively.

Table 9 – Consequences of a Positive Technology Shock Originating in the Durable Good Sector

	Impact over durable good sector (i.e. $\uparrow\lambda_{D}$ as a *sector-specific* shock)	Impact over non-durable good sector (i.e. $\uparrow\lambda_{D}$ as a *cross-sector* shock)
$\uparrow\lambda_{D}$	$\uparrow n_{D}$	$\approx n_{ND}$
	$\uparrow\pi_{D}$	$\approx\pi_{D}$

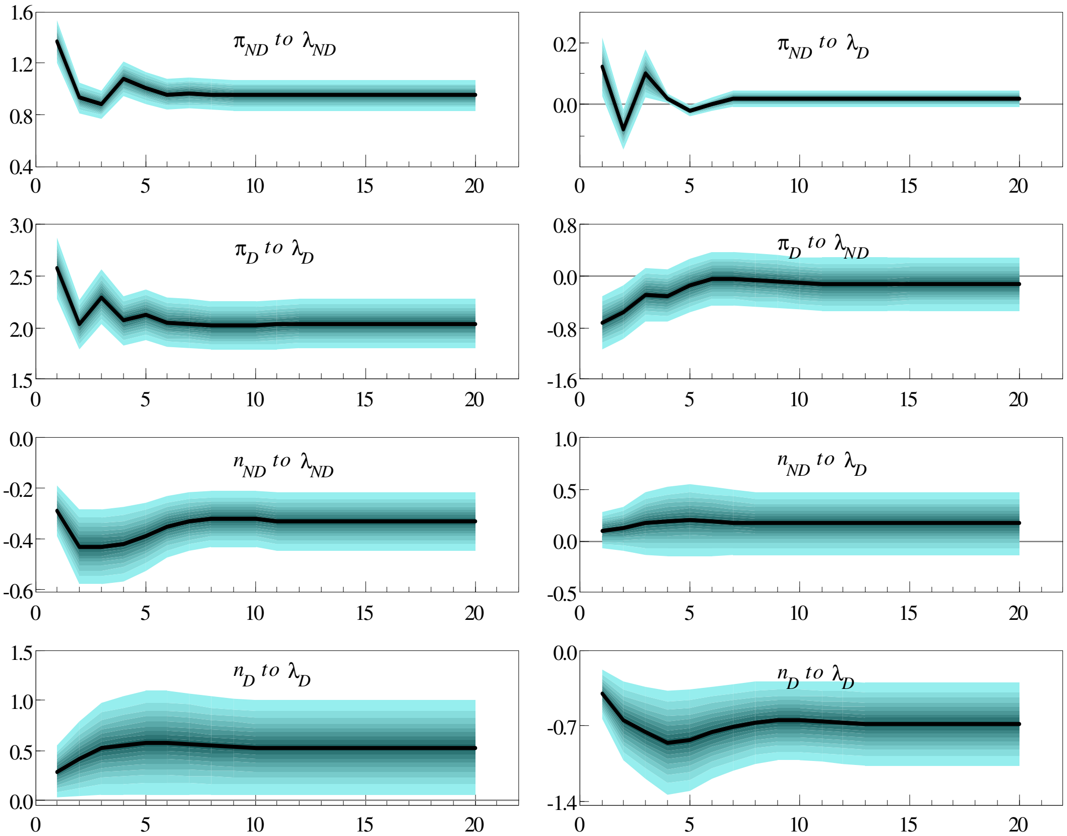
Note. λ_{ND} denotes a technology shock originating into the non-durable sector; n_{ND}, n_D : employment in the non-durable and in the durable sectors, respectively; π_{ND}, π_D : labor productivity in the non-durable and in the durable sectors, respectively.

*Table 10 – Variance Decomposition: the **durable good regime***

	$\Delta\pi_D$	Δn_D	$\Delta\pi_{ND}$	Δn_{ND}	μ	Origin	Nature
Sector-specific Shocks							
Technology Shocks (*D*, *ND*)	75.95	5.70	76.15	20.84	44.65	71.86	48.46
Non-technology Shocks (*D*, *ND*)	13.88	73.69	9.18	12.07	27.21		
Cross Sector Shocks							
Technology Shocks (*D*, *ND*)	5.16	8.76	0.44	0.88	3.81	28.14	51.54
Non-technology Shocks (*D*, *ND*)	5.04	11.85	14.22	66.21	24.33		

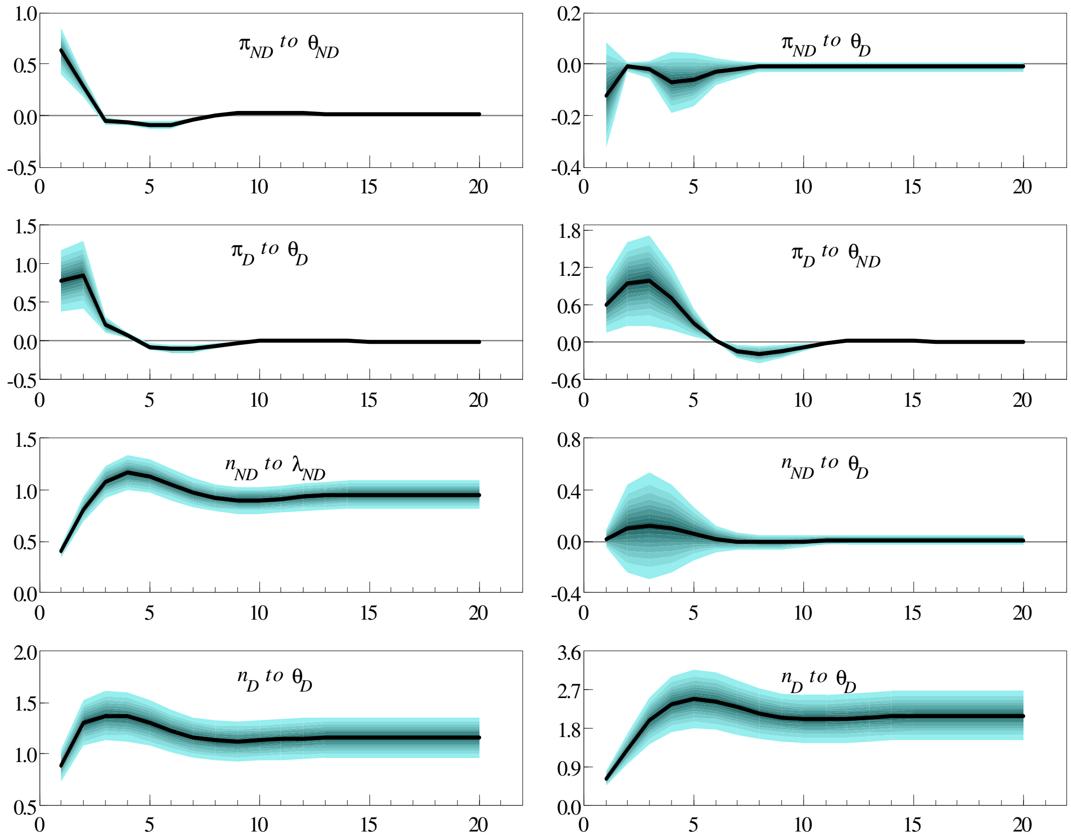
Note. Average contribution of sector-specific and relative technology and non-technology shocks for each variable of the system and for the model as a whole (μ-column) over the entire simulation horizon. "Origin" indicates the share of variability due to sector-specific and to cross-sector shocks. "Nature" specifies the relative contribution of technology and non-technology shocks in explaining the variability of the system as a whole.

Figure 1 – Response Functions to Technology Shocks



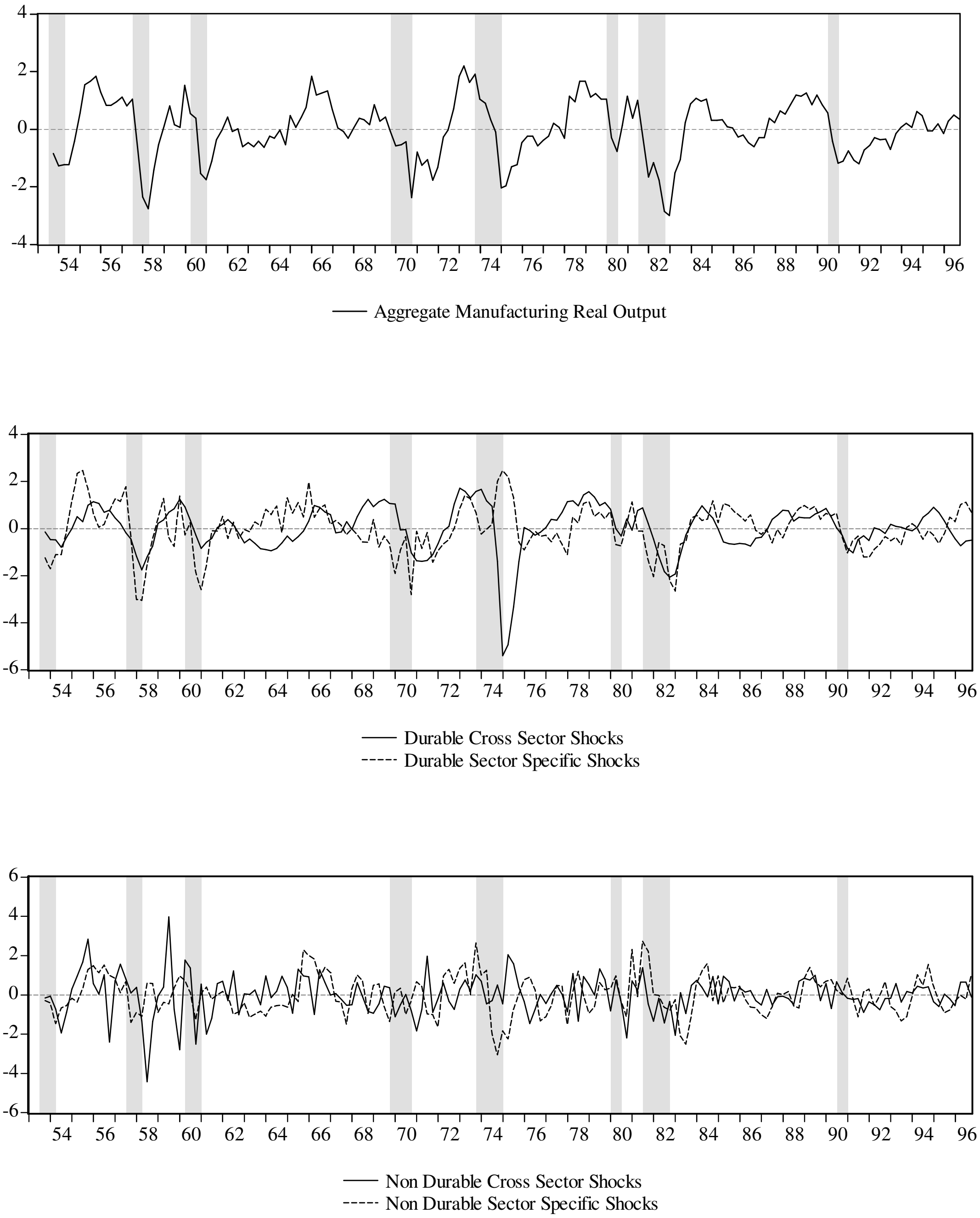
Note. Responses to sector-specific (cross-sector) technology shocks are reported on the left (right). The vertical axis denotes percentage changes from the pre-shock level (solid lines). The horizontal axis indicates quarters after the shocks. Shaded area represents the 80-percent confidence intervals based on bootstrapping 5000 draws.

Figure 2 – Response Functions to Non-technology Shocks



Note. Responses to sector-specific (cross-sector) non-technology shocks are reported on the left (right). The vertical axis denotes percentage changes from the pre-shock level (solid lines). The horizontal axis indicates quarters after the shocks. Dashed lines: bootstrapped confidence intervals.

Figure 3 –Recessions for the Aggregate US Economy



Note. Shaded areas indicate recessions for the United States economy identified by the National Bureau of Economic Research (NBER). The HP-filtered cyclical components of the series have been normalized. The smoothing parameter of the HP filter is set equal to 1600.

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