Factor Demand Linkages, Technology Shocks and the Business Cycle

Sean Holly and Ivan Petrella

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Sean Holly†
University of Cambridge and CIMF

Ivan Petrella‡
University of Cambridge and CIMF

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Abstract

This paper argues that factor demand linkages are crucial in the transmission of both sectoral and aggregate shocks. We show this using a panel of highly disaggregated manufacturing sectors together with sectoral structural VARs. When sectoral interactions are explicitly accounted for, a contemporaneous technology shock to all manufacturing sectors implies a positive response in both output and hours at the aggregate level. Otherwise, there is a negative correlation as in much of the existing literature. Furthermore, we find that technology shocks are important drivers of business cycles.

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†University of Cambridge, Faculty of Economics and Centre for International Macroeconomics and Finance (CIMF), Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, UK. *E-mail*: sh247@cam.ac.uk.

‡University of Cambridge, Faculty of Economics and Centre for International Macroeconomics and Finance (CIMF), Austin Robinson Building, Sidgwick Avenue, Cambridge CB3 9DD, UK. *E-mail*: ip245@cam.ac.uk.

1 Introduction

Input-output linkages are a pervasive feature of modern economies. Neglecting them could lead to a significant loss in understanding the dynamics of the supply-side of an economy. Intermediate goods used in one sector are produced in other sectors, which in turn use the output from the first sector as an input to their own production. Therefore there are complex circular networks of input-output interactions that need to be taken into account. The presence of an intermediate input channel is emphasized by Hornstein and Praschnik (1997) and recently analyzed in detail in Kim and Kim (2006).

In this paper we consider explicitly the empirical relevance of this channel. We study fluctuations at the sectoral and the aggregate level and we show that it is important to model the interactions between sectors if we want to fully understand the propagation of shocks across the economy. Typically, reduced form time series methods, in conjunction with the long run identifying assumptions, are used to disentangle disturbances to an economy. With few exceptions, the literature has applied these methods to aggregate time series. However, modelling aggregate time series directly implies that sectors are relatively homogeneous and most importantly, that interactions among sectors are of second order importance for aggregate fluctuations.[1]

Following the pioneering work of Long and Plosser (1983), RBC models have been generalized into a multi-sectoral environment where industry specific shocks are propagated through sectoral inter-dependencies which can generate business cycle fluctuations. The idea was revitalized by Horvath (1998, 2000) who shows

[1] See Dupor (1999) for a discussion of the theoretical conditions under which the latter hypothesis is verified, and Horvath (1998) and Carvalho (2009) for a critique.

how the input-output structure of the economy is a good way of capturing the relations between sectors in the economy. Also, Conley and Dupor (2003) and Shea (2002) emphasize sectoral complementarities as the main mechanism for propagating sectoral shocks at the aggregate level, the main idea being intrinsically related to the original result of Jovanovic (1987).

We proceed by modelling the dynamics of a panel of highly disaggregated manufacturing sectors. We assume that industry dynamics are mainly driven by technology and non-technology shocks. We use a simplified version of a multi-sectoral real business cycle with factor demand linkages to derive restrictions that allow us to understand how shocks from one sector can affect productivity in other sectors. Those long run restrictions are then used in a 'structural' VAR in order to identify the shocks. We then construct an industry VAR (SecVAR) using the GVAR approach of Pesaran et al. (2004) and link sectors through the input-output matrix. The main novelty is that all sectors in the economy are related by factor demand linkages captured by the input-output matrix. This allows us to distinguish between the contribution made by technology shocks to particular sectors and the overall effect amplified by sectoral interactions. Therefore, for each sector we identify technology and non-technology shocks, where these shocks alone can explain industry and aggregate fluctuations only if all sectors are analyzed contemporaneously, i.e. not in isolation. We establish that the intermediate input channel is crucial for propagating shocks to the aggregate economy.

Furthermore, we consider the implications of our results for the relative roles played by real and nominal shocks in explaining aggregate fluctuations in manufacturing. Real business cycle theory attributes the bulk of macroeconomic fluctuations to optimal responses to technology shocks. This in turn implies that there is a positive correlation between hours worked and labour productivity. The source of this correlation is a shift in the labour demand curve, as a result of a technology shock, combined with an upward sloping labour supply curve. However, there is a large literature suggesting that this is inconsistent with the data. Gali (1999) uses the identifying assumption that innovations to technology are the only type of shocks that have permanent effects on labour productivity, and finds that hours worked fall after a positive technology shock. Furthermore, he finds that technology shocks account for only a minimal part of aggregate fluctuations. A number of studies have reported similar results (see Gali and Rabanal, 2005, for a review), which if confirmed would make a model of technology-driven business cycles unattractive. This has led many to conclude that the technology driven real business cycle hypothesis is "dead" (Francis and Ramey, 2005a). Gali (1999) suggests that the paradigm needs to be changed in favour of a business cycle model driven instead by preference shocks and featuring sticky prices.

Most of the empirical macroeconomic literature evaluating the effect of technology shocks focus on the analysis of aggregate data. So sectoral interactions through factor demand linkages do not matter. Chang and Hong (2006) and Kiley (1998) examine the technology-hours question with sector level data, however, they consider each sector as a separate unit in the economy. In this paper we consider the implications of factor demand linkages for the econometric analysis of the effect of technology shocks on hours. A contemporaneous technology shock to all sectors in manufacturing then implies a positive aggregate response in both output and hours. The positive aggregate response is directly related to the role of factor demand linkages in the transmission of shocks. When sectoral interactions are ignored we find a negative correlation as with much of the literature. This suggests that the standard technology driven Real Business Cycle paradigm is a reasonable approximation of a more complicated model featuring heterogeneously interconnected sectors.

The input-output channel is not only qualitatively, but also quantitatively, important for the transmission of shocks. Sectoral interactions prove to be an important amplifier of sector-specific and aggregate shocks.[2] Technology shocks appear to account for most sectoral fluctuations; most significantly, shocks to other sectors (transmitted though sectoral interactions) are fundamental for tracking individual sectoral cycles. Furthermore, our analysis suggests, once sectoral interactions are accounted for, that technology and non-technology shocks seems to be equally important in explaining aggregate economic fluctuations in US manufacturing. Interestingly our results tend to show that the role of technology shocks has gained in importance since the mid 1980s.

The remainder of the paper is organized as follows. In section 2, we employ a basic multi-sectoral RBC model to derive long run restrictions that we then use in the empirical analysis. Specifically, we show that changes in relative prices reflect changes in labor productivity in each sector. In section 3 we show how to identify technology and non-technology shocks in a way consistent with the restrictions of the multi-sectoral model, employing a structural VAR but applied to industrial sectors. Section 4 describes the data, and discusses some of the theoretical motivation for the specification of the model. In section 5, we report estimates of the effects of technology shocks and disentangle the different contributions made to the

[2] This is also illustrated in Horvath (2000), who describes a multisector dynamic general equilibrium model calibrated to US industry data. He finds that when the amplification mechanism due to sectoral interactions is correctly specified, aggregate fluctuations are driven by independent sectoral shocks. In this paper we provide an empirical assessment of the importance of this channel.

aggregate outcome for manufacturing. In Section 6 we consider some robustness exercises. Finally, section 7 contains concluding remarks.

2 A simple multi-sectoral growth model

The purpose of the simplified model of this section is to derive the structural restrictions that will allow us to identify the different shocks that affect the economy at the sectoral level. Furthermore this simplified model will allow us to throw light on the way shocks are propagated through the economy. The focus is on the long run properties of the model that are useful for structural identification. In order to simply the discussion we focus on an economy only buffeted by idiosyncratic shocks at the sectoral level.

The model economy consists of N sectors, indexed by i. Households allocate labor to all sectors, and make consumption-saving decisions. The representative household maximizes discounted expected utility

$$E_0 \sum_{t=0}^{T} \beta^t \left\{ \log C_t + \chi V\left(L_t\right) \right\},$$

subject to the budget constraint

$$\sum_{i=1}^{N} P_{it} C_{it} + B_t = W_t H_t + \left(1 + R_t\right) B_{t-1} + \sum_{i=1}^{N} \Psi_{it}.$$

Here E_0 is the expectation operator conditional on time $t = 0$; β is the discount factor; $V\left(L_t\right)$ is a twice differentiable concave function that captures the disutility of supplying labor. The household receives nominal labor income $W_t H_t$, where W_t is the nominal wage and H_t employment; interest payment R_t on bond holdings

B_{t-1} and profits paid from N sectors, Ψ_{it}, which are then allocated between consumption of different goods and saving, where P_{it} is the price of the good, C_{it}, produced in sector i. The log utility specification implies separability of households' preferences for different consumption goods. This specification is consistent with aggregate balanced growth, as discussed in Ngai and Pissarides (2007). The aggregate consumption and leisure index C_t and L_t are defined as

$$C_t = \prod_i \xi_i^{-\xi_i} \widetilde{C}_{it}^{\xi_i},$$

$$L_t = 1 - H_t = 1 - \sum_i H_{it},$$

where $\xi_i \in [0,1]$ are aggregatation weights that satisfy $\sum_i \xi_i = 1$. In order to allow for possible shocks to preferences as well as to technologies the consumption bundle is subject to a preference shock of the form:

$$\widetilde{C}_{it} = \frac{C_{it}}{Z_{it}^P}.$$

The shocks to preferences are exogenous and are assumed to follow an autoregressive process of the form $Z_{it}^P = \left(Z_{it-1}^P\right)^{\varrho} \exp\left[\Phi_i^p(L)\varepsilon_{it}^p\right]$ where $|\varrho| \leq 1$, $\Phi_i^p(L) = (1 - \phi_i L)^{-1}$ is a square summable polynomial in the lag operator ($|\phi_i| < 1$) and ε_{it}^p is white noise. Notice that the log of the exogenous preference shock follows a unit root process whenever $\varrho = 1$. The shocks are assumed to be idiosyncratic at the sectoral level, i.e. $Cov(\varepsilon_{it}^p, \varepsilon_{jt}^p) = 0$, $\forall i \neq j$. Furthermore, is convenient to assume that the shocks are normalized such that $\prod_i \left(Z_{it}^P\right)^{\xi_i} = 1$, i.e. idiosyncratic shocks do not directly affect aggregates (see e.g. Franco and Philippon, 2007).

Maximization of consumption gives the demand function

$$C_{it} = \xi_i \left(\frac{P_{it}}{Z_{it}^P P_t} \right)^{-1} C_t,$$

with $P_t = \prod_i \left(Z_{it}^P P_{it} \right)^{\xi_i}$.

On the supply side, the goods market operates under perfect competition and besides labor, production of each good uses inputs from other sectors. The production function is a Cobb-Douglas with constant return to scale

$$Y_{it} = Z_{it} M_{it}^{\alpha_i} H_{it}^{1-\alpha_i},$$

where intermediate inputs, M_{it}, are aggregated as

$$M_{it} = \prod_{j \in S_i} \gamma_{ij}^{-\gamma_{ij}} M_{ijt}^{\gamma_{ij}},$$

M_{ijt} is the intermediate input j used in the production of good i, S_i is the set of supplier sectors of sector i, and γ_{ij} the share of the intermediate input j in sector i, and $\sum_j \gamma_{ij} = 1$. The technology shock of each sector is also assumed to follow a autoregressive stochastic process of the form $Z_{it} = (Z_{it-1}) \exp\left[\mu_i^z + \Phi_i^z(L)\varepsilon_{it}^z\right]$ where μ_i^z is a constant drift, and $\Phi_i^z(L) = (1 - \rho_i L)^{-1}$ is a square summable polynomial in the lag operator (i.e. $|\rho_i| < 1$) and ε_{it}^z is a white noise innovation to the idiosyncratic technology shock to sector i. Also in this case we assume that the shocks are idiosyncratic at the sectoral level, i.e. $Cov(\varepsilon_{it}^z, \varepsilon_{jt}^z) = 0$, $\forall i \neq j$.

The profit maximization problem for each sector i is

$$\max\{P_{it} Y_{it} - W_{it} H_{it} - P_t^{M_i} M_{it}\}.$$

Given the aggregator for intermediate inputs, the price index for intermediate goods can be written as

$$P_t^{M_i} = \prod_{j \in S_i} P_{jt}^{\gamma_{ij}}.$$

The cost minimization problem for each sector i yields the following expression for the optimum allocation of inputs:

$$MC_{it}Y_{it} = \frac{W_{it}H_{it}}{1-\alpha_i} = \frac{P_t^{M_i}M_{it}}{\alpha_i} = \frac{P_{jt}M_{ijt}}{\alpha_i\gamma_{ij}}.$$

In perfect competition, equilibrium requires that the price equals the marginal cost of production ($P_{it} = MC_{it}$). This in conjunction with the Cobb-Douglas production function implies constant expenditure shares on all intermediate inputs. Moreover, perfect labor mobility across sectors requires that (at the margin) nominal wages need to be equalized

$$W_{it} = W_{jt} = W_t \qquad \forall i, j.$$

Free mobility of intermediate inputs across sectors then implies that the marginal productivity of inputs (i.e. the prices of intermediate inputs) need to be equal across sectors. This implies that the relative price can be expressed as an inverse function of relative (labor) productivity

$$\frac{P_{it}}{P_{jt}} = \kappa_{ij}\left(\frac{Y_{jt}/H_{jt}}{Y_{it}/H_{it}}\right), \tag{1}$$

where κ_{ij} reflects differences in the labor intensity of the production functions.[3] These relative prices act as an important conduit for the transmission of technology

[3] Notice that if sectoral production functions are identical in each sector the previous expression would be: $P_{it}/P_{jt} = Z_{jt}/Z_{it}$ (see also Ngai and Samaniego, 2008).

shocks. A positive technology shock to the jth sector lowers the price of the intermediate input to the ith sector which in turn lowers the price in the ith sector. From the definition of the price index for intermediate goods, the relative price of intermediate goods is

$$\frac{P_t^{M_i}}{P_{it}} = \frac{\prod_{j \in S_i} P_{jt}^{\gamma_{ij}}}{P_{it}} = \left[\frac{\prod_{j \in S_i} (\kappa_{ij} Y_{jt}/H_{jt})^{\gamma_{ij}}}{Y_{it}/H_{it}} \right]^{-1}. \tag{2}$$

Output in sector i and labor productivity can be calculated from the production function as

$$\frac{Y_{it}}{H_{it}} = \phi_i Z_{it} \left[\prod_{j \in S_i} (Y_{jt}/H_{jt})^{\gamma_{ij}} \right]^{\alpha_i}, \tag{3}$$

where ϕ_i is a convolution of the production parameters. The expression (3) above makes it clear that in a multi-sectoral model the long run level of labor productivity is driven only by technology shocks, either originating in the same sector or in other sectors that supply intermediate inputs. Specifically, define x_{it} as the logarithm of labor productivity and z_{it} as the logarithm of the technology shock. Stacking all the sectoral variables in vectors, $\mathbf{x}_t$ and $\mathbf{z}_t$ respectively, the equilibrium solution for the labor input can be written as

$$(\mathbf{I} - \mathbf{A\Gamma})\, \mathbf{x}_t = \mathbf{z}_t \tag{4}$$

where $\mathbf{I}$ is the identity matrix, $\mathbf{A} = diag\begin{pmatrix} \alpha_1, & \dots & \alpha_I \end{pmatrix}$ and $\mathbf{\Gamma}$ is the "use" input-output matrix whose generic elements are the parameters $\gamma_{\iota j}$ introduced above. The second inequality follows from the specific process assumed for the technology shocks. Therefore, the long run response of the labor input in sector i

to the innovation to technology is

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{z}_{it}} = \boldsymbol{\iota}'_i\left[(\mathbf{I}-\mathbf{A\Gamma})(\mathbf{I}-\mathbf{D})\right]^{-1}\boldsymbol{\iota}_i \neq 0, \tag{5}$$

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{z}_{jt}} = \boldsymbol{\iota}'_i\left[(\mathbf{I}-\mathbf{A\Gamma})(\mathbf{I}-\mathbf{D})\right]^{-1}\boldsymbol{\iota}_j \neq 0 \qquad \forall j\neq i, \tag{6}$$

where $\mathbf{D}=diag\begin{pmatrix}\rho_1, & \dots & \rho_I\end{pmatrix}$ and $\boldsymbol{\iota}_k$ is an indicator vector of dimension $N\times 1$, whose elements are all 0 with the exception of the $k-$th entry equal to 1. Notice that in the case where factor demand linkages are not taken into consideration $\alpha_i = 0\ \forall i$ and:

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{z}_{it}} = \boldsymbol{\iota}'_i(\mathbf{I}-\mathbf{D})^{-1}\boldsymbol{\iota}_i = \frac{1}{1-\rho_i} < \boldsymbol{\iota}'_i\left[(\mathbf{I}-\mathbf{A\Gamma})(\mathbf{I}-\mathbf{D})\right]^{-1}\boldsymbol{\iota}_i,$$

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{z}_{jt}} = 0 \qquad \forall j\neq i.$$

Furthermore, permanent preference shocks have no effect on labor productivity because in this case the idiosyncratic shocks do not affect aggregate price or quantities. Therefore the long run restrictions that permit the identification of the shocks are

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{p}_{it}} = 0, \tag{7}$$

$$\lim_{h\to\infty}\frac{\partial\log\left(\frac{Y_{it+h}}{H_{it+h}}\right)}{\partial\varepsilon^{p}_{jt}} = 0 \qquad \forall j\neq i. \tag{8}$$

The labor market clearing condition for sector i equates labour supply - determined by the households' marginal rate of substitution between consumption and leisure - to the marginal productivity of labor which drives sectoral labour demands. Specifically, this can be written as

$$
\begin{aligned}
\frac{\partial Y_i}{\partial H_i} &= -\left(\frac{\partial U}{\partial L}\frac{\partial L}{\partial H_i}\right) \times \left(\frac{\partial U}{\partial C}\frac{\partial C}{\partial C_i}\right)^{-1}, \\
H_{it} &= \frac{(1-\alpha_i)\,\xi_i Z_{it}^P}{\chi}\frac{Y_{it}}{C_{it}}\frac{\partial V(L_t)}{\partial L_t}, \qquad (9)
\end{aligned}
$$

which clearly depends on the sectoral preferences as well as on sectoral technology shocks, that is

$$
\begin{aligned}
\lim_{h\to\infty} \frac{\partial \log(H_{it+h})}{\partial \varepsilon_{jt}^{p}} &\neq 0 \qquad \forall j, \\
\lim_{h\to\infty} \frac{\partial \log(H_{it+h})}{\partial \varepsilon_{jt}^{z}} &\neq 0 \qquad \forall j.
\end{aligned}
$$

Moreover, the presence of factor demand linkages among sectors is such that the labor input in each sector is influenced by shocks originating in other sectors

3 The econometric specification

Reduced form time series methods, in conjunction with the long run identifying assumptions are used to disentangle two fundamental (orthogonal) disturbances, technology and non-technology shocks.

Following Gali (1999), many studies adopt the identifying assumption that the only type of shock that affects the long-run level of labour productivity is a permanent shock to technology. This assumption is satisfied by a large class of standard business cycle models.[4] However, the discussion in the previous section points to

[4] See, for example, the real business cycle models in King et al. (1988), King et al. (1991)

the need to go further than this when there are factor demand linkages. Labor productivity in *ith* sector in the long run is also affected by labor productivity in the sectors that supply intermediate goods to the *ith* sector, through changes in relative prices as in equation (3). Therefore, to identify technology and non-technology shock we need to take into account the role of the intermediate input channel as well.

Estimating a VAR for all industries in the economy is infeasible for any reasonably large number of industries. A consistent way of identifying the technology shocks is to estimate a VARX for each sector and to apply to these the restrictions implied by the multi-sectoral model with factor demand linkages. Specifically for each industry we estimate a sector model as:[5]

$$(\mathbf{A}_{i0} - \mathbf{A}_{i1}L)\,\varkappa_{it} = (\mathbf{C}_{i0} + \mathbf{C}_{i1}L)\,\varkappa_{it}^{*} + \boldsymbol{\lambda}_i \mathbf{d}_t + \boldsymbol{\varepsilon}_{it}, \tag{10}$$

where $\varkappa_{it} = [\Delta x_{it},\, \Delta h_{it}]'$ and Δx_{it} and Δh_{it} denote respectively the growth rate of labor productivity and labor-hours[6], and $\varkappa_{it}^{*}$ are appropriate industry specific

and Christiano and Eichenbaum (1992) which assume that technology shocks are a difference stationary process. Gali (1999) discusses the assumptions which are jointly sufficient to yield the identifying restrictions used. Notice that increasing returns, capital taxes, and some models of endogenous growth would all imply that non-technology shocks can change long-run labour productivity, thus invalidating the identifying assumption. Francis and Ramey (2005a) investigate the distortion that may come from the exclusion of the permanent effect of capital taxes, but find that this does not affect the outcome of the simpler bivariate specification.

[5] For ease of exposition we focus on the simple VARX(1,1) without any deterministic component, but the discussion applies equally to a more general formulation. In principle an appropriate number of lags of the endogenous and weakly exogenous variables are included such that the error term (i.e. the identified shocks) are serially uncorrelated. Given the short annual time series we choose a single lag specification in the empirical section. This is also consistent with the Akaike and Schwarz information criteria for most of the sectors.

[6] There is an issue in the literature concerning whether labor input (hours) shoud be modeled as stationary in level or in first difference when extracting the technology shock (Christiano et al., 2003). The fact that aggregate labor input is stationary is often motivated by balanced growth path considerations. However, at the industry level the reallocation of the labor input could produce different sectoral trends (see e.g. Campbell and Kuttner, 1996, and Phelan and

weighted cross sectional averages of the original variables in the system and reflect interactions between sectors. Specifically, the industry cross sectional average are constructed in order to capture factor demand linkages between manufacturing sectors in the economy, i.e. $\varkappa_{it}^{*} = \left[\sum_{j=1}^{N} \omega_{ij} \Delta x_{jt},\ \ \sum_{j=1}^{N} \omega_{ij} y_{jt}\right]'$, where the weights, ω_{ij}, correspond to the (possibly time varying) share of commodities j used as an intermediate input in sector i (i.e. $\omega_{ij} \approx \gamma_{ij}$). The specification includes a set of k exogenous aggregate variables, $\mathbf{d}_t$, which are meant to control for the effect of aggregate (nominal and real) shocks hitting the economy.[7] The sectoral idiosyncratic shocks $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}'_{1t}, ..., \boldsymbol{\varepsilon}'_{Nt}]'$ are such that for each industry $\boldsymbol{\varepsilon}_{it} = [\varepsilon_{it}^{z}, \varepsilon_{it}^{p}]'$, where ε_{it}^{z} denotes the technology shock and ε_{it}^{p} denotes the non-technology shock for the ith sector. The key identifying assumption is that $E(\boldsymbol{\varepsilon}'_{it}\boldsymbol{\varepsilon}_{it}) = \boldsymbol{\Omega}_{i\varepsilon}\ \forall i$ is a diagonal matrix and $E(\boldsymbol{\varepsilon}'_{it}\boldsymbol{\varepsilon}_{is}) = \mathbf{0}\ \forall t \neq s$.

To estimate the effect of technology shocks we follow the procedure outlined in Shapiro and Watson (1988), and discussed in Christiano et al. (2003). The restriction that the technology shock is the only source of variation in labor productivity in the long run, allows us to identify sector specific shocks. For the ith sector this restriction has to be imposed on shocks originating in the ith sector and on shocks originating in other sectors that supply inputs to the ith sector. The equilibrium relation for labor productivity in equation (4) states that labor productivity in

Trejos, 2000). Evidence that labor productivity and labor input follow unit root processes is available from the authors.

[7] Notice that the role of the factor demand linkages and aggregate shocks are not separately identifiable in the model (see also Foerster et al., 2008). In the empirical section we include two measures of aggregate shocks and identify the idiosyncratic shocks and the role of factor demand linkages conditional on the exogenous aggregate variables correctly capturing variation in aggregate shocks. Notice that we are implicitly assuming that the same dynamic apply to aggregate and idiosyncratic shocks. This for instance would be consistent with the model above where the technology shock at the industry level is the sum of an idiosyncratic and a common component.

the long run in the ith sector is affected only by direct technology shocks to the ith sector and by the technology shocks (of other sectors) that impact on labor productivity of supplying sectors **(8).** Therefore, equation (4) imposes two sets of restrictions. The first restriction is the standard restriction given by equation (7), which requires that $A_{i0}^{12} = -A_{i1}^{12}$. However, we also need to impose a similar restriction on the coefficients of the cross sectional averages, as equation (8) also requires that $C_{i0}^{12} = -C_{i1}^{12}$.

It is possible to recover the VAR specification for all sectors by stacking the sector specific models in (10). The model can be rewritten as

$$\mathbf{G}_0 \boldsymbol{\kappa}_t + \mathbf{G}_1 \boldsymbol{\kappa}_{t-1} = \mathbf{u}_t, \tag{11}$$

where $\boldsymbol{\kappa}_t = [\varkappa_{1t}', ..., \varkappa_{Nt}']'$ are the matrix of coefficients are

$$\begin{aligned} \mathbf{G}_{i0} &= \begin{pmatrix} \mathbf{A}_{i0}, & -\mathbf{C}_{i0} \end{pmatrix} \mathbf{W}_i, \\ \mathbf{G}_{i1} &= -\begin{pmatrix} \mathbf{A}_{i1}, & \mathbf{C}_{i1} \end{pmatrix} \mathbf{W}_i. \end{aligned}$$

The $4 \times 2N$ weighting matrix is constructed such that for each sector this selects the sector specific variables and constructs the sector specific cross sectional averages in (10), as outlined in Pesaran et al. (2004).[8] The weights for the sector specific cross sectional averages reflect the factor demand linkages between sectors observable from the input-output matrix. The linear approximation to the equilibrium of any economic model has a moving average representation. Therefore, the reduced

[8]Appendix B provides more details on the construction of the SecVAR model, and how to recover the MA representation, as well as some detailed discussion of the transmission mechanism of idiosyncratic shocks.

form representation of the dynamics of labor productivity and labor input at the sectoral level can be specified as

$$\boldsymbol{\kappa}_t = \mathbf{B}(L)\mathbf{u}_t. \tag{12}$$

The transmission mechanism is captured by $\mathbf{B}(L)$, a matrix polynomial in the lag operator, L, and the innovations are such that $E(\mathbf{u}_t'\mathbf{u}_t) = \boldsymbol{\Omega}_u$ and $E(\mathbf{u}_t'\mathbf{u}_s) = \mathbf{0}\ \forall t \neq s$. The specification in (12) does not impose any particular restriction on the nature of the shocks. Specifically, shocks at the industry level can be either idiosyncratic or need to be decomposed into an aggregate and an industry specific component ($\mathbf{u}_{it} = \boldsymbol{\lambda}_i \mathbf{d}_t + \boldsymbol{\varepsilon}_{it}$). Therefore, the matrix polynomial of the MA specification of the model (12) can be recovered by inverting $\mathbf{G}(L)$.

Chang and Hong (2006) and Kiley (1998) make use of the restriction that labor productivity is driven solely by technology shocks in the long run in a bivariate VAR to recover (industry specific) technology shocks. However, they neglect the role of factor demand linkages between sectors. Their specification can be cast in the general specification (12) with each sector analyzed in isolation, that is the matrix polynomial $\mathbf{B}(L)$ is composed of block diagonal matrices. The specification in (10) encompasses the specification of Kiley (1998) and Chang and Hong (2006) by setting the coefficients reflecting factor demand linkages to zero ($\mathbf{C}_{il} = \mathbf{0}$, $\forall i$ and $l = 0, 1$). However the model in the previous section makes it clear that this would only be appropriate if intermediate inputs had a negligible role to play in production. This is a rather strong restriction, as it implies that in order to replicate the widely documented comovement between sectors we would have to rely only on aggregate shocks. The specification in (10), instead, allows us recover a mechanism by which idiosyncratic and aggregate shocks are propagated by sectoral interactions, as emphasized by the simplified model in the previous section.

The SecVAR model analyzed in this section provides a further application of the GVAR model described in Pesaran et al. (2004) but at the industry level. The difference is we consider a fully structural model, i.e. the contemporaneous relationships are constrained not only between the endogenous and the weakly exogenous aggregate variables, but also includes the contemporaneous relationships between the endogenous variables.[9]

4 Data and Estimation Results

4.1 Data description

The data used are collected from the NBER-CES Manufacturing Industry Database (Bartelsman et al., 1996). The database covers all 4-digit manufacturing industries from 1958 to 1996 (39 annual observations) ordered by 1987 SIC codes (458 industries).[10] Labour input is measured as total hours worked, while productivity is measured as real output divided by hours. Each variable is included as a log difference, where this choice is supported by panel unit root tests discussed below.

We match the dataset with the standard Input-Output matrix at the highest disaggregation, provided by the Bureau of Economic Activity.[11] Specifically, we

[9] Specifically, the matrix of coefficients $\mathbf{A}_{i0}$, $\forall i$, are not constrained to be an identity matrix as in the non structural formulation of the GVAR. Furthermore, the coefficients describing the dynamic of the model are restricted to impose the long run restrictions as described above.

[10] As in other studies we exclude the "Asbestos Product" industry (SIC 3292) because the time series ends in 1993.

[11] The data are available at http://www.bea.gov/industry/io_benchmark.htm. The original

employ the "use" table, whose generic entry ij corresponds to the dollar value, in producers' prices, of commodity produced by industry j and used by industry i. This table is transformed into a weighting matrix by row standardization, such that each row sums to one. Note that before the transformation each row sum corresponds to total intermediate use, this information is likely to be recovered in the estimation of the coefficients $\mathbf{C}_{il}$, $i = 1, ..., I$ and $l = 0, 1$, in (10).[12]

The input-output "use" table clearly reflects factor demand linkages and therefore is a good measure of the intermediate input channel. Shea (2002) and Conley and Dupor (2003) use the same matrix to investigate factor demand linkages and sectoral complementarities. Ideally, we would need a time varying input-output matrix to take into consideration the change in the factor linkages between sectors in the economy, or the steady state input-output matrix as in (4). In the empirical analysis we use the average of the input-output matrix in 1977 and 1987.[13] In the robustness section we investigate whether the results are affected when we take into consideration changes in the IO structure.

4.2 Labor productivity and TFP

Chang and Hong (2006) have argued that total factor productivity (TFP) and

input output matrix when constrained to the manufacturing sector has 355 entries only. This means that the BEA original classification for the construction of the input output matrix aggregates more (4 digit SIC) sectors. As the entries in the original data correspond to the dollar value, in producers' prices, of each commodity used by each industry and by each final user, when more than one SIC sector corresponds to a single sector in the IO matrix we split the initial value equally between the SIC sectors. The original IO matrix includes also within sectors trade. We exclude this from the calculation of the standardised weighting matrix.

[12] The industry that has the larger use of intermediate goods in production is likely to have larger coefficients associated with the cross sectional averages in (10).

[13] For the IO matrix in 1987 there exists an exact match between the classification of the NBER-CES database and the IO matrix from the BEA. For the IO matrix in 1977 we match the 1977 SIC codes to the closest 1987 SIC codes. Detailed tables are available from the authors upon request.

not labor productivity is the correct measure from which to identify technology shocks. This is because the latter reflects both improved efficiency and changes in the input mix as a result, for example, of a change in the relative price of intermediate inputs. In support of their argument they show that labor productivity and TFP are not cointegrated, therefore the long run component of labor productivity does not truly identify technology shocks. In Table 1 we confirm this analysis using panel unit root tests applied at the 4 digit industry level. Since labor productivity and TFP are integrated of order 1, in the top panel we report tests for cointegration between TFP and labor productivity using both the IPS test and the CIPS test that takes account of cross sectional dependence using the method of Pesaran(2006). In both cases, as with Chang and Hong (2006), the null cannot be rejected at the conventional level. In the bottom panel we report tests of the null of a unit root, but this time the residuals are generated from a regression that includes the cross sectional *weighted* averages of labor productivity. This is in line with what would be implied by the multi-sectoral model of section 2, specifically equation (3). In this case, we are now able to reject the null of a unit root. This re-inforces the importance of factor demand linkages. While TFP and labor productivity are not generally cointegrated on their own, when we augment the model with weighted cross sectional averages of labor productivity they are. The weighted cross sectional averages reflect the role played by relative productivity. The multi-sectoral model of section 2 shows in equation (1) that relative price changes at the sectoral level are driven by changes in relative labor productivity. So our approach of using labor productivity augmented by intermediate inputs instead of TFP is consistent with the arguments of Chang and Hong (2006).

[Insert table 1]

We chose to use labor productivity rather than TFP because we are also interested in the overall behavior of the model and in its ability to capture the transmission of shocks across sectors.The simple sectoral bivariate VAR for TFP and labor input that Chang and Hong (2006) employ cannot capture fully the dynamic effects of shocks to technology because it implicitly neglects the effect on relative prices. Indeed, a technology shock at the industry level has a first order effect on relative prices, which itself gives rise to an additional channel of propagation of the shock that has to be taken into consideration when we analyze the dynamic response to a technology shock. This channel, is implicitly shut down when each sector is analyzed separately from the others. Instead, the specification in (10) allows us to investigate the empirical relevance of sectoral interactions in a more complete way.

4.3 Preliminary investigation of cross sectional dependence

In this section we turn to a preliminary analysis of dependence across sectors in manufacturing. Although we have previously stressed the role of sectoral interactions, in the first part of this section we put them to one side and conduct a preliminary investigation of cross sectional dependence by ignoring the role of the sectoral interdependence. Table 3 provides evidence of cross sectional dependence between (the growth rate of) productivity and hours. The first row of the first panel shows the average cross section correlation between sectors. In the second row we report the cross-section dependence (CD) test of Pesaran (2004).

[Insert table 2]

The results in Table 2 highlight substantial positive comovement, especially for total hours worked. The CD test statistics clearly show that the cross correlations are highly significant. The second panel reports tests for cross sectional dependence in the residuals recovered from the SecVAR using the standard identification method for technology and non-technology shocks without allowing for the intermediate input channel, i.e. without including the cross sectional averages. Again the residuals exhibit considerable cross-section dependence especially for the non-technology shocks.[14]

The number of possible common factors is reported in the bottom half of each panel in Table 2.[15] The information criteria of Bai and Ng select the number of common factors that minimizes a penalized square sum of residuals.[16] The test of Onatski (2007) starts from an a priori maximum number of factors, k_{max}, where the null hypothesis of the test is $H_0 : r = k$ while the alternative is $k < r = k + s \leq k_{max}$. The picture that emerges from the analysis of the number of possible common factors is mixed. On the one hand, the information criteria of Bai and Ng (2002) suggest a specification with 1 aggregate factor for labor

[14]Franco and Philippon (2007) find similar results when they identify the shocks from a reduced form VAR applied at the level of the firm.

[15]The information criteria of Bai and Ng (2002) and the test introduced by Onatski (2007) determine the number of common static factors. As observed by Stock and Watson (2002b), the number of static factors imposes a upper bound on the possible number of dynamic common factors.

[16]The original information criteria might have substantial loss of power for pervasive weak cross sectional dependence. This is recognized by Bai and Ng (2002) and proved in Onatski (2005). Bai and Ng (2002, p.207) observe that BIC3 has very good properties in the presence of cross sectional correlation. This last point is very important as it is to be expected that there will be non-trivial cross sectional correlation due to the presence of inter-sectoral linkages. For this reason the Table also report the BIC3 information criteria.

productivity and one for non-technology shocks (in the lower panel of Table 3). On the other hand, the test of Onatski (2007) points to the presence of 2 common factors driving both productivity and hours, as well as two common factors driving the technology shocks. However, despite the high level of cross sectional correlation among non-technology shocks, no common factors are detected.

The question whether it is common aggregate shocks or idiosyncratic industry shocks amplified by interactions between sectors that give rise to comovement among sectors, is closely related to the statistical property of weak and strong cross sectional dependence proposed by Pesaran and Tosetti (2007). Strong dependence between sectors is essential to replicate the aggregate cycle. Pesaran and Tosetti (2007) and Chudik and Pesaran (2007) show how strong dependence between sectors could arise if one or more sectors are dominant and/or if the shocks have a common factor structure, i.e. there are aggregate shocks to the economy. A similar argument is used by Horvath (1998), who relates the amplification mechanism of intersectoral linkages to a particular feature - the sparseness, of the input-output matrix. Carvalho (2009) shows that strong cross-sectional dependence arises in a multi-sectoral model from the presence of a power law distribution of sectoral links in the input-output matrix. By contrast, weak cross-sectional dependence implies that independent sectoral shocks will tend to average out in the aggregate, as positive and negative shocks to disaggregated sectors will offset each other (Lucas, 1981, and Dupor, 1999).

The weighted cross sectional averages play an important role in allowing us to extract sector specific shocks. But one argument against our approach is that by using cross sectional averages we are actually identifying common (aggregate) factors. Given the results in table 2 we seek to control for the effect of possible common factors (aggregate shocks) by including measures that proxy for aggregate shocks so that these appear as additional conditioning variables when we estimate each sectoral model. Two exogenous shocks are included, consistent with a maximum number of 2 factors in table 3. Notice that, as long as we have included at least as many exogenous aggregate shocks as the true number of factors, then the exogenous shocks should be able to control for the effect of (unobserved) aggregate shocks hitting the economy. Specifically, we include the aggregate technology shock (ζ_t) constructed by Basu et al. (2006); and an aggregate monetary policy shock (μ_t) which is derived from an exactly identified VAR, estimated on quarterly data averaged for each year[17], following the procedure adopted by Christiano et al. (1999). Furthermore, we enter the monetary shocks in the reduced form model for the labor input in first difference, so that there is no long run effect on labor productivity, consistent with the restriction discussed above.[18]

4.4 The exogeneity of cross section averages and estimation results

The contemporaneous relations between the sector specific variables and the cross sectional averages in (10) can be estimated consistently as long as the weighted cross sectional averages are weakly exogenous.[19] In table 3 we put this condition

[17] Basu et al (2006) construct their measure controlling for aggregation effects, varying utilization of capital and labour, non-constant returns and imperfect competition. The data are provided by Basu et al. (2006) and are available in the AER website (http://aea-web.org/aer/). Notice that the two shocks are orthogonal by construction.

[18] In a previous version of this paper we included the monetary policy shock in levels in the specification for labor productivity, with the result that the coefficients associated with these shocks were on average not significant.

[19] Pesaran et al. (2004) shows that this condition is satisfied for $I \to \infty$, when the sum of the squared weights is $o\left(1/I^2\right)$, or equivalently when the weights of each sector are $o\left(1/I\right)$.

to the test. One requirement for instrumental variable estimation is that the instruments are orthogonal to the error process, when the number of instruments exceeds the moment conditions it is possible to test the overidentified restrictions using the Hansen (1982) J-test. Furthermore, the C-test (Eichenbaum et al., 1988) allows us to test a subset of the original set of orthogonality conditions, specifically we can test whether the subset of instruments - comprising the contemporaneous cross sectional averages - respect the orthogonality condition by looking at the differences between the J-statistics associated with (10). We make use of two different instrument sets, i.e. one instrument set does not include $\varkappa_{it}^{*}$. Table 3 reports the average p-value as well as the number of sectors where the test is rejected at the 5% level. The results suggest that we cannot reject the null hypothesis of orthogonality, both for the whole set of instruments and for the specific set of instruments $\varkappa_{it}^{*}$.

[Insert table 3]

In an overidentified context, if some of the instruments are redundant then the large-sample efficiency of the estimates is not improved by including them. It is well known, moreover, that using a large number of instruments or moment conditions can produce have poor finite sample performance. Dropping redundant instruments may therefore lead to more reliable results. Given the results of the C-test in table 3, we use for now on the instrument set A, but we do not include $\mathbf{d}_{t-1}$ among the instruments used. The partial R^2 of Shea (1997) gives a measure of the usefulness of the instruments in IV regressions. The measure reported in table 3 suggests that the inclusion of the cross sectional averages among the instrument set enhances the fit of the model. Notice that, the presence of industry specific cross sectional averages enlarges the set of instruments that can be used to identify technology shocks.[20] Therefore, the fact that we model the intersectoral linkages also allows us to address some of the concerns raised in Christiano et al. (2003) about possible biases arising from the use of weak instruments.

We now turn to the estimation of equation (10) for all 458 industries. The mean estimates of the coefficients on the aggregate shocks reported in table 4 indicate that these are in general significant at the appropriate confidence level, and that indeed the null is rejected for many industries in the manufacturing sector. Furthermore, the sign of the coefficient on the monetary shock is consistent with the common finding that loose monetary policy has a expansionary effect. Furthermore, the aggregate technology shock has a contractionary effect on labor input, consistent with the evidence in Basu et al. (2006).

The fact that the coefficients associated with the aggregate exogenous controls are significant, and the signs are consistent with prior beliefs makes us confident that the controls are capturing the role of the aggregate technology and monetary policy shocks. The table also reports the average value of the generalized R^2 (Pesaran and Smith, 1994), which is a measure of the fit of the model. The relatively high value of this statistic suggests that the reduced form specification in (10) is able to capture the transmission mechanism of shocks at the sectoral level.

[Insert table 4]

[20] In appendix A we show that Δh^*_{it-1} can be used as an additional instrument.

4.5 Aggregate and Sector specific shocks

The positive comovement across sectors is a stylized fact that needs to be addressed by any theory of the business cycle. Whether the comovement between sectors and the aggregate business cycle originates from aggregate shocks or sectoral shocks amplified by sectoral interactions, or a combination of the two is not clear a priori. This is a question that has attracted the interest of many researchers (see e.g. Cooper and Haltiwanger, 1996).

[Insert table 5]

In table 5 we consider what contribution the two aggregate shocks we have used make to the total variation of aggregate manufacturing productivity and hours. We compute the partial R^2 and the cross section pairwise correlations of the contribution of the aggregate shocks, $\boldsymbol{\lambda}_i\mathbf{d}_t$. The partial R^2 suggests that relatively little role can be assigned to aggregate shocks in explaining sectoral cycles. Furthermore, the aggregate component is able to explain only a limited part of the comovement of the sectors - as measured by the average pairwise correlation.

In figure 1 we decompose the historical aggregate business cycle for manufacturing into that attributable to sectoral shocks and that attributable to the aggregate technology and monetary shocks. The figure clearly shows that the bulk of aggregate volatility is to be attributed to sectoral shocks.[21] The aggregate technology

[21] On empirical grounds Long and Plosser (1987) first investigated whether the source of business cycle fluctuations is aggregate or sector specific. Their analysis is consistent with the existence of a single aggregate disturbance whose explanatory power is, however, limited. Similar results are reported by Cooper and Haltiwanger (1996), Conley and Dupor (2003) from a completely different prospective propose an empirical strategy to identify the driving force of the business cycle, and conclude that the data support the sectoral origin of the business cycle. On the other hand, Foerster et al. (2008) report evidence that most of the variance of industrial

shock has a very limited role. However, a bigger role can be assigned to monetary policy shocks. Interestingly, monetary policy seems to account for the recession in the early 1980s, corresponding to the Volcker disinflation.

[Insert figure 1]

The results in table 6 and figure 1 suggest that the role of the aggregate shocks, in particular technology, in explaining the aggregate business cycle in manufacturing is limited.[22]

The bottom panel of table 5 shows that the shocks identified by the sectoral model (10), once factor demand linkages among sectors are taken into account are (almost) independent. The average pairwise cross sectional correlation is about 1%, and both the information criteria of Bai and Ng (2002) and the test of Onatski (2007) agree on the absence of any aggregate shock. Taken together the results of table 5 suggest that the stylized facts of the aggregate business cycle and comovements among sectors, can be explained by input-output linkages in the production process.

Something that is worth noticing from the results in table 5 is that even though the average pairwise cross sectional correlation is greatly reduced when we allow for sectoral interactions, the CD test is still highly significant. This implies that shocks to one sector are likely to be correlated with shocks to other sectors, i.e. the

production at the sectoral level is explained by the presence of two aggregate factors, even after controlling for the role of factor demand linkages.

[22]In results not reported in the paper we computed the dynamic response to an aggregate technology shock. The total effect on the labor input is negative, but up to ten times smaller in magnitude compared with a contemporaneous shock to all the individual sectors. See figure 2. Of course, we cannot rule out the existence of other aggregate shocks that we exclude from the analysis.

covariance matrix of the idiosyncratic shocks in (12), $\mathbf{\Omega}_\varepsilon$, is not fully diagonal.[23] Even though we can exclude the presence of unidentified aggregate shocks (given the results of the information criteria of Bai and Ng, 2002, and the test of Onatski, 2007) there are still local interactions among sectors that the specification in (10) is not able to capture.[24]

In order to quantify how widespread is the rejection of orthogonality, we computed the number of significant correlations between sectors. The number of rejections vary from a minimum of 11 to a maximum of 67 (median 36) for technology shocks, and 17 and 73 (median 39) for non-technology shocks, out of 458 sectors. To establish whether there is any connection between the number of rejections and characteristics of sectors, we compute the correlation between the number of rejections and the size of the sector, the column sum of the weighting matrix used in the estimation and the number of connections of each sector, where the latter two measure the importance of the sector as a supplier to other sectors (see Pesaran and Tosetti, 2007, and Carvalho, 2009). Overall, there seems to be no relation with technology shocks (the correlations are rather small and all are insignificant), whereas there seems to be significant correlations with non-technology shocks, as the number of rejections is marginally (positively) related to the importance of the sector as input supplier. To understand how much information we lose by assuming that the shocks we have identified are cross sectionally independent, the aggregate output and hours (growth) series were simulated assuming that $\mathbf{\Omega}_\varepsilon$ is diagonal. The correlation between the aggregated series for manufacturing and

[23] Conley and Dupor (2003) use a nonparametric technique to model the off diagonal elements of the covariance matrix $\mathbf{\Omega}_\varepsilon$. Here the issue is complicated as we identify not one, but two types of shock.

[24] For instance Shea (2002) studies other forms of sectoral interaction that might be important for aggregate cyclical fluctuations.

the sum of sectors is approximately 99% for both series. This can be taken as evidence that the remaining cross sectional dependence is weak, and therefore of little importance for explaining aggregate fluctuations in manufacturing. Therefore in the sections that follow we proceed as if $\mathbf{\Omega}_{\varepsilon}$ is diagonal. If anything, this assumption is likely to understate the importance of sectoral shocks in the variance decomposition and to overstate the (already limited) importance of sectoral shocks when we ignore sectoral interactions.

5 Technology shocks and the business cycle

Real business cycle theory assigns a central role to technology shocks as source of aggregate fluctuations. Moreover, positive technology shocks should lead to positive comovements of output, hours, and productivity. However, Gali (1999) finds that positive technology shocks appear to lead to a decline in labor input. Furthermore technology shocks can explain only a limited part of business cycle fluctuations. This section re-examines these issues and contributes to the technology-hours debate by focussing on the implications of the presence of factor demand linkages for the propagation of sector specific technology shocks to the aggregate economy.

5.1 The dynamic response to technology shocks

In figure 2 we show the response of labour productivity and hours to a 1-standard deviation technology shock to all industries, disregarding sectoral interactions.[25]

[25] Pesaran and Tosetti (2007) and Chudik and Pesaran (2007) show that neglecting cross section dependence could cause the estimator to be biased. In order to overcome this bias we estimate (10) and then set $\mathbf{C}_{il}$ ($\forall i$ and $l = 0, 1$) arbitrarily equal to $\mathbf{0}$. Estimating the bivariate model

The panel on the left displays the aggregate response of the manufacturing sector, whereas the panel on the right displays the aggregate response of each of the I sectoral shocks.[26] Specifically, the aggregate response in the right panel is the sum of the disaggregate responses in the left panel. In this case, without interactions among sectors, each sectoral shock only affects the sector from where the shock originates.

The aggregate response for hours is negative, furthermore the effect persists in the long run. The right hand panel indicates that the impact response is positive only for a limited number of sectors (92 sectors). The results are similar to Kiley (1998) (and Chang and Hong, 2006, when they use labor productivity) and confirm previous findings in the literature (see e.g. Gali, 1999, Francis and Ramey, 2005a).[27]

[Insert figure 2]

In figure 3, when we allow for sectoral interactions, we obtain a very different outcome. A technology shock to all sectors now has a positive (short and long run) aggregate impact on total hours in manufacturing. The impact of the shock is also generally much larger in magnitude, highlighting the importance of sectoral interactions as an amplifier of sectoral shocks (Cooper and Haltiwanger, 1996). Even though the confidence intervals on the impulse responses are wide, the effect

without including the cross sectional variance (as Kiley, 1998, and Chang and Hong, 2006) would give similar results.

[26] The weights are proportional to the average shipment value. The average impulse response calculated in this way is very close to the actual impulse response to the manufacturing sector as a whole, up to an approximation error. Even though some sectors have a bigger share in total shipments, the unweighted average of the impulse responses would be very similar.

[27] Similar results are found in Franco and Philippon (2007), who use firm level data. They do not consider interdependencies (and their consequences) among firms. Basu et al. (2006) reach the same conclusion identifying the shocks from a completely different prospective. They also identify the shocks at the sectoral level (2 digit SIC), but do not consider sectoral interactions.

of technology on hours is always significant. The right hand panel reports the response of each sector where the weighted sum of these impulse responses is equal to the aggregate response in the left hand panel. Many sectors (169) show a positive impact of a technology shock on hours, and even though this is not the majority, the weighted effect is positive for manufacturing as a whole. From figure 3 it is also evident that the total positive effect is driven by a few large sectors, interestingly these are also the largest supplier sectors.[28] The fact that shocks to those sectors that are most connected, are strongly amplified by factor demand linkages between sectors. Therefore are the sectors most likely to explain the aggregate business cycle, is in line with the argument put forward by Horvath (1998) and recently emphasized by Carvalho (2009). What is interesting is that the shocks to these sectors give rise to a positive aggregate response. In the next section we analyze in detail how the presence of factor demand linkages among sectors is likely to amplify the expansionary effect of technology shocks.

[Insert figure 3]

5.1.1 The role of sectoral interactions

In the reduced form model in (10) and (11) all sectors interact, and idiosyncratic sectoral shocks propagate to the manufacturing sector as a whole through input-output linkages. Because shocks to sector i affect all other sectors, the response of other sectors echoes back to the original sector i, therefore amplifying the original

[28] The most important five sectors are all part of the "chemicals and allied products" (specifically SIC codes 2812-13-16 and 2865-69), and largely correspond to sectors with the highest column sum of the weighting matrix. These are the sectors with the largest number of supply linkages to other sectors.

effect of the shock. So sectoral interactions induce a rich set of short-run dynamics. The first effect from sector i to all the other sectors in the economy is a downstream propagation from supplier to user (Shea, 2002), but at the same time we have the second round effect, i.e. a reflex response, as the original sector is also a user of other sectors' supply.

In figure 4 we separate out the two components - the *direct* component, i.e. the effect of a shock to sector i on the same ith sector and the *complementary* component, i.e. the effect of this shock on all other sectors.[29] We scale the direct and complementary effects such that the aggregate response in the left panel of figure 3 can be recovered by summing up all the direct and complementary effects.

[Insert figure 4]

There is considerable heterogeneity in the dynamic response to a technology shock; from figure 4 it is clear that the direct effects on hours are generally negative, being positive for only 96 sectors. However, the direct effect is also relatively small. The complementary effect usually overwhelms the effect of the shock to the same sector. This is especially true for the dynamic response of hours.

Therefore, the resolution of the puzzle why technology shocks appear to have negative effects on hours worked at the aggregate level, lies with the importance of sectoral interactions. A shock to a large input supplier will propagate throughout the economy as a large fraction of other sectors are affected by it. Positive shocks to sectors which are most connected are more likely to get transmitted to other sectors, as the marginal costs of production in other sectors decreases as input

[29] In Appendix B we derive the expressions for the direct and the complementary component.

prices decline and demand increases. The impulse response analysis in Carvalho (2009) supports the presence of this broad comovement in the production of each sector after a positive technology shock to the sectors that are the bigger suppliers in the economy. This results into a positive shift in the aggregate response especially when it comes to shocks to the sectors that are more connected in the economy. In this sense the procyclical effect due to the intermediate input channel illustrated above is generally amplified and overcomes the effect due to the marginal productivity of leisure.[30] This is consistent with the empirical evidence in figure 4. The impact response of the complementary effect is generally positive for most of the sectoral shocks (273 sectors). Furthermore, the aggregate positive comovement between labor and productivity is driven in particular by the very strong positive complementary effect in those sectors which are more connected through the input-output linkages.[31]

Furthermore, figure 4 makes clear that the dynamic response following a technology shock to a particular sector is indeed different depending upon whether the shock originates in the sector itself or whether it is a shock to other sectors transmitted through factor demand linkages. According to the aggregation theorem in

[30] The standard RBC model assumes that the substitution effect due to higher wages and higher real interest rates after a technology shock dominates the wealth effect, therefore impling a postive shift in labor input. Francis and Ramey (2005a) and Vigfusson (2004) show how the introduction of habit consumption and investment adjustment costs invert the relative importance of substitution and wealth effect giving rise to a temporary fall in labor supply. Chang et al. (2009) show that inventory holding costs, demand elasticities, and price rigidities potentially all affect employment decisions in the face of productivity shocks. Kim and Kim (2006) enphatize the role of the intermediate input channel in producing positive comovement in labor input.

[31] There is a statistically significant positive correlation of 0.44 between the impact response of the complementary effect and the column sum of the weighting matrix used in (10), a measure of the sector's importance as an input supplier. At the same time there is a positive, but limited, correlation of 0.14 between the impact response and the size of the sector. Notice that this last correlation might be simply a reflection of the fact that the larger input suppliers tend to be larger is size, the correlation between these two measures is 0.28.

Blanchard and Quah(1989, p.670), the effect of the intermediate goods channel or the effect of aggregate shocks is correctly captured by the standard bivariate procedure applied to each sector separately, *if and only if* the response of a sector to other sectors' shocks is the same as the response of a sector to its own idiosyncratic sectoral shocks up to a scalar lag distribution.[32] Our results suggest that the convention of using aggregate data to identify shocks, when these shocks are likely to originate at the sectoral level may be very misleading.[33]

Overall, these results highlight the quantitative and qualitative importance of the intermediate input channel as a way by which idiosyncratic sectoral shocks are propagated. It also highlights the importance of this channel for understanding the dynamic response of the labor input following a technology shock.

5.2 Variance decomposition.

In this section we decompose forecast variances at the sectoral level. This allows us to evaluate the relative role played by technology relative to non-technology shocks. Furthermore, we are able to evaluate the importance of the factor demand linkages among sectors as a transmission mechanism for idiosyncratic shocks. Table 6 shows the mean (weighted average) variance decomposition. Since each sector is in turn related to other sectors, productivity and hours in sector j are explained by shocks to the jth sector, and also by shocks (technology and non-technology) originating in other sectors. Overall, table 6 shows that aggregate shocks have a limited role to play in explaining sectoral movements. Aggregate technology

[32] This view has been challanged empirically by Fisher (2006) who shows the qualitative difference between sector neutral and investment specific technology shocks. The sectoral specification we consider in this paper is fully consistent with the presence of investment specific shocks which would correspond to a contemporaneous shock to all investment goods sectors.

[33] We are indebted to one of the referees for pointing this out.

shocks account for about 5% of the overall variation in labor productivity. For hours it declines from an initial 10% to 5%. The role of the monetary policy shock is also limited. Technology shocks account for much of volatility in labor productivity, but with a quite sizable part (20 to 25%) originating in other sectors. Most interestingly, the variation in labor input is initially dominated by non-technology shocks, nevertheless, technology shocks coming from other sectors are also important. On impact technology shocks account for roughly 20% of the variation in hours, with its role rising steadily to roughly 40%, but where this increase is due entirely to the increasing role of technology shocks in other sectors. This demonstrates why the complementary effect dominates the direct effect in the aggregate response of the labor input to a technology shock. Sectoral interactions in total account for roughly 20% of the variation in productivity and 40% of the variation in total hours worked. Clearly we would get a very misleading picture if we ignored sectoral interactions. Technology shocks account for most of the variability in productivity, but its role in the explanation of total hours would be completely underestimated, as it accounts for only $15-20\%$ of the variation when we ignore sectoral interactions.

[Insert Table 6]

In summary, sectoral interactions are a vital driver of sectoral fluctuations. Furthermore, once their role is correctly pinned down technology shocks appear to be important drivers of aggregate fluctuations.

5.3 Technology versus non-technology shocks and the role of sectoral interactions.

Another way to assess the role of technology shocks for aggregate fluctuations is to look at a simulated series when one type of shock at a time is shut down. Figure 5 shows simulated aggregate hours and output growth implied by the technology and non technology shocks.[34] Of the total variation explained by industry specific shocks, the technology shocks are responsible for almost 50% of the variation in aggregate manufacturing output and 40% of the variation in the change in total hours. Overall technology and non-technology shocks seems to be equally important for explaining aggregate fluctuations. Nevertheless, some difference are clear. Technology shocks appear to account for most of the cyclical volatility in the second part of the sample, from approximately 1980 the share of variance to be accounted by the technology shocks rises from (approximately) 37 to 73% for output and 27 to 70% for hours. These results are generally consistent with the view that demand shocks were the main driver of the business cycle before the 80s', whereas supply side shocks have gained importance since the 80s (Gali and Gambetti, 2009). Interestingly the latest period also corresponds to a steady decrease in aggregate volatility, the so called 'great moderation' (see e.g. Stock and Watson, 2002). By contrast, non-technology shocks appear to match the period from 1960 to 1980. Furthermore, the slow down at the beginning of the 90's seems

[34] Given that labor productivity is defined as output per hours worked, output growth can be recovered as a linear combination of the variables in the system. The exact procedure for aggregation is discussed in Appendix C. Notice that the simulated series for the contribution that technology and non-technology shocks make to the aggregate variation sum to the aggregate contribution of the idiosyncratic shocks shown in the left panel of figure 1.

to be largely as the result of technology shocks (Hansen and Prescott, 1993).

[Insert figure 5]

Franco and Philippon (2007) argue that the main source of aggregate fluctuations can be identified by looking at the pair-wise cross-sectional correlations between the shocks at a disaggregated level. The intuition can be traced back to Lucas (1981), with the law of large number at work, shocks at the disaggregated level need to be highly correlated in order for idiosyncractic shocks to be able to explain aggregate volatility. However, this does not take into account the amplification mechanism due to sectoral interactions that we have stressed. The low level of cross sectional correlation of shocks once factor demand linkages have been taken into consideration (table 5) compared to when they are not (table 2) suggest that their results may be misleading. In figure 6 we show that shocks that are almost equally uncorrelated with each other are able to explain a large part of the aggregate variation in manufacturing once the amplification mechanism coming from sectoral interactions is allowed for.

[Insert figure 6]

In the previous section we also emphasized the amplification due to factor demand linkages. Based on the impulse responses and the forecast variance decomposition of sectoral cycles, sectoral interactions appear to be the main driver of aggregate fluctuations. In Figure 6 we show the decomposition of the aggregate cycle that is directly attributable to the shocks, both aggregate and sector specific, and the realized data (the difference can be attributed to the amplification role of the intermediate input channel). The pattern that emerges from this figure is revealing. Whether the shocks are idiosyncratic or aggregate, the propagation mechanism arising from the presence of factor demand linkages among sectors seems to be the key to explaining the aggregate business cycle.

6 Some Robustness Checks

As a robustness check, we have replicated our results using different measures of labor input, employment, hours worked and labor productivity. The results confirm the previous analysis.

[Insert figure 7]

The results we have reported use a simple average of two different input-output matrices for 1977 and 1987. As a robustness check we generated the cross sectional averages by using the first IO matrix for the subsample up until 1980 and the second thereafter. The left panel of figure 7 plots the short run responses of hours worked to a permanent shock to labor productivity for this case vis a vis the baseline specification. The general results do not seem to be altered; the cross sectional correlation between the two estimates across 458 industries is 0.99.

In order to overcome the problem related to the limited time series dimension of the data[35], we have repeated the analysis with a new dataset which pooled the sectors at the 3 digit SIC. This implicitly assumes that the heterogeneity among

[35] Franco and Philippon (2007) observe that even though the time series dimension is relatively small, the relatively large cross section helps to identify the structural shocks and the aggregate impulse responses.

industries in the same 3 digit industry class is limited relative to the heterogeneity across different industries. The impulse responses are different as the linkages between sectors differ. The right panel of figure 7 reports the short run response of hours worked to a technology shock for the two specifications. Again the overall conclusions are not qualitatively affected, the correlation between the two results is 0.82. However, the baseline specification with more sectors gives rise to a larger impulse response of hours in aggregate. This is consistent with the theoretical findings of Swanson (2006), who shows that the heterogeneity of agents in the economy might itself be a source of amplification for the shocks hitting the economy.

[Insert figure 8]

Even though (4) suggests that the specification for labor input is able to correctly identify the technology shocks by capturing the variations in factor prices through the cross sectional averages in (10), we replicated the results using TFP as suggested by Chang and Hong (2006). Specifically, we identify technology shocks a permanent shocks to TFP, and approximate the role of the intermediate input channel by including the cross sectional average of TFP as in (10). Figure 8 provides evidence of the direct and complementary effect on labor input when shocks are identified using TFP. The main difference is that in this case the direct effect of the shocks is generally positive. However, even with using TFP the aggregate response of labor input is dominated by the complementary effect, which is positive and much larger than the direct effect. As for the shocks identified in the previous section, the effect of the shocks is larger the larger is the role of the sector as an input supplier in the economy. The intermediate input channel continues to provide a strong amplification mechanism for idiosyncratic shocks, and to be the key mechanism for understanding the aggregate responses.

Even though the impulse responses of TFP are not strictly comparable to those for labor productivity (TFP also excludes capital) the similarity between the identified responses is still surprisingly high. The correlation between the short run responses of this specification of the model with respect to the baseline, is 0.59 for labor input , whereas for labor productivity and TFP the correlation is 0.88

7 Conclusions

This paper has investigated the role of factor demand linkages in the propagation of shocks across the economy. Using data on highly disaggregated manufacturing industries from 1958 to 1996 we construct a sectoral structural VAR and estimate a series of bivariate models for productivity and hours. Weighted averages of sectoral variables, where the weights are derived from the input-output matrix, are used to recover the effect of the intermediate input channel. We show that taking into consideration sectoral interactions is important because they prove to be an important amplifier for aggregate and sector specific shocks, both technological and non-technological. This is in line with the real business cycle model of Long and Plosser (1983), Horvath (1998, 2000) and Carvalho (2009). Most importantly, we show that the contraction in hours worked in response to a technology shock found in many other studies remains if sectoral interactions via the input-output matrix are ignored. When these are incorporated into the model we find a positive response. This is because the intermediate input channel itself provides an additional motivation for a positive shift in labor input. Our results are important as they clearly show which problems may arise when sectoral interactions are ignored.

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Appendix A: Estimation issues

To estimate the dynamic effect of a technology shock we follow the procedure outlined in Shapiro and Watson (1988), and discussed in Christiano et al (2003). As in Pesaran, Schuermann and S.M. Weiner (2004) the contemporaneous relationships between sector specific variables and the aggregate variables can be estimated consistently as long as the weighted aggregate variables in the system are weakly exogenous. To estimate the contemporaneous relationship between the endogenous variables we need to rely on instrumental variables. Specifically, we make use of long run identification restrictions, in line with the literature. The analysis of disaggregated sectors as in (10)-(11) provides both a theoretically consistent estimate of an economy with sectoral interdependence and/or both sectoral and aggregate shocks to the economy and a new set of instruments. In this case, the weak instrument problem usually described in the literature might be avoided by using the industry specific cross sectional averages of the original variables in the system.

Specifically, for a specific sector i the system of simultaneous equations to be estimated is

$$(\mathbf{A}_{i0} - \mathbf{A}_{i1}L) \begin{bmatrix} \Delta x_{it} \\ \Delta h_{it} \end{bmatrix} = (\mathbf{C}_{i0} - \mathbf{C}_{i1}L) \begin{bmatrix} \Delta x_{it}^{*} \\ \Delta h_{it}^{*} \end{bmatrix} + \begin{bmatrix} \varepsilon_{it}^{1} \\ \varepsilon_{it}^{2} \end{bmatrix}, \tag{A1}$$

where $\mathbf{A}_{il}$ and $\mathbf{C}_{il}$, $\forall i$ and $l = 1, 2$, are 2×2 matrices, with the generic $xj-$element denoted with a subscript. The restriction that only technological shocks have a permanent effect on productivity implies that $A_{i0}^{12} = -A_{i1}^{12}$. A similar restriction for technology shocks to other sectors is also imposed, i.e. $C_{i0}^{12} = -C_{i1}^{12}$. It follows that the technology shock for sector i, ε^z_{it}, can be recovered from

$$\Delta x_{it} = A^{12}_i \Delta^2 h_{it} + C^{11}_{i0} \Delta x^*_{it} + C^{12}_i \Delta^2 h^*_{it} + A^{11}_{i1} \Delta x_{it-1} + C^{11}_{i1} \Delta x^*_{it-1} + \varepsilon^z_{it}, \quad \text{(A2)}$$

with $A^{12}_i = A^{12}_{i0} = -A^{12}_{i1}$ and $C^{12}_i = C^{12}_{i0} = -C^{12}_{i1}$. To estimate the equation above we need at least a single instrument to estimate the contemporaneous effect of productivity and labor input growth, A^{12}_i, the usual procedure of using Δh_{it-1} has been criticized as this practice may suffer from a weak instrument problem[36]. Specifically, consider the reduced form VARX representation of the system

$$\mathbf{\Phi}_i(L) \begin{pmatrix} \Delta x_{it} \\ \Delta h_{it} \end{pmatrix} = \mathbf{\Psi}_i(L) \begin{pmatrix} \Delta x^*_{it} \\ \Delta h^*_{it} \end{pmatrix} + \mathbf{e}_{it},$$

The first difference of the second variable ($\Delta^2 h_{it}$), in the simple case of a VARX(1,1), i.e. $\mathbf{\Phi}_i(\mathbf{L}) = (I - \mathbf{\Phi}_{i1} L)$ and $\mathbf{\Psi}_i(L) = (\mathbf{\Psi}_{i0} - \mathbf{\Psi}_{i1} L)$, can written as

$$\Delta^2 h_{it} = \Phi^{21}_{i1} \Delta x_{it-1} + (\Phi^{22}_{i1} - 1) \Delta h_{it-1} + \Psi^{21}_{i0} \Delta x^*_{it} + \Psi^{22}_{i0} \Delta h^*_{it} + \Psi^{21}_{i1} \Delta x^*_{it-1} + \Psi^{22}_{i1} \Delta h^*_{it-1} + e^2_{it},$$

therefore the validity of Δh_{it-1} as an instrument clearly depends on the condition $\Phi^{22}_{i1} \neq 1$. So if Φ^{22}_{i1} is close enough to 1 then the use of Δh_{it-1} as instrument for $\Delta^2 h_{it}$ is subject to the weak instrument problem[37]. Rewriting the expression as a

[36] See Staiger and Stock (1997) for a discussion of the weak instrument problem.

[37] This is the well known condition $A(1) \neq 0$ for a general VAR of order p, see e.g. Christiano et al. (2003).

function of $\Delta^2 h^*_{it-1}$ we obtain

$$\begin{aligned}\Delta^2 h_{it} &= \Phi^{21}_{i1}\Delta x_{it-1} + (\Phi^{22}_{i1} - 1)\Delta h_{it-1} + \\ &\quad \Psi^{21}_{i0}\Delta x^*_{it} + \Psi^{22}_{i0}\Delta^2 h^*_{it} + \Psi^{21}_{i1}\Delta x^*_{it-1} + (\Psi^{22}_{i1} + \Psi^{22}_{i0})\Delta h^*_{it-1} + e^2_{it}.\end{aligned}$$

The expression above makes clear that the aggregate labor input, Δh^*_{it-1}, constitutes an additional appropriate instrument for $\Delta^2 h_{it}$ if $(\Psi^{22}_{i0} + \Psi^{22}_{i1}) \neq 0$, i.e. if the long run effect of an aggregate non-technology shock on the sector specific labour input is not zero. This condition corresponds to the long run neutrality of aggregate shocks to the labour input, as considered in Campbell el al. (1996). However, as they recognize this restriction is quite restrictive and not entirely innocuous[38]. In the light of this we include Δh^*_{it-1} as an additional instrument for the identification of A^{12}_i above.

Once (A2) has been estimated the residual (the technology shock, ε^z_{it}) can be used to instrument the second relation for the labour input in (A1), which will deliver the non-technology shock to sector i, ε^p_{it}, from

$$\begin{aligned}\Delta h_{it} &= A^{21}_{i0}\Delta x_{it} + C^{21}_{i0}\Delta x^*_{it} + C^{22}_{i0}\Delta h^*_{it} + \\ &\quad A^{21}_{i1}\Delta x_{it-1} + A^{22}_{i1}\Delta h_{it-1} + C^{21}_{i1}\Delta x^*_{it-1} + C^{22}_{i1}\Delta h^*_{it-1} + \varepsilon^p_{it}.\end{aligned}$$

The assumption of independence between the shocks insures that the shock is a good instrument to recover the contemporaneous effect of labour productivity on the labour input.

[38] See Campbell el al. (1996), footnote 4 p. 96. For instance, theories of "reallocation timing" suggest that transitory aggregate shocks may be associated with permanent changes in industry size.

Appendix B: Some details of the transmission mechanism of shocks

Here we discuss the interpretation of the impulse response function of a shock to a particular sector i. We focus on the impact effect, the generalization to any other horizon is straightforward. Recall that the SecVAR system estimates a separate $(2-$dimensional) system for each sector i

$$\mathbf{A}_{i0}\varkappa_{it} = \mathbf{C}_{i0}\varkappa_{it}^{*} + \mathbf{A}_{i1}\varkappa_{it-1} + \mathbf{C}_{i1}\varkappa_{it-1}^{*} + \varepsilon_{it},$$

stacking all the sectors in the economy a model for the full economy can be written as

$$\mathbf{G}_0\boldsymbol{\kappa}_t = \mathbf{G}_1\boldsymbol{\kappa}_{t-1} - \mathbf{u}_t,$$

where $\mathbf{x}_t$ is a $2N \times 1$ vector containing all the 2 variables of the N sectors in the economy, (abstracting from the presence of the aggregate shocks) $\mathbf{u}_t$ is a vector of the same size as the corresponding identified shocks. The matrix of coefficients $\mathbf{G}_l$ for $l = 0, 1$ is an $2N \times 2N$ matrix composed such that

$$\mathbf{G}_l = \begin{bmatrix} \mathbf{B}_{1l}\mathbf{W}_1 \\ \cdots \\ \cdots \\ \mathbf{B}_{lN}\mathbf{W}_N \end{bmatrix},$$

with $\mathbf{B}_{i0} = \begin{bmatrix} \mathbf{A}_{i0}, & -\mathbf{C}_{i0} \end{bmatrix}$ and $\mathbf{B}_{i1} = \begin{bmatrix} \mathbf{A}_{i1}, & \mathbf{C}_{i1} \end{bmatrix}$, 2×4 matrices. The sector specific weighting matrices $\mathbf{W}_i$ are $4 \times 2N$ matrices, and (in this specific case) can be written as

$$\begin{aligned}\mathbf{W}_i &= \begin{bmatrix} \underbrace{\mathbf{0}}_{2\times(i-1)2} & \mathbf{I}_2 & \underbrace{\mathbf{0}}_{2\times(N-i)2} \\ & \mathbf{IO}_i \otimes \mathbf{I}_2 & \end{bmatrix} \\ &= \boldsymbol{\Xi}_i \otimes \mathbf{I}_2\end{aligned}$$

where $\mathbf{I}_2$ is the $2-$dimension identity matrix, $\mathbf{IO}$ is the input-output matrix denoting the relation between the sectors in the economy, normalized such that the diagonal is all 0 and the row sum is equal to 1. Therefore, $\mathbf{io}_i$ denotes the row i of the normalized matrix $\mathbf{IO}$. $\boldsymbol{\Xi}_i$ for a particular sector i can be written as

$$\boldsymbol{\Xi}_i = \begin{bmatrix} \mathbf{ind}_N(i) \\ \mathbf{io}_i \end{bmatrix}$$

where $\mathbf{ind}_N(i)$ is a $1 \times N$ indicator vector, where the $i-$th element is equal to 1 and the rest equal to 0.

Note that the matrices $\mathbf{G}_l$ can be rewritten such that the position in the matrix of the coefficients of the endogenous variables and the exogenous variables appears clearly in the matrix. This specification can be useful for disentangling the direct and complementary (through the input-output matrix) effect of a shock. Notice that the diagonal block of the matrix $\mathbf{G}_l$ is composed of the matrices $\mathbf{A}_{il}$ for $i = 1, ..., N$ and $l = 0, 1$.

As we focus on the impact effect the only relevant variable is $\mathbf{G}_0$, and we focus on this from now onwards. Let us introduce the $2N \times 2$ indicator matrix, $\mathbf{IND}_{2N}^i$, that extracts the $i-$th block of an $2N \times 2N$ matrix.

$$\mathbf{IND}_{2N}^{i} = \mathbf{ind}_N(i) \otimes \mathbf{I}_2,$$

where $\mathbf{ind}_N(i)$ is the $1 \times N$ indicator vector introduced above and $\mathbf{I}_2$ the usual identity matrix. Then, $\mathbf{G}_0$ can written such that the $i-$th 2×2 block diagonal element is $\mathbf{A}_{i0}$ and in general the $i-$th $2 \times 2N$ block of the matrix can be written as

$$\left(\mathbf{IND}_{2N}^{i}\right)' \times \mathbf{G}_0 = \left[\begin{array}{ccc} \mathbf{io}_i^{[1:(i-1)]} \otimes (-\mathbf{C}_{i0}), & \mathbf{A}_{i0}, & \mathbf{io}_i^{[i+1:N]} \otimes (-\mathbf{C}_{i0}) \end{array} \right],$$

where $\mathbf{io}_i^{[j:k]}$ is the $1 \times (k-j)$ vector corresponding to the j to k elements of $\mathbf{io}_i$. Let us focus on the impulse response to the first sector, the matrix of coefficients $\mathbf{G}_0$ can therefore be easily partitioned as

$$\mathbf{G}_0 = \left[\begin{array}{cc} \mathbf{G}_{01} & \mathbf{G}_0^{12} \\ \mathbf{G}_0^{21} & \mathbf{G}_0^{22} \end{array} \right],$$

with $\mathbf{G}_0^{12} = \mathbf{io}_1^{[2:I]} \otimes (-\mathbf{C}_{10})$ $(2 \times (N-1)2$ matrix), and the $(N-1)2 \times 2$ matrix $\mathbf{G}_0^{21}$

$$\mathbf{G}_0^{21} = \left[\begin{array}{c} \mathbf{io}_2^{[1]} \otimes (-\mathbf{C}_{20}) \\ \ldots \\ \mathbf{io}_N^{[1]} \otimes (-\mathbf{C}_{N0}) \end{array} \right],$$

Understanding the role of the matrices $\mathbf{G}_0^{12}$ and $\mathbf{G}_0^{21}$ is essential for the decomposition of the impulse response into all its components (direct and complementary, and the amplification mechanism). Note that $\mathbf{G}_0^{11} = \mathbf{A}_{10}$ and therefore it corresponds to the coefficients of the VAR for the first sector. $\mathbf{G}_0^{21}$ summarizes the effect of a shock to sector 1 on all the other sectors. Specifically, for each sector different from 1, this is equal to the effect of the aggregate variables in those sectors scaled by the importance of sector 1 in those sectors, where this is measured by the factor share of intermediate inputs from sector 1. In addition, $\mathbf{G}_0^{12}$ reflects the effect of the aggregate variables on sector 1, where the aggregate variables are constructed by scaling the variables in the other sectors by size. The latter is the impact effect on suppling sectors of sector 1.

The contemporaneous effect of an idiosyncratic shock in sector 1 to all the variables in the system can now be found as follows. The SecVAR above is inverted to give

$$\begin{aligned}
\mathbf{G}_0\boldsymbol{\kappa}_t &= \mathbf{G}_1\boldsymbol{\kappa}_{t-1} - \mathbf{u}_t, \\
\boldsymbol{\kappa}_t &= \mathbf{G}_0^{-1}\mathbf{G}_1\boldsymbol{\kappa}_{t-1} + \mathbf{G}_0^{-1}\mathbf{u}_t,
\end{aligned}$$

Denote the matrix $\mathbf{G}_0^{-1}\mathbf{G}_1 = \mathbf{F}$. The impulse response at any horizon h from the shock j to sector i can be written as

$$\boldsymbol{\psi}(h) = \mathbf{F}^h\mathbf{G}_0^{-1}\mathbf{s}_{ji}$$

where $\mathbf{s}_{ji}$ is a $2N \times 1$ selection vector with the only non-null element, which selects the appropriate shock j in sector i. Here we consider the effect of a technology shock in the first sector, therefore ordering the variables as in the main text, such that productivity comes first, $\mathbf{s}_{11} = \begin{bmatrix} \boldsymbol{\varrho}_1' & \underbrace{\mathbf{0}}_{1\times[(N-1)2]} \end{bmatrix}' = \begin{bmatrix} 1 & \underbrace{\mathbf{0}}_{1\times(2N-1)} \end{bmatrix}'$, as in the bivariate model $\boldsymbol{\varrho}_1 = \begin{bmatrix} 1 & 0 \end{bmatrix}'$. The contemporaneous impulse response (i.e. the impact effect)[39] is

$$\boldsymbol{\psi}(0) = \mathbf{G}_0^{-1}\mathbf{s}_{11}$$

therefore, to understand the different effect we need to understand what happens when we invert $\mathbf{G}_0$. Applying the partition matrix inversion lemma

$$\mathbf{G}_0 = \begin{bmatrix} \mathbf{A}_{01} & \mathbf{G}_0^{12} \\ \mathbf{G}_0^{21} & \mathbf{G}_0^{22} \end{bmatrix},$$

$$\mathbf{G}_0^{-1} = \begin{bmatrix} \mathbf{A}_{01}^{-1}\left(\mathbf{I}_n + \mathbf{G}_0^{12}\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\right) & -\mathbf{A}_{01}^{-1}\mathbf{G}_0^{12}\boldsymbol{\Gamma}_0 \\ -\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1} & \boldsymbol{\Gamma}_0 \end{bmatrix},$$

with $\boldsymbol{\Gamma}_0 = \left(\mathbf{G}_0^{22} - \mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\mathbf{G}_0^{12}\right)^{-1}$. Notice that for the impact effect the selection vector $\mathbf{s}_{11}$ implicitly selects the first n column of $\mathbf{G}_0^{-1}$, specifically

$$\begin{aligned} \boldsymbol{\psi}(0) &= \mathbf{G}_0^{-1}\mathbf{s}_{11}, \\ &= \begin{bmatrix} \mathbf{A}_{01}^{-1}\left(\mathbf{I}_k + \mathbf{G}_0^{12}\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\right)\boldsymbol{\varrho}_1 \\ -\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 \end{bmatrix}, \\ &= \begin{bmatrix} \mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 + \mathbf{A}_{01}^{-1}\mathbf{G}_0^{12}\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 \\ -\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 \end{bmatrix}, \end{aligned}$$

The $((2N-2)\times 1)$ subvector $\boldsymbol{\chi}_{comp} = \left(-\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1\right)$ is what we have referred to as the *complementary effect*, i.e. this is the effect that a shock to sector 1 has on all the other sectors in the economy through sectoral complementarity.

[39] Starting from the impact effect, the impulse response for any horizon h can be calculated as $\boldsymbol{\psi}(h) = \mathbf{F}\boldsymbol{\psi}(h-1)$.

This is equal to the effect that the shock would have had on sector 1, if the sector was not connected to other sectors, $\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1$, which is first transmitted to the other sectors through the downstream supplier user relations, capptured by $\mathbf{G}_0^{21}$. These effects are further amplified by the interconnetitivity properties of the input-output matrix, that directly or indirectly (i.e. through a third sector) links up all the sectors in the economy. This mechanism is embodied in Γ_0. Notice that the minus sign on $\boldsymbol{\chi}_{comp}$ balances the negative sign on $\mathbf{G}_0^{21}$ that come by the fact that the matrix of coefficients associated with the intermediate input channel, the $\mathbf{C}_{i0}, \forall i \neq 1$, enters the system with a negative sign. Therefore, the sign of $\boldsymbol{\chi}_{comp}$ reflects the sign of the estimated $\mathbf{C}_{i0}, \forall i \neq 1$.

What we label in the text as the *direct effect* is the effect on to the sector from which the shock originates. This corresponds to the first 2×1 subvector of $\boldsymbol{\psi}(0)$. Rewriting this as

$$\begin{aligned} \boldsymbol{\kappa}_{dir} &= \mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 + \mathbf{A}_{01}^{-1}\mathbf{G}_0^{12}\boldsymbol{\Gamma}_0\mathbf{G}_0^{21}\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1, \\ &= \mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1 - \mathbf{A}_{01}^{-1}\mathbf{G}_0^{12}\boldsymbol{\chi}_{comp}, \end{aligned}$$

makes clear that this is composed of the effect that the shock would have had if there were no interactions, $\mathbf{A}_{01}^{-1}\boldsymbol{\varrho}_1$, plus a component that comes as an echo from the complementary effect[40].

To underline the fact that the effect of a shock in a system with no interactions corresponds only to the first part of the *direct effect,* notice that if each sector is considered in isolation, the matrix $\mathbf{G}_0$ block diagonal and its $i-th$ diagonal element is the generic matrix $\mathbf{A}_{i0}$. Therefore, the inverse matrix $\mathbf{G}_0^{-1}$ is itself a

[40] Note that also in this case the negative sign is neutralized by the fact that the $\mathbf{C}_{01}$ enters $\mathbf{G}_0^{12}$ with a negative sign.

block diagonal matrix whose $i-th$ diagonal element is the generic $\mathbf{A}_{i0}^{-1}$. It follows that in this case the impact effect is $\boldsymbol{\psi}(0) = \left[\begin{array}{cc} \left(\mathbf{A}_{10}^{-1}\boldsymbol{\varrho}_1\right)', & \underbrace{\mathbf{0}'}_{1\times[(N-1)2]} \end{array} \right]'$.

Appendix C: Aggregation

Here we explain how to obtain the aggregate series and impulse responses for output and hours[41]. Small capitals indicate the logarithms of the variables, aggregate variables are denoted with a tilda. By definition aggregate hours is

$$\widetilde{H}_t = \sum_i H_{it},$$

therefore the growth rate of (aggregate) total hours can be written as

$$\begin{aligned}
\Delta\widetilde{h}_t &= \log\left(\frac{\widetilde{H}_t}{\widetilde{H}_{t-1}}\right) = \log\left(\frac{\sum_i H_{it}}{\sum_i H_{it-1}}\right) \\
&\simeq \log\left(\sum_i \omega_i \exp(\Delta h_{it})\right),
\end{aligned}$$

where ω_i is an appropriate aggregation weight that reflects industry size. In the application we use fixed weights and construct them from the average shipment value of sales over the sample period.

Similarly, aggregate output growth is computed as

$$\Delta\widetilde{q}_t \simeq \log\left(\sum_i \omega_i \exp(\Delta x_{it} + \Delta h_{it})\right).$$

[41] Note that in the text we defined log of hours as n_{it}, and (labor) productivity as x_{it}. Labor productivity is defined as output per hours worked, therefore we can define (the log of) output as $q_{it} = x_{it} + n_{it}$.

TABLES:

TABLE 1 - THE COINTEGRATION OF TFP AND LABOR PRODUCTIVITY

	$\epsilon_{it}= x_{it}-\alpha_0-\alpha_1 z_{it}$		
IPS	-2.032	-1.939	-1.653
$p-value$	0.284	0.322	0.417
$CIPS$	-1.973	-2.451	-2.121
	$e_{it}= x_{it}-a_0-a_1 x^*_{it}-a_2 z_{it}$		
IPS	-3.17*	-2.861*	-2.52
$p-value$	0.032	0.07	0.127

Notes: Table 1 report unit root tests for two different relations between labor producitivity and TFP. All series enter in log form, x_{it} is labor productivity, z_{it} is total factor productivity, $x^*_{it} = \sum_{j=1}^{I} \omega_{ij} x_{jt}$, where the weights ω_{ij} are computed from the "use" input-output matrix as described above. e_{it} and ϵ_{it} are cointegrating vectors computed as shown. IPS report the averages of the Augmented Dickey-Fuller test statistics for 0, 1 and 2 lags. Below it are reported the associated asymptotic p-values (Im, Pesaran and Shin, 2003). Given the high degree of cross sectional dependence in ϵ_{it} $(\bar{\hat{\rho}} = 0.334)$, for this variable the table includes the Cross Sectional IPS test (CIPS). The critical values for this test are tabulated in Pesaran (2007). The superscript "*" signifies the test is significant at the ten per cent level.

TABLE 2 - PRELIMINARY ANALYSIS OF COMOVEMENT			
		Labor Productivity	Hours
$\bar{\hat{\rho}}$		0.055	0.202
CD		109.28	403.44
IP1		0	2
BIC3		0	1
Onatski	$(H_0: r = 0)$	33.089*	6.621*
	$(H_0: r = 1)$	33.089*	6.621*
	$(H_0: r = 2)$	1.243	3.904
No sectoral interactions[a]		Technology	Non Technology
$\bar{\hat{\rho}}$		0.046	0.183
CD		91.12	356.86
IP1		0	1
BIC3		0	1
Onatski	$(H_0: r = 0)$	6.838*	5.661
	$(H_0: r = 1)$	6.838*	—
	$(H_0: r = 2)$	1.405	—

Notes: The first part of the table reports measures of the strength of the cross sectional dependence between sectors, $\bar{\hat{\rho}}$ is the simple average of the pair-wise cross section correlation coefficients, $\bar{\hat{\rho}}= [2/I(I-1)] \sum_{i=1}^{I-1} \sum_{j=i+1}^{I} \hat{\rho}_{ij}$ with $\hat{\rho}_{ij}$ being the correlation coefficient for the i^{th} and j^{th} cross section units. The test of the null hypothesis of no cross sectional dependence (Pesaran, 2004) is $CD = \sqrt{2T/I(I-1)} \sum_{i=1}^{I-1} \sum_{j=i+1}^{I} \hat{\rho}_{ij}$, which tends to $N(0,1)$ under the null. It does not require an a priori specification of a weighting matrix and is applicable to a variety of panel data models, including heterogeneous panels with structural breaks, with short time dimension, T, and large cross section, N . The second part of the table reports the choice of the number of static factors consistent with the information criteria of Bai and Ng (2002). In the table we report $k_{\max} = 5$ is also the choice of the maximum possible aggregate factors allowed in the Bai and Ng (2002) procedure. The second part of the table reports the Onatski (2007) test of the number of static factors. The critical values depend on $\kappa = k_{\max} - k$, and these are tabulated in Onatski (2008). In the table we report the test for $k_{\max} = 5$. The 5% values are 5.77 for $\kappa = 5$, 5.40 for $\kappa = 4$ and 4.91 for $\kappa = 3$. The superscript "*" signifies the test is significant at the five per cent level.

[a] Specifically, this corresponds to setting the matrices C_{il} ($\forall i$ and $l = 0, 1$) arbitrarily equal to the null matrix 0 in (10), i.e. the matrix of coefficients G_l, for $l = 0, 1$, in (11) are block diagonal matrices.

TABLE 3 - PRELIMINARY ANALYSIS INSTRUMENTS				
	INSTRUMENT SET A		INSTRUMENT SET B	
	Labor Productivity	Hours	Labor Productivity	Hours
J-test	0.588	0.640	0.506	—
	5	9	24	—
C-test	0.763	0.736	—	—
	2	7	—	—
R^2	0.552	0.960	0.437	0.738
	0	0	12	23
$\overline{R}^2$	0.373	0.941	0.270	0.647
	25	0	87	55

Notes: Table 3 reports the Hansen J-test for overidentification, specifically the average p-value of the test and the number of sectors where the test is rejected at the 5% level. and the C-statistic for the validity of the cross sectional averages κ_{it}^* as a subset of instruments. In the table we report the average p-value and the number of sectors where the null is rejected at the 5% level. The bottom part of the table report Shea (1997) partial R^2 which gives a measure of the goodness of the instruments and the corresponding adjusted value denoted $\overline{R}^2$. The R^2 refers to the identification of the idiosyncratic contemporaneous level of labor input and labor productivity The table report the average value of the statistic and the number of sector where the statistic value is less than 10%.

The instrument set A includes the instruments $X_{it}^A = [\kappa_{it}^*, \mathbf{d}_{t-1}, \phi_{it}]$ whereas $X_{it}^B = [\mathbf{d}_{t-1}, \phi_{it}]$, $\phi_{it} = \left[\Delta h_{it-1}, \Delta h_{it-1}^*\right]$ when applied to the regression of labor productivity and $\phi_t = [\varepsilon_{it}^z]$ when applied to labor input. Counting among the variables to be instruments also κ_{it}^*, the number of required instruments are 3 in both regressions whereas the number of instruments for labor productivity (labor input) are 6 (5) in instrument set A and 4 (3) in instrument set B.

TABLE 4 - ESTIMATION RESULTS							
	Δx_{it}^*	$\Delta^2 h_{it}^*$	Δx_{it-1}^*		ζ_t	$\Delta\mu_t$	$\overline{GR}^2$
Δx_{it}	0.436*	-0.060*	0.164*		0.236*	-0.431*	
	(0.038)	(0.015)	(0.032)		(0.053)	(0.096)	0.2917
	168	96	104		85	104	
	Δx_{it}^*	Δh_{it}^*	Δx_{it-1}^*	Δh_{it-1}^*	ζ_t	μ_t	$\overline{GR}^2$
Δh_{it}	0.316*	0.692*	0.042	0.162*	-0.285*	-0.494*	
	(0.035)	(0.022)	(0.032)	(0.019)	(0.064)	(0.097)	0.5467
	126	323	110	142	100	98	

Notes: The first row of table 4 provides the mean group estimates. The second row in parenthesis provides the standard deviation of the mean group estimator, calculated with the nonparametric estimator in Pesaran (2006). "*" denotes that the coefficient is significant at the 5% critical value. The third row shows the number of sectors where the null hypothesis that the coefficient of interest is equal to 0 is rejected at the 10% level (the total number of sectors is 458). $\overline{GR}^2$ is the average value of the generalized R^2 criterion for instrumental variables regressions (Pesaran and Smith, 1994).

TABLE 5 - AN ANALYSIS OF COMOVEMENTS: Aggregate vs Idiosyncratic Shocks			
Contribution of aggregate shocks on		Labor Productivity	Hours
Partial R^2		0.079	0.080
$\bar{\hat{\rho}}$		0.050	0.044
Identified idiosyncratic shocks		Technology	Non Technology
$\bar{\hat{\rho}}$		0.009	0.010
CD		18.89	20.93
IP1-3		0	0
BIC3		0	0
Onatski	$(H_0: r = 0)$	2.295	2.501

Notes: The first part of the table reports the partial R^2 contribution of aggregate shocks to the growth rate of labor productivity and hours. The idiosyncratic shocks are identified through the SecVAR procedure in (10). $\bar{\hat{\rho}}$ is the average cross sectional correlation and CD is the cross sectional dependence statistic. See notes to Table 1.

TABLE 6: FORECAST VARIANCE DECOMPOSITION

LABOR PRODUCTIVITY

	Sect. Technology		Sect. Non-Technology		Aggregate Technology	Monetary Policy
HORIZON	Same Sector	Other sectors	Same Sector	Other sectors		
1	74.11	12.33	2.40	2.12	3.62	5.38
	(69.7 – 79.1)	(6.5 – 16.0)	(1.6 – 2.9)	(0 – 3.4)	(0.3 – 5.5)	(1.8 – 8.2)
2	72.35	21.49	0.24	0.82	3.47	1.60
	(66.7 – 79.5)	(13.6 – 27.1)	(0.09 – 0.3)	(0 – 1.5)	(0 – 6.3)	(0 – 3.1)
3	73.66	22.52	0.04	0.15	3.39	0.20
	(67.2 – 81.3	(13.9 – 28.7)	(0 – 0.08)	(0 – 0.4)	(0 – 6.2)	(0 – 0.5)
5	73.76	22.91	0.003	0.01	3.28	0.01
	(66.6 – 82.3)	(14.0 – 29.7)	(0 – 0.01)	(0 – 0.06)	(0 – 6.2)	(0 – 0.06)
10	73.83	22.86	0.0	0.0	3.29	0.0
	(66.6 – 83.0)	(13.3 – 29.2)	(0 – 0)	(0 – 0.003)	(0 – 6.1)	(0 – 0.001)

HOURS

	Sect. Technology		Sect. Non-Technology		Aggregate Technology	Monetary Policy
HORIZON	Same Sector	Other sectors	Same Sector	Other sectors		
1	12.76	9.69	41.80	19.79	8.83	7.11
	(11.0 – 14.7)	(2.6 – 14.3)	(37.0 – 46.6)	(10.4 – 26.5)	(1.2 – 14.4)	(3.9 – 9.1)
2	11.42	20.14	32.10	22.81	7.67	5.82
	(9.4 – 13.4)	(9.9 – 27.8)	(28.0 – 35.9)	(13.2 – 30.6)	(0 – 13.6)	(2.4 – 8.1)
3	10.96	26.44	31.92	20.11	5.76	4.78
	(8.6 – 13.1)	(14.9 – 36.6)	(27.0 – 36.6)	(9.7 – 27.8)	(0 – 9.6)	(0.5 – 7.6)
5	10.97	28.73	31.43	19.95	4.09	4.81
	(8.4 – 13.3)	(15.5 – 40.4)	(26.2 – 36.4)	(10.1 – 28.0)	(0 – 6.9)	(0 – 7.5)
10	10.97	29.12	31.18	19.86	4.01	4.82
	(8.2 – 13.5)	(14.3 – 41.1)	(25.8 – 36.6)	(9.6 – 27.9)	(0 – 6.6)	(0 – 7.5)

Notes: Entries are point estimates at a given horizon (in years) of the percentage contribution to the forecast error for labor productivity and hours (in level). In parentheses are the associated 90 percent confidence intervals, based on 500 bootstrap draws.

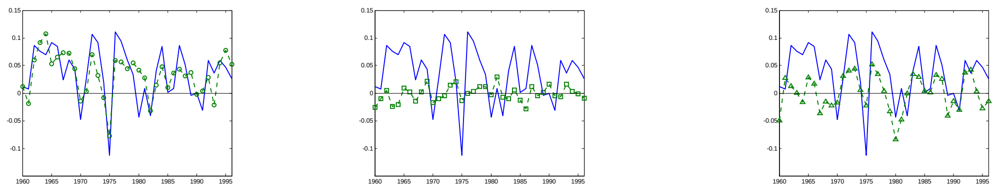
FIGURES:

FIGURE 1 - BUSINESS CYCLE, HISTORICAL DECOMPOSITION

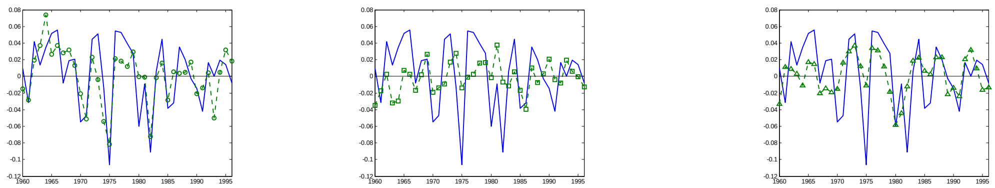
Sectoral vs aggregate shocks

SECTORAL SHOCKS AGGREGATE TECH. SHOCK MONETARY POLICY SHOCK

OUTPUT



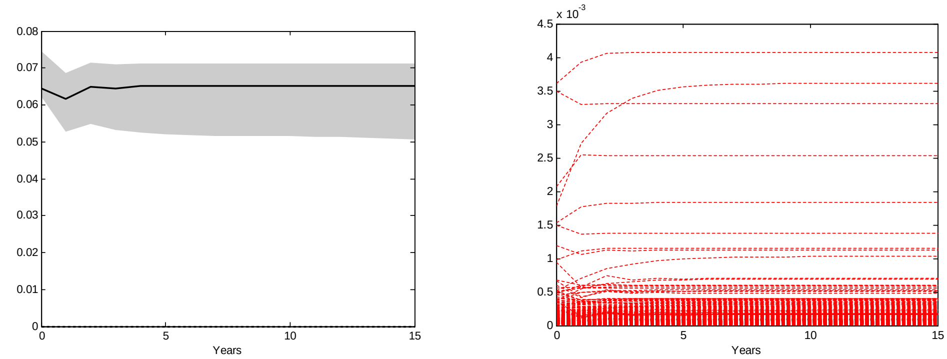
HOURS



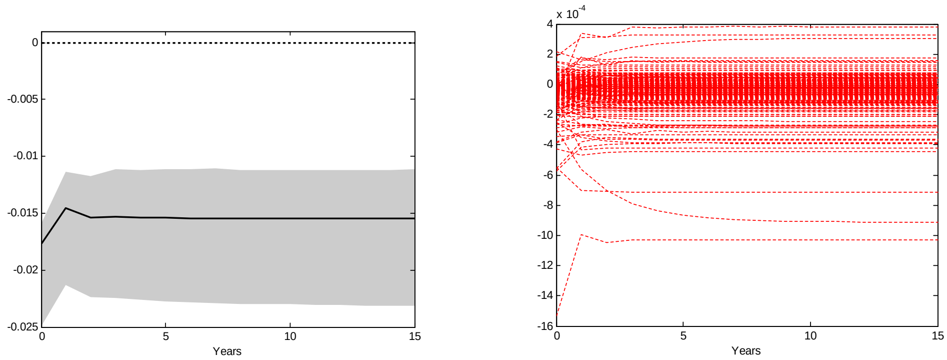
Notes: The figure shows a historical decomposition of the aggregate growth rate of output and hours into sector specific and aggregate shocks. The blue continuous (——) line represents the actual data, the green dashed line with circles $(-\bigcirc-\bigcirc-)$ the simulated data with only sector specific shocks, and the green dashed line with squares $(-\square-\square-)$ with the aggregate technology shock and the green dashed line with triangles $(-\triangle-\triangle-)$ is the component associated with monetary policy shocks.

FIGURE 2 - IMPULSE RESPONSES TO AN AGGREGATE TECHNOLOGY SHOCK (WITHOUT SECTORAL INTERACTIONS)

PRODUCTIVITY



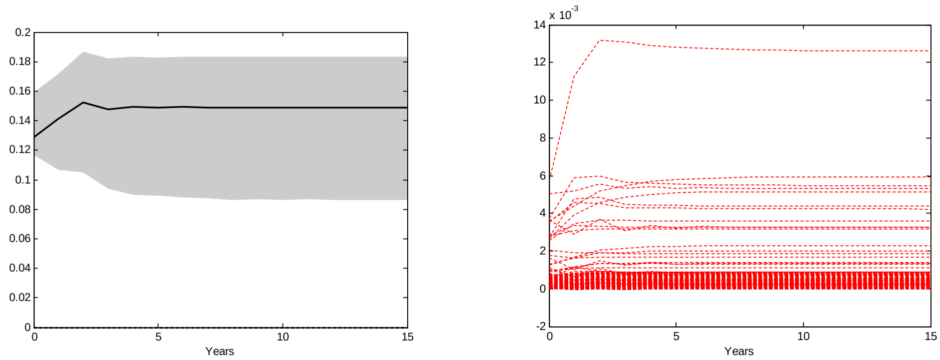
HOURS



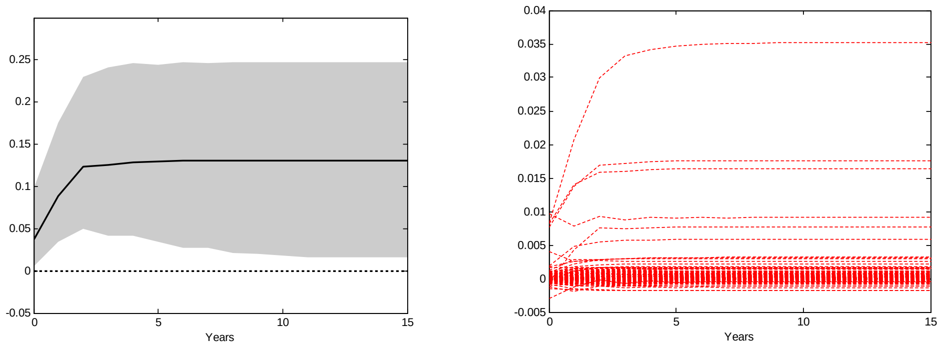
Notes: The figure shows estimated impulse responses of labor productivity and hours to a contemporaneous shock, where no interaction between sectors is allowed. The left hand panel provides the aggregate response, the shaded area represents the 90-percent confidence intervals (Hall's "percentile interval", see Hall, 1992) based on bootstrapping 500 draws. The right hand panel shows the sectoral responses weighted by sectoral average real shipment value, such that the sum of these corresponds to the figure on the left hand side.

FIGURE 3 - RESPONSES TO AN AGGREGATE TECHNOLOGY SHOCK
(WITH SECTORAL INTERACTIONS)

PRODUCTIVITY



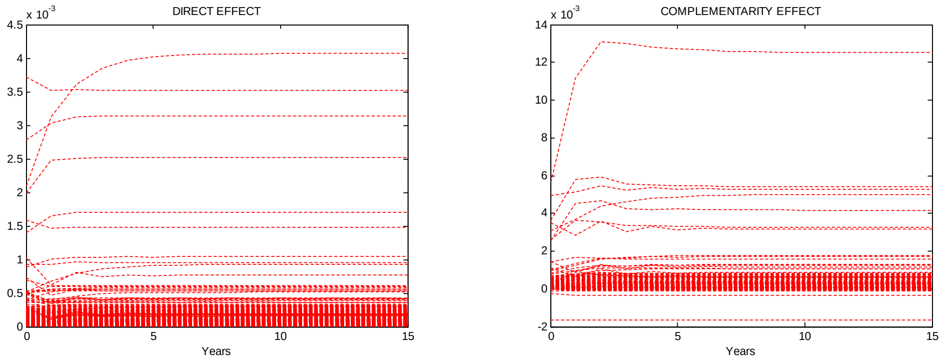
HOURS



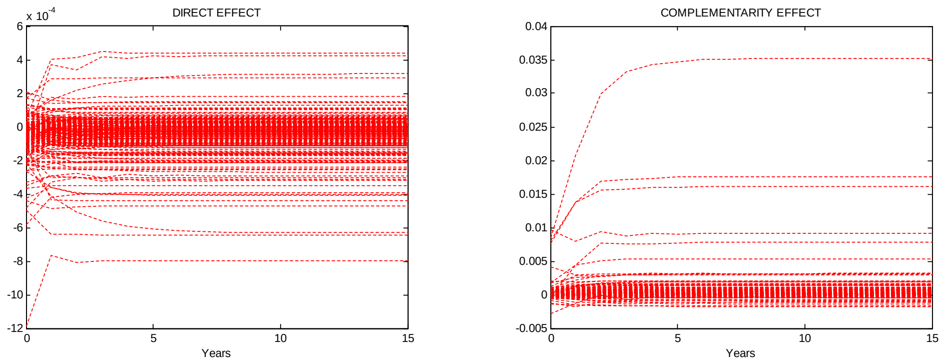
Notes: The figure shows impulse responses of labor productivity and hours to a contemporaneous change to the idiosyncratic sectoral technology shock when sectoral interactions are at work. The left hand panel provides the aggregate response, the shaded area represents the 90-percent confidence intervals (Hall's "percentile interval", see Hall, 1992) based on bootstrapping 500 draws. The right hand panel shows the aggregate response to each of the 458 idiosyncratic technology shocks the sum of these corresponds to the figure on the left hand side.

FIGURE 4 - DECOMPOSITION OF THE DYNAMIC RESPONSE TO A TECHNOLOGY SHOCK

PRODUCTIVITY



HOURS

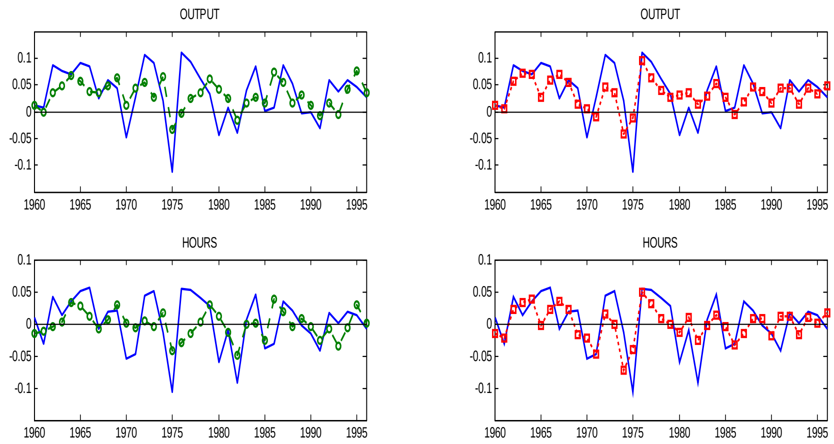


Notes: The figure shows the response of hours to an idiosyncratic technology shock at the sectoral level. The original impulse responses are weighted according to industry size, measured by the real value of shipments; in this way the sum of the sectoral impulse responses exactly match the aggregate response reported in Figure 3.

FIGURE 5 - BUSINESS CYCLE, HISTORICAL DECOMPOSITION

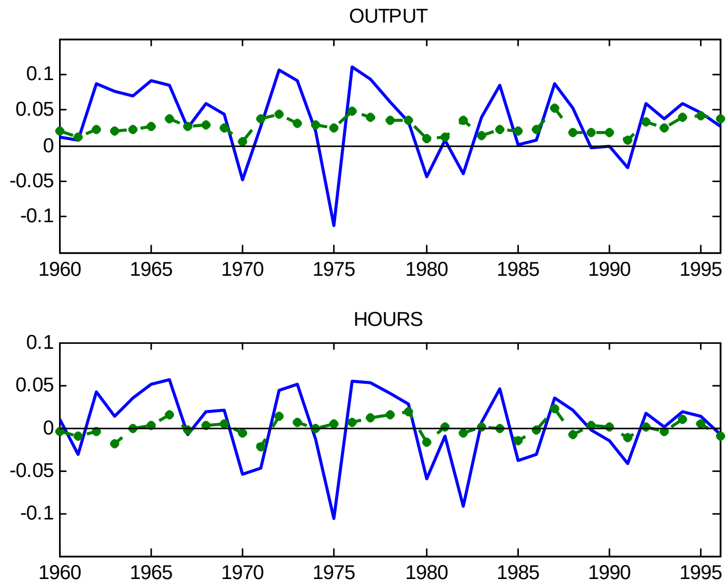
Technology vs non-technology shocks

Technology Component	Non Technology Component



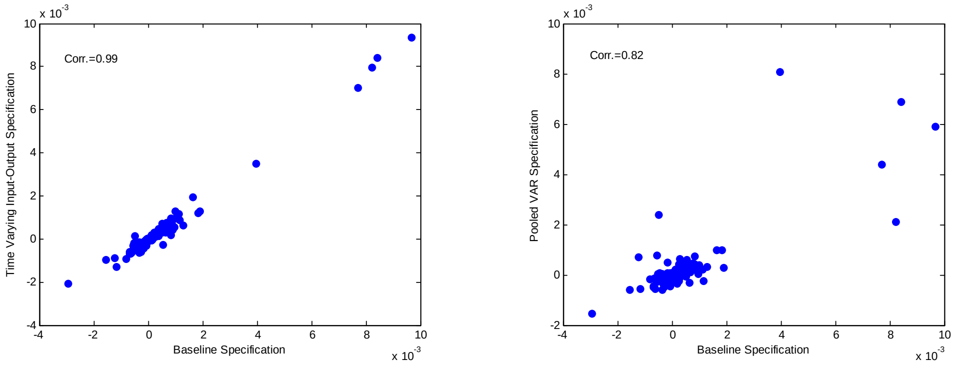
Notes: The figure shows a historical decomposition of the aggregate growth rate of manufacturing output and hours into that attributable to technology (left panel) and non-technology shocks (right panel). The blue continuous (—-) line represents actual data, the green dashed line with circles (− ◯ − ◯ −) simulated data with only technology shocks, the red dotted line with squares (· ⊡ · ⊡ ·) denotes that due to non technology shocks.

FIGURE 6 - BUSINESS CYCLE, HISTORICAL DECOMPOSITION
The role of factor demand linkages



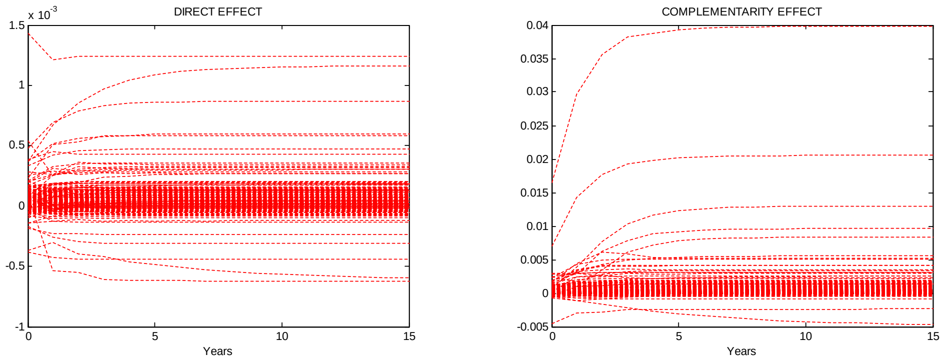
Notes: The figure shows the aggregate growth rate of output and hours and the simulated series with aggregate and idiosyncratic shocks but excluding sectoral interactions. The blue continuous (—) line represents the actual data, the green dashed line with stars (-*-*-) the simulated data with aggregate and idiosyncratic shocks, but excluding sectoral interactions.

FIGURE 7 - ROBUSTNESS



Notes: x-axis: short-run responses of hours to permanent shocks to labor productivity from the industry VAR. y-axis: short run response of hours to permanent shocks to labor productivity, controlling for time-varying input-output relationships (left panel) and pooling sectors to the 3 digit SIC level (right panel).

FIGURE 8 - Dynamic Response of Total Hours Worked to a permanent shock to TFP



Notes: Figure 8 reports the direct and complementary effect on total hours of a technology shock identified from the bivariate VAR with TFP and total hours as suggested by Chang and Hong (2006). The shocks are identified from (10) which uses the cross-sectional average computed from the input-output matrix to proxy for sectoral interactions.

Additional results (Not for publication)

Unit root versus stationary hours

There is an issue in the literature concerning how the labor input (hours) should be modeled when extracting the technology shock.[42] The fact that aggregate labor input is stationary is often motivated by balanced growth path considerations. However, the reallocation of the labor input among industries could produce different sectoral trends. Specifically, Campbell and Kuttner (1996) and Phelan and Trejos (2000) highlight the role of sectoral shifts in modelling employment at the industry level and their importance for a better understanding of the driving forces of aggregate employment.

In (10) we have not assumed any particular process for hours. Indeed either the level or the difference specification for labor input can be accommodated (Pagan and Pesaran, 2008). To determine the correct stationary transformation of the variables we apply the panel unit root test developed by Pesaran et al. (2007)[43]. The null hypothesis is that all the series have a unit root and are not cointegrated with the underlying factors. The results for the industry data are summarized in Table xx. Specifically, the null hypotheses cannot be rejected for the level of log labour productivity (x_{it}) and hours (h_{it}), regardless of whether an intercept or an intercept and a linear trend are included whereas it is rejected for the growth rates. In the light of these results and the theoretical considerations outlined above we assume that there is a unit root in the labor input. Therefore we estimate and analyse (12)-(10) with both variables in log difference.

There may be a variety of reasons for a failure to reject the unit root hypothesis, including lack of power, shifts in mean, or misspecification of the low frequency deterministic components, or other forms of non-linearity.[44] Nevertheless, the

[42] The empirical evidence on the stationarity of aggregate hours worked is mixed (see e.g. Shapiro and Watson, Shapiro and Watson (1988)). Christiano et al. (2003) argue that the negative response of the labor input to a technology shock might be the result of a misspecification of the original model and specifically, the mistreatment of labour input in the empirical model. Indeed, they find that the effect of a technology shock on the labour input clearly depends on the treatment of the labour input; if this is included in levels the puzzling result disappears.

[43] This test extends the original test of Pesaran (2007) to the case with multiple common factors. With respect to other tests, this has the advantage of not requiring prior specification of the factor structure. Specifically, for each variable we augment the ADF regression with the weighted average of both productivity and hours. The weights are computed from the input output matrix as described above. We obtain similar results if a simple average is used to control for the cross sectional dependence. Perron and Moon (2007) highlight that this type of test has a better performance than the other panel unit root tests with cross sectional dependence for small panels where the estimation of factors is difficult.

[44] Note that this problem would persist even in the difference specification. Fernald (2007) and Francis and Ramey (2005b) document trend breaks in productivity and hours.

presence of industry specific cross sectional averages as weakly exogenous variables in the system will help to avoid most of the problems related to the particular specification of the labour input. Indeed, the forcing variables will be acting to balance the distortionary effect of any low frequency components of the labour input, as well as possible breaks or nonlinearity in the variable.

TABLE xx - UNIT ROOT TEST

With intercept and linear trend				
	$CADF(0)$	$CADF(1)$	$CADF(2)$	$CADF(3)$
x_{it}	-3.052^{*}	-2.609	-2.181	-2.072
h_{it}	-2.615	-2.476	-2.22	-2.081
With intercept				
	$CADF(0)$	$CADF(1)$	$CADF(2)$	$CADF(3)$
x_{it}	-2.819^{*}	-2.392^{*}	-2.004	-1.904
h_{it}	-2.374^{*}	-2.241	-2.031	-1.921
Δx_{it}	-6.306^{*}	-4.547^{*}	-3.29^{*}	-2.671^{*}
Δh_{it}	-7.409^{*}	-4.477^{*}	-3.523^{*}	-2.857^{*}

Notes: The reported values are CIPS(p) statistics, which are cross section averages of cross-sectionally Augmented Dickey-Fuller test statistics (Pesaran, Smith and Yagamata, 2007). The critical values for this test depends on the cross section, time dimension and number of lags included as well as the number of cross sectional averages included. The values are tabulated in Pesaran, Smith and Yagamata (2007). When only the intercept is included the 5% critical value is -2.29 for when no lag is included, -2.24 for 1 lag, -2.10 for 2 lags and -2.03 for three lags. When an intercept and linear trend are included the critical value is -2.72 when no lag is included, -2.67 for 1 lag, -2.50 for 2 lags and -2.41 for three lags. The superscript "*" signifies the test is significant at the five per cent level.