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Abstract

This paper argues that factor demand linkages can be important for 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 cycle.

JEL Classification: E20, E24, E32, C31

Keywords: Technology Shocks, Multisectors, Business Cycle, Long-run Restrictions, Cross Sectional Dependence.

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1 Introduction

Input-output linkages are a pervasive feature of modern economies. 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. Neglecting them could lead to a significant loss in understanding the dynamics of the supply-side of an economy.

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 explicitly consider 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 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 arising from the input-output structure of the economy, which can generate business cycle fluctuations. The idea was revitalized by Horvath (1998, 2000) and more recently by Carvalho (2009). 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 use a simplified version of a multi-sectoral real business cycle model with factor demand linkages to derive restrictions that allow us to understand how shocks in one sector can affect productivity in other sectors. We then make use of those long run restrictions to disentangle technology and non-technology shocks in a structural VAR, for a panel of highly disaggregated manufacturing sectors. The main novelty is that all sectors in the economy are related by factor demand linkages captured by the input-output matrix. A sectoral VAR where all industries are linked through the input-output matrix (SecVAR) is then constructed using the approach of Pesaran, Schuermann, and Weiner (2004). This allows us to distinguish between the contribution made by technology shocks to particular sectors and the overall effect amplified by sectoral interactions. As a result, the shocks that we identify can explain industry and aggregate fluctuations only if all sectors are analyzed contemporaneously, i.e. not in isolation. In this setting, the intermediate input channel becomes crucial for propagating shocks to the aggregate economy.

Furthermore, we consider the implications of our results for the relative roles played by technology and non-technology 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

[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.

worked and labor productivity. The source of this correlation is a shift in the labor demand curve, as a result of a technology shock, combined with an upward sloping labor supply curve. There is, however, a substantial literature suggesting that this is inconsistent with the data. Gali (1999) uses the identifying assumption that innovations to technology are the only type of shock that have permanent effects on labor productivity, and finds that hours worked decline 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 favor of a business cycle model driven by non-technology shocks and featuring sticky prices.

Most of the empirical macroeconomic literature evaluating the effect of technology shocks focuses on the analysis of aggregate data, where 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, but they consider each sector as a separate unit in the economy. Instead, in this paper, we explicitly consider the implications of factor demand linkages for the econometric analysis of the effect of technology shocks on hours. We show that a contemporaneous technology shock to all sectors in manufacturing implies a positive aggregate response in both output and hours, and this 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. The input-output channel can not only be qualitatively, but also quantitatively important for the transmission of shocks. Indeed, sectoral interactions prove to be an important amplifier of sector-specific and aggregate shocks. The incorporation of factor demand linkages appears to revive the importance of technology shocks as drivers of the aggregate business cycle. In fact, technology shocks appear to account for a large share of sectoral fluctuations; most significantly, shocks to other sectors (transmitted though sectoral interactions) are fundamental for tracking individual sectoral cycles. Our analysis suggests that, once sectoral interactions are accounted for, technology and non-technology shocks seem 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 which we then use in the empirical analysis. 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. We describe the data in Section 4. In section 5, we report our findings. In Section 6, we consider some robustness checks. 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 shed light on the way shocks are propagated through the economy in a model that explicitly takes into account factor demand linkages among sectors. The focus is on the long run properties of the model that are useful for structural identification. In order to simplify the discussion we focus on an economy only buffeted by sector specific shocks.

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 usual intertemporal budget constraint. 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 log utility specification is consistent with aggregate balanced growth and structural change at the sectoral level, as discussed in Ngai and Pissarides (2007). With perfect labor mobility across sectors the leisure index is $L_t = 1 - H_t = 1 - \sum_i H_{it}$. The aggregate consumption index is $C_t = \prod_i \xi_i^{-\xi_i} \widetilde{C}_{it}^{\xi_i}$, where $\xi_i \in [0,1]$ are aggregation 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.[2]

On the supply side, the goods market operates under perfect competition and besides labor, production of each good also 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

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

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, 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 an autoregressive stochastic process of the form $Z_{it} = \left(Z_{it-1}\right) \exp\left[\mu_i^z + \Phi_i^z(L)\varepsilon_{it}^z\right]$ where μ_i^z is a constant drift, and $\Phi_i^z(L) = (1 - \rho_i L)^{-1}$ is

[2] It 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 also Franco and Philippon, 2007).

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. Furthermore, we assume that the shocks are idiosyncratic at the sectoral level, i.e. $Cov(\varepsilon_{it}^z, \varepsilon_{jt}^z) = 0$, $\forall i \neq j$. Given the aggregator for intermediate inputs, the price index for intermediate goods can be written as $P_t^{M_i} = \prod_{j \in S_i} P_{jt}^{\gamma_{ij}}$, where P_{it} is the price of the good produced in sector i.

In perfect competition equilibrium requires that the price equals the marginal cost of production. Therefore, the cost minimization problem for each sector i in conjunction with the Cobb-Douglas production function implies constant expenditure shares for all inputs. Free mobility of intermediate inputs across sectors implies that the marginal productivity of inputs (i.e. the prices of intermediate inputs) needs to be equal across sectors and perfect labor mobility across sectors requires that (at the margin) nominal wages need to be equalized, i.e. $W_{it} = W_{jt} = W_t$ $\forall i, j$. The latter implies that the relative price of two goods is inversely related to 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] From the definition of the price index for intermediate goods, the relative price of intermediate goods is

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

The relative prices act as an important conduit for the transmission of technology shocks. A positive technology shock to the *jth* sector lowers the price in the same sector. Since part of the production of the *jth* sector is supplied to the *ith* sector as an intermediate input, positive shocks occurring in one sector also have a negative impact on the prices of other sectors.

Labor productivity in sector i 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 through the intermediate inputs channel. Define x_{it} as the logarithm of labor productivity and z_{it} as the logarithm of the technology shock and stacking sectoral variables in vectors, $\mathbf{x}_t$ and $\mathbf{z}_t$ respectively, the equilibrium solution for labor productivity can be written as

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

where $\mathbf{I}$ is the identity matrix, $\mathbf{A} = diag(\alpha_1, \ldots, \alpha_N)$, $\boldsymbol{\phi} = [\log \phi_1, ..., \log \phi_N]'$ and $\boldsymbol{\Gamma}$ is the "use" input-output matrix whose generic elements are the parameters $\gamma_{\iota j}$ introduced above. The long

[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).

run response of labor productivity in sector i to the innovation to technology is then:

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

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

where $\mathbf{D} = diag\left(\rho_1,\ldots,\rho_N\right)$ and ι_k is the k-th column of the $N-$dimensional identity matrix. Note that when factor demand linkages are not taken into consideration $\alpha_i = 0\ \forall i$ and

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

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

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

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

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

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

$$H_{it} = \frac{\left(1-\alpha_i\right)\xi_i Z_{it}^P}{\chi}\frac{Y_{it}}{C_{it}}\frac{\partial V\left(L_t\right)}{\partial L_t}, \tag{9}$$

and clearly depends on the sectoral preferences as well as on sectoral technology shocks. Moreover, the presence of factor demand linkages is such that hours in each sector are influenced by shocks originating in other sectors:

$$\lim_{h\to\infty}\frac{\partial\log\left(H_{it+h}\right)}{\partial\varepsilon_{jt}^{p}} \neq 0 \qquad \forall i,j,$$

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

The empirical analysis in the next section will make use of the fact that in this simplified economy the long run response of labor productivity is directly influenced by technological developments specific to a given sector, as well as by changes in productivity in sectors that supply inputs (see equation 3). This allows us to identify technology shocks and their flows across sectors. However, it is worth emphasizing that in more general specifications of a multisectoral model the same type of relations might not hold. Indeed, labor productivity in a given sector will still be influenced by technology shocks originating in the other sectors, yet, the relationship may not be so neatly dependent on the input-output structure of the economy (see e.g. Horvath, 2000, Kim and Kim, 2006, and Foerster et al., 2008).

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 labor 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 the need to go further than this when there are factor demand linkages. Labor productivity in the *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 shocks we need to take into account the intermediate input channel as well.

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

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

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 input[6], and $\varkappa_{it}^{*}$ are appropriate industry specific weighted cross sectional averages of the original variables in the system which reflect interactions between sectors. Specifically, the industry cross sectional averages are constructed in order to capture factor demand linkages between manufacturing sectors in the economy, i.e. $\varkappa_{it}^{*} = \left[\sum_{j=1}^{N} \omega_{ij}\Delta x_{jt},\ \sum_{j=1}^{N} \omega_{ij}\Delta h_{jt}\right]'$, where the weights, ω_{ij}, correspond to the (possibly time varying) share of commodities j used as

[4] See, for example, King, Plosser, and Rebelo (1988), King, Plosser, Stock, and Watson (1991) and Christiano and Eichenbaum (1992). Notice that increasing returns, capital taxes, and some models of endogenous growth would all imply that non-technology shocks can change long-run labor 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 on aggregate data.

[5] For ease of exposition we focus on the simple VARX(1,1) without any deterministic component, but the discussion equally applies 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. For most sectors this choice is supported by the Akaike and Schwarz information criteria.

[6] There is an issue in literature concerning whether labor input (hours) should 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 Trejos, 2000). Evidence that labor productivity and labor input follow unit root processes is provided in the Appendix.

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 $\boldsymbol{\varepsilon}_{it} = [\varepsilon^z_{it}, \varepsilon^p_{it}]'$, where ε^z_{it} denotes the technology shock and ε^p_{it} 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, Eichenbaum, and Vigfusson (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 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 have an impact on labor productivity of supplying sectors (6). Therefore, equation (4) imposes two sets of restrictions. The first one is the standard restriction given by equation (7), which requires that $A^{12}_{i0} = -A^{12}_{i1}$. The second restriction, which is non-standard, is derived from equation (8) and requires that $C^{12}_{i0} = -C^{12}_{i1}$.

It is possible to recover the SecVAR specification 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 $\boldsymbol{\kappa}_t = [\varkappa'_{1t}, ..., \varkappa'_{Nt}]'$ and the matrix of coefficients are

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

where the $4 \times 2N$ weighting matrix, $\mathbf{W}_i$, 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, Schuermann, and Weiner (2004). The reduced form moving average representation of the dynamics of labor productivity and hours at the sectoral level can be recovered by inverting $\mathbf{G}(L)$ in (11), more specifically

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

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 $E(\mathbf{u}'_t\mathbf{u}_s) = \mathbf{0}$ $\forall t \neq s$.[8] The specification in (12) does not impose any particular restriction on the nature of the shocks; shocks at the industry level can be either idiosyncratic or a combination of an aggregate and an industry

[7] Foerster, Sarte, and Watson (2008) emphasize that a factor error structure at the industry level can arise both from the presence of aggregate shocks and input-output linkages.

[8] Appendix B provides more details on the construction of (11), and how to recover the MA representation, as well as some detailed discussion of the transmission mechanism of idiosyncratic shocks.

specific component ($\mathbf{u}_{it} = \boldsymbol{\lambda}_i \mathbf{d}_t + \boldsymbol{\varepsilon}_{it}$).

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. Therefore, 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, i.e. 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 ($\mathbf{C}_{il} = \mathbf{0}$, $\forall i, l$). 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 due to factor demand linkages, as illustrated by the simplified model in the previous section.

The model analyzed in this section provides a further application of the method described in Pesaran, Schuermann, and Weiner (2004) but at the industry level. The difference is that 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 include the contemporaneous relationships between the endogenous variables.

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).[9] Labor input is measured as total hours worked, while productivity is measured as real output divided by hours.[10] Each variable is included as a log difference, where this choice is supported by panel unit root tests.

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

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

[10] Chang and Hong (2006) have argued that total factor productivity (TFP) and not labor productivity is the correct measure from which to identify technology shocks. In Appendix A we address this question. Furthermore, in Section 6 below we show that our results are robust to whether we use TFP or labor productivity.

[11] The data are available at http://www.bea.gov/industry/io_benchmark.htm. The original input output matrix when constrained to the manufacturing sector has only 355 entries. 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 also includes within sectors trade, we exclude this from the calculation of the standardized weighting matrix.

The input-output "use" table clearly reflects factor demand linkages and is, thus, 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 in order 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, however, we use the average of the input-output matrix in 1977 and 1987.[12] In the robustness section we investigate whether the results are affected by changes in the IO structure.

4.2 Preliminary investigation of comovement across sectors

In this section we turn to a preliminary analysis of comovement across sectors in manufacturing. The first panel of Table 1 provides evidence of cross sectional dependence in (the growth rate of) productivity and hours, i.e. the raw data. The first row shows the average cross section correlation between sectors, whereas the second row reports the associated cross-section dependence (CD) test of Pesaran (2004).

[Insert table 1]

The results in Table 1 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 now takes the residuals recovered from the SecVAR described by equation (10) but without allowing for the input-output channel (so for each i, $\mathbf{C}_{i0} = \mathbf{C}_{i1} = 0$). Again the residuals - corresponding to technology and non-technology shocks - exhibit considerable cross-section dependence, especially for the non-technology shocks.

In absence of any sectoral interaction, the comovement is entirely attributed to the presence of aggregate factors. The information criteria of Bai and Ng (2002) suggest a specification with one or two aggregate factors for total hours and one for non-technology shocks, whereas it identifies no aggregate factors for the labor productivity series and the technology shocks.[13] The bottom half of each panel in Table 1 reports the results of the test of Onatski (2007), which 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 $k < r = k + s \leq k_{max}$. This test, applied to both the raw data (panel 1) and the shocks identified without allowing any sectoral interaction (panel 2), points to the presence of two 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, no common factors are detected for non-technology shocks.[14]

[12] 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.

[13] These results are consistent with Bai and Ng (2002) IC_{P1} and BIC_3 criteria with a maximum number of factor set to 5. The BIC_3 criteria is reported given that it performs well in the presence of pervasive weak cross sectional dependence (see Bai and Ng, 2002, p. 207, and Onatski, 2005).

[14] 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 an upper bound on the possible number of dynamic common factors. Foerster, Sarte, and Watson (2008) also find evidence consistent with 1 or 2 static common factors in their analysis of sectoral industrial production.

We now turn to the residuals recovered from the full SecVAR in equation (10), where we allow for sectoral interactions. Given the results in Table 1, suggesting the presence of possible common factors (aggregate shocks), two proxies for the aggregate shocks have been added as conditioning variables when we estimate each sectoral model (10). Specifically, we include the aggregate technology shock constructed by Basu, Fernald, and Kimball (2006) and a monetary policy shock which is derived from an exactly identified VAR, estimated on quarterly data averaged for each year, following the procedure adopted by Christiano, Eichenbaum, and Evans (1999).[15] The bottom panel of Table 1 shows that the shocks identified by the sectoral model (10) are (almost) independent, once factor demand linkages among sectors and the aggregate shocks are taken into account. The average pairwise cross sectional correlation is about 1%, and the information criteria of Bai and Ng (2002), as well as the test of Onatski (2007), suggest the absence of any aggregate factor.

It is worth noting that even though the average pairwise cross sectional correlation is greatly reduced when we allow for sectoral interactions, cross sectional dependence is still significant according to the CD test. This implies that shocks to one sector are likely to be correlated with shocks to other sectors, i.e. the covariance matrix of the idiosyncratic shocks in (12), Ω_ε, is not fully diagonal. Although we can exclude the presence of unidentified aggregate shocks since no factors could be identified, there are still local interactions among sectors that (10) is not able to capture[16].

In order to quantify how widespread the rejection of orthogonality is, 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 a total of 458 sectors. To establish whether there is any connection between the residual cross-sectional dependence and the characteristics of the sector, we looked at the relation of the latter with the number of significant correlations for each sector. Specifically, we considered (a) the size of the sector, (b) the importance of the sector as an input supplier (measured by the column sum of the weighting matrix used in estimation and the number of connections of each sector, see also Pesaran and Tosetti, 2007, and Carvalho, 2009) and (c) the importance of a sector as an input user (measured by the number of supplying sectors and by the size of the input material bill). Overall, for (a) and (c) there seems to be no relation (the correlations are rather small and are all insignificant). For (b), even though there is no relation for technology shocks, there seems to be a significant correlation for non-technology shocks, as the number of rejections is marginally (positively) related to the importance of the sector as an 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

[15] 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. We enter the monetary shocks in the reduced form model for labor productivity in first difference, so that there is no long run effect of a monetary shock on productivity. In a previous version of this paper we included the monetary policy shock in levels, with the result that the coefficients associated with these shocks were, on average, not significant and the qualitative overall results were not affected.

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

assuming that Ω_ε is diagonal. The correlation between the aggregated series for manufacturing and the sum of sectors is approximately 99% for both series. This can be taken as evidence to support the hypothesis that the remaining cross sectional dependence is weak, and therefore of little importance for explaining aggregate fluctuations in manufacturing. Therefore, in the rest of the paper we proceed as if Ω_ε is diagonal.

4.3 The exogeneity of cross sectional averages

An important issue for the consistent estimation of (10) is whether the weighted cross sectional averages are weakly exogenous. Here we consider the soundness of this assumption.

Imposing the long run restrictions (which require that, in 10, $A_{i0}^{12} = -A_{i1}^{12}$ and $C_{i0}^{12} = -C_{i1}^{12}$) the two set of equations that need to be estimated for each sector are

$$\Delta x_{it} = A_{i0}^{12}\Delta^2 h_{it} + \left(C_{i0}^{11} + C_{i1}^{11}L\right)\Delta x_{it}^* + C_{i0}^{12}\Delta^2 h_{it}^* + A_{i1}^{11}\Delta x_{it-1} + \boldsymbol{\lambda}_{xi}\mathbf{d}_t + \varepsilon_{it}^z, \tag{13}$$

and

$$\Delta h_{it} = \left(A_{i0}^{21} + A_{i1}^{21}L\right)\Delta x_{it} + \left(C_{i0}^{21} + C_{i1}^{21}L\right)\Delta x_{it}^* + A_{i1}^{22}\Delta h_{it-1} + \left(C_{i0}^{22} + C_{i1}^{22}L\right)\Delta h_{it}^* + \boldsymbol{\lambda}_{hi}\mathbf{d}_t + \varepsilon_{it}^p. \tag{14}$$

Estimation of (13) and (14) requires three instruments in each equation. The long run restrictions on the effect of non-technology shocks allow the use of the lagged (growth) of hours and the associated cross sectional average, Δh_{it-1} and Δh_{it-1}^*, among the instruments in the equation for labor productivity. Furthermore, the identified technology shock from (13) can be used to identify the contemporaneous relation between labor productivity and hours in (14). Therefore, full identification requires the choice of one additional instrument for the equation for labor productivity, and two for the equation for hours. If the cross sectional averages are weakly exogenous, then they can be used directly in estimation, otherwise past values of the aggregate exogenous shocks, $\mathbf{d}_{t-1}$, can be used as additional instruments.[17] Therefore the weak exogeneity of the cross sectional averages can be tested by looking at the difference between the J-statistics of the instrument sets with and without the inclusion of the contemporaneous cross sectional averages among the instruments (see e.g. Eichenbaum et al., 1988). The p-value of the C-test averaged across sectors is 0.763 and 0.737 for the productivity and hours equations respectively, whereas the null is rejected at the 5% level in only 2 industries for productivity and in only 7 industries for hours (out of 458).[18] These results seem to support the assumption that the cross sectional averages are weakly exogenous and that therefore the contemporaneous relations between the sector specific variables and the cross sectional averages in (10) can be estimated consistently. As such, there is only one variable for each equation that needs to be instrumented (i.e. the contemporaneous relation between sector specific labor productivity and hours in each of the equations). Furthermore, the long run restriction on the cross sectional average in the first equation automatically provides an additional instrument that can be used to identify the technology shock from the first equation of (10), thus partially addressing some of the concerns of Christiano, Eichenbaum, and Vigfusson (2003) about possible biases arising

[17] Shea (1997) partial R^2 suggest that those are relevant instruments.

[18] None of the sectors where we reject the null is a large input supplier.

from the use of weak instruments.[19]

5 Technology shocks and the business cycle

Real business cycle theory assigns a central role to technology shocks as a source of aggregate fluctuations. Moreover, positive technology shocks should lead to positive comovement of output, hours and productivity. However, Gali (1999) finds that positive technology shocks appear to lead to a decline in hours, suggesting that technology shocks can only explain 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 1 we show the response of labor productivity and hours to a 1-standard deviation technology shock to all industries, disregarding sectoral interactions.[20] The panel on the left displays the aggregate response of manufacturing to a contemporaneous shock to all sectors, whereas the panel on the right displays the aggregate response to each of the N sectoral shocks.[21] Specifically, the aggregate response in the left panel is the sum of the disaggregated responses in the right panel. Clearly, in this case (without interactions among sectors) each sectoral shock only affects the sector from which the shock originates. The aggregate response for hours is negative and the effect persists in the long run. The right hand panel indicates that the impact response is positive only for a minority 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).[22]

[Insert figure 1]

When we allow for sectoral interactions, we obtain a very different outcome. Figure 2 shows that technology shock to all sectors now has a positive (short and long run) aggregate impact on total hours in manufacturing. Even though the confidence intervals on the impulse responses are wide, the effect of technology on hours is always significant. The impact of the shock is

[19] In appendix C we show that Δh^*_{it-1} can be used as an additional instrument in the productivity equation and that, under fairly general conditions, should improve the identification in (13). Indeed, the inclusion of this instrument increases the average value of the partial R^2 of Shea (1997) by approximately 20% (and the average adjusted partial R^2 by 30%). Since including redundant moment conditions might result in poor finite sample performance, the results reported below do not include the lagged aggregate shocks, $\mathbf{d}_{t-1}$, among the instruments used.

[20] Pesaran and Tosetti (2007) and Chudik and Pesaran (2007) show that neglecting cross section dependence (i.e. estimating 10 without the cross-sectional averages) could cause the estimator of the coefficients A_{il} ($\forall i$ and $l = 0, 1$) 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 without including the cross sectional averages (as Kiley, 1998, and Chang and Hong, 2006) would give similar results.

[21] The aggregation weights are proportional to the average shipment value of each sector. Even though some sectors have a bigger share in total shipments, the unweighted average of the impulse responses would be very similar.

[22] Basu, Fernald, and Kimball (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.

generally also much larger in magnitude, highlighting the importance of sectoral interactions as an amplifier of sectoral shocks (Cooper and Haltiwanger, 1996). The right hand panel reports the response of each sector (weighted as discussed above). Many sectors (169) show a positive impact of a technology shock on hours, and despite the fact that this is not the majority, the weighted effect is positive for manufacturing as a whole. From Figure 2 it is also evident that the total positive effect is driven by the large response in a few sectors; interestingly, these are also the largest supplier sectors.[23] Shocks to sectors that are most connected are strongly amplified by factor demand linkages. Therefore, shocks to these sectors are the most likely to explain the aggregate business cycle, 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 2]

5.1.1 The role of the factor demand linkages

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, thus amplifying the original effect of the shock. Sectoral interactions, therefore, 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). 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' supplies. In Figure 3 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.[24]

[Insert figure 3]

There is considerable heterogeneity in the dynamic response to a technology shock, the direct effects on hours are generally negative, only being positive for 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.

Sectoral interactions appear to be key to re-establishing a positive aggregate response of hours to technology shocks. 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, in fact the marginal costs of production in other sectors decrease as input prices decline and as a consequence demand increases. The impulse response analysis in Carvalho (2009) supports the presence of this broad

[23] 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.

[24] In Appendix B we derive expressions for the direct and the complementary effects. We scale them so that the aggregate response in the left panel of figure 3 can be recovered by summing up all the direct and complementary effects.

comovement in the production of each sector after a positive technology shock to the sectors that are the bigger suppliers in the economy. In this sense, the procyclical effect due to the intermediate input channel is amplified and overwhelms the effect coming from the marginal productivity of leisure.[25] This is, in fact, consistent with the empirical evidence in Figure 3. 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 most connected through input-output linkages.[26]

Moreover, Figure 3 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 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. 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 misleading.

Overall, these results highlight the quantitative and qualitative importance of the intermediate input channel as a way by which idiosyncratic sectoral shocks are propagated. They also draw attention to the potentially important role this channel might have for understanding the dynamic response of hours 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 compared to non-technology shocks. Furthermore, we evaluate the importance of the factor demand linkages among sectors as a transmission mechanism for idiosyncratic shocks. Since each sector is 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) to other sectors. Table 2 shows that aggregate shocks have a limited role to play in explaining sectoral movements. In fact, aggregate technology shocks account for about 5% of the overall variation in labor productivity. For hours it declines from an initial 10% to 5%.

[25] The standard RBC model assumes that the substitution effect after a technology shock dominates the wealth effect, therefore implying a positive shift in labor input. Francis and Ramey (2005a) and Vigfusson (2004) show how the introduction of habits in consumption and investment adjustment costs inverts their relative importance, giving rise to a temporary fall in labor supply. Chang, Hornstein, and Sarte (2009) also show that inventory holding costs, demand elasticities, and price rigidities all have the potential to affect employment decisions in the face of productivity shocks. Canova, Lopez-Salido, and Michelacci (2007) show that a negative response of the labor input is consistent with a Schumpeterian model of creative destruction, where improvements in technology trigger adjustments along the extensive margin of the labor market. Kim and Kim (2006) emphasize the role of the intermediate input channel in producing positive comovement in labor input.

[26] 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 simply be a reflection of the fact that the larger input suppliers tend to be larger in size (the correlation between these two measures is 0.28).

The role of the monetary policy shock is also limited. As for sectoral shocks, technology shocks account for much of the volatility in labor productivity, but with a sizable part (20 to 25%) originating in other sectors. The variation in hours is initially dominated by non-technology shocks, but, nevertheless, technology shocks coming from other sectors are also important. On impact technology shocks account roughly for 20% of the variation in hours, with its role rising steadily to roughly 40%, though this increase is entirely due to the role of technology shocks to other sectors. This reflects the fact that the complementary effect dominates the direct effect in the aggregate response of hours 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 because in such a case the role of technology shocks in the explanation of total hours would be completely underestimated, as it would only account for only $15-20\%$ of the variation.

[Insert Table 2]

Once the role of factor demand linkages is accounted for, the positive conditional correlation between productivity and hours is re-established and technology shocks appear to be important drivers of aggregate fluctuations.

5.3 A historical decomposition of the Business Cycle

In this section we provide a historical decomposition of business cycle fluctuations in the manufacturing sector. We first consider the importance of aggregate and sectoral specific shocks. It is widely agreed that the positive comovement across sectors is a stylized fact that needs to be accounted for by any theory of the business cycle. Whether this comovement and the aggregate business cycle originates from aggregate or sectoral shocks amplified by sectoral interactions, or a combination of the two is not clear a priori (see e.g. Cooper and Haltiwanger, 1996). To evaluate the importance of the aggregate shocks we compute the contribution of those to the total variation in aggregate manufacturing productivity and hours by looking at the partial R^2 and the cross section pairwise correlations which can be attributed to the aggregate shocks, $\boldsymbol{\lambda}_i \mathbf{d}_t$. The average partial R^2 is approximately just 8% for both labor productivity and hours.[27] Furthermore, the aggregate component is able to explain only a small part of the comovement (see top panel of Table 1), indeed the average pairwise correlation of the aggregate component is 0.05 for labor productivity and 0.044 for hours.

In Figure 4 we decompose the historical aggregate business cycle for manufacturing into that which is attributable to sectoral shocks and that which is attributable to the aggregate technology and monetary shocks.[28] The figure clearly shows that the bulk of aggregate volatility is to be attributed to sectoral shocks.[29] The aggregate technology shock plays a very limited

[27] The fit of the whole SVARX (10) measured by the average value of the generalized R^2 (Pesaran and Smith, 1994), is approximately 0.29 for labor productivity and 0.55 for hours.

[28] Labor productivity is defined as output per hours worked, so output growth can be recovered. The exact procedure for aggregation is discussed in Appendix D.

[29] 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 Halti-

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 4]

These results suggest that the role of aggregate shocks, in particular those to technology, in explaining the aggregate business cycle in manufacturing is limited.

In order to assess the role of different types of shocks originating at the sectoral level, Figure 5 shows simulated aggregate hours and output growth implied by the industry specific technology and non-technology shocks. Of the total variation explained by industry specific shocks, 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 seem 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 accounted for by technology shocks rises from (approximately) 37 to 73% for output and 27 to 70% for hours. By contrast, non-technology shocks appear to be more important in the earlier period from 1960 to 1980. Furthermore, the slow down at the beginning of the 90s seems to be largely the result of technology shocks (Hansen and Prescott, 1993). These results are generally consistent with the view that demand shocks were the main driver of the business cycle before the 1980s, whereas supply side shocks have gained importance since then (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).

[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 numbers 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 that might result from sectoral interactions. In Figure 5 we show that shocks that are almost equally uncorrelated with each other (see bottom panel of Table 1) are able to explain a large part of the aggregate variation in manufacturing once the amplification mechanism coming from sectoral interactions is allowed for.

The results above underline the role of factor demand linkages in reproducing aggregate fluctuations. In Figure 6 we show a decomposition of the business cycle that is directly attributable to shocks, both aggregate and sector specific, and plot them against the actual data (the difference can be attributed to the amplification role of the intermediate input channel).

wanger (1996). Conley and Dupor (2003) also support the sectoral origin of the business cycle. On the other hand, Foerster, Sarte, and Watson (2008) report evidence that most of the variance of industrial production at the sectoral level is explained by the presence of two aggregate factors, even after controlling for the role of factor demand linkages.

The pattern that emerges is revealing. With our specification, the propagation and amplification mechanism arising from the presence of factor demand linkages among sectors appears to be key to reproducing aggregate business cycle fluctuations.

[Insert figure 6]

6 Some Robustness Checks

In order to test the robustness of our results we have performed a number of checks. First, we replicated our results using different measures of hours, employment, hours worked and labor productivity. The results, not reported here, confirm the previous analysis.

[Insert figure 7]

Secondly, we generated the cross sectional averages by using the first IO matrix for the subsample up until 1980 and the second thereafter, instead of using the simple average of two different input-output matrices for 1977 and 1987. The left panel of Figure 7 plots the short run responses of hours 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.

Thirdly, to address possible problems with only 37 annual observations for each industry, we repeated the analysis by pooling sectors at the 3 digit SIC level, i.e. each more aggregated sector is estimated as a pooled VAR (as in Chang and Hong, 2006). This implicitly assumes that heterogeneity among industries in the same 3 digit class is limited relative to heterogeneity across different industries. The right panel of Figure 7 reports the short run response of hours 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 at the 4 digit level gives rise to a larger impulse response of hours in aggregate. This is consistent with the theoretical findings of Swanson (2006), who shows that heterogeneity might itself be a source of amplification for shocks hitting the economy.

[Insert figure 8]

Next we examined the robustness of our results to the choice of conditioning aggregate shocks. Which shocks/factors to include is not uncontroversial. Earlier we used a measure of aggregate technology so as not to attribute all the effect of technology shocks to the sector specific shocks. However, the measure derived by Basu et al. (2006) does not explicitly consider possible amplification due to the input-output linkages. To check the robustness of our findings we have computed the impulse responses for hours worked to a permanent productivity shock for different aggregate factors. We consider three different combinations of possible aggregate shocks. In the left panel of Figure 8 we include shocks similar to Shea (2002). Specifically, we have included an exogenous oil production shock[30] as well as the spread between 6 month

[30] The data for the oil production shock is from Kilian (2008). This series measures the shortfall of OPEC oil production caused by exogenous political events such as wars or civil disturbances. This paper's yearly shock is

commercial paper and the Treasury-Bill interest rate, which is intended to proxy for monetary policy (Friedman and Kuttner, 1992).[31] In the central panel of Figure 8 we include the oil production shock and the growth rate of real government defense spending to proxy for exogenous government spending shocks.[32] In the last panel we use the growth rate of real government defense spending and the monetary policy shock. As shown in Figure 8, which aggregate factor we use does not significantly alter the results of the previous section. All specifications give quantitatively similar results and the short run response for all sectors is strongly correlated with the baseline specification (furthermore the correlation increases if longer horizons are considered). Moreover, all specifications show a positive aggregate response of hours to a productivity shock.

[Insert figure 9]

As a final robustness check following Chang and Hong (2006) we replicated the results using TFP. Specifically, we identify technology shocks as 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 9 provides evidence of the direct and complementary effect on hours 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 by using TFP, the aggregate response of hours is dominated by the complementary effect, which is positive and much larger than the direct effect. Similarly to the shocks identified from labor productivity, the larger the role of the sector as an input supplier in the economy, the larger the effect of the shocks will be. The intermediate input channel continues to provide a strong amplification mechanism for idiosyncratic shocks, and to be the key mechanism for understanding aggregate responses. Furthermore, even though the impulse responses of TFP are not strictly comparable to those for labor productivity, 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 hours, 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 (SecVAR) 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 sectoral interactions. In line with the real business cycle model of Long and Plosser (1983), Horvath (1998, 2000) and Carvalho (2009) factor demand linkages prove to be an important amplifier of the shocks hitting the economy. Most importantly, we show that the contraction in hours worked in

the sum of the quarterly shocks.

[31] The inclusion of the commercial paper spread as a measure of monetary policy, produces results which are quantitatively and qualitatively very similar to those with a monetary policy shock measured as in Christiano, Eichenbaum, and Evans (1999) and reported in the previous sections.

[32] Ramey and Shapiro (1998) highlight that military buildups correspond to the big upswings in military spending during the period under analysis. Using dummy variables corresponding to the military buildups dates would give very similar results.

response to a technology shock found in many other studies remains if sectoral interactions via the input-output matrix are ignored. However, when the latter are incorporated into the model, technology shocks generate an increase in hours and are an important source of fluctuations in output. This is because the intermediate input channel itself provides an additional explanation for a positive shift in hours.

This paper clearly points to some of the potential problems that may arise when sectoral interactions are ignored.

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Tables

TABLE 1 - PRELIMINARY ANALYSIS OF COMOVEMENT

		Labor Productivity	Hours
$\bar{\hat{\rho}}$		0.055	0.202
CD		109.28	403.44
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
Onatski	$(H_0: r = 0)$	6.838*	5.661
	$(H_0: r = 1)$	6.838*	—
	$(H_0: r = 2)$	1.405	—
Identified idiosyncratic shocks		Technology	Non Technology
$\bar{\hat{\rho}}$		0.009	0.010
CD		18.89	20.93
Onatski	$(H_0: r = 0)$	2.295	2.501

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, $\bar{\hat{\rho}} = [2/N(N-1)] \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$ 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 $CD = \sqrt{2T/N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$, which tends to $N(0,1)$ under the null. The second part of each panel 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.

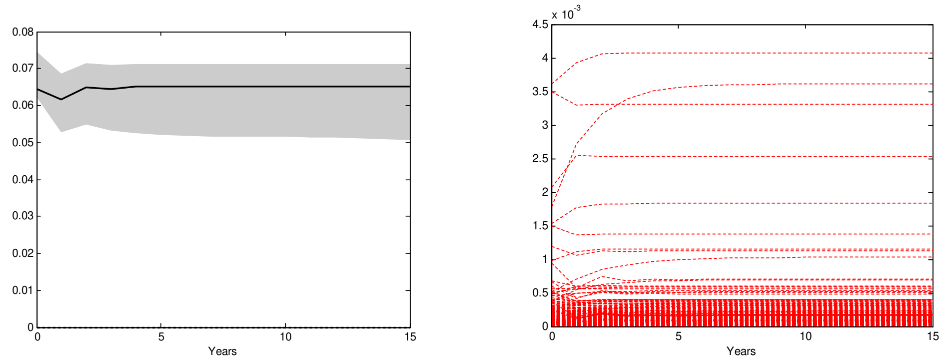
TABLE 2: FORECAST VARIANCE DECOMPOSITION						
LABOR PRODUCTIVITY						
	Sect. Technology		Sect. Non-Technology		Aggregate Technology	Monetary Policy
HORIZON	Same Sector	Other sectors	Same Sector	Other sectors		
1	74.11	12.33	2.40	2.12	3.62	5.38
	(69.7 – 79.1)	(6.5 – 16.0)	(1.6 – 2.9)	(0 – 3.4)	(0.3 – 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: The table reports the mean (weighted average) of the forecast error variance decomposition of productivity and hours. 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.

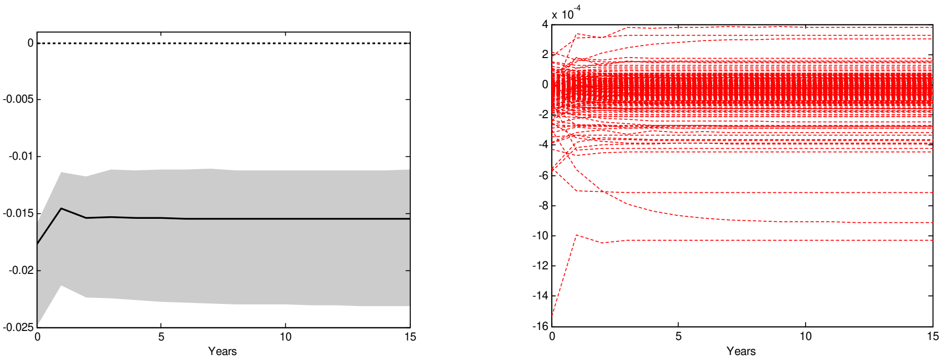
Figures

FIGURE 1 - IMPULSE RESPONSES TO AN AGGREGATE TECHNOLOGY SHOCK (WITHOUT SECTORAL INTERACTIONS)

PRODUCTIVITY



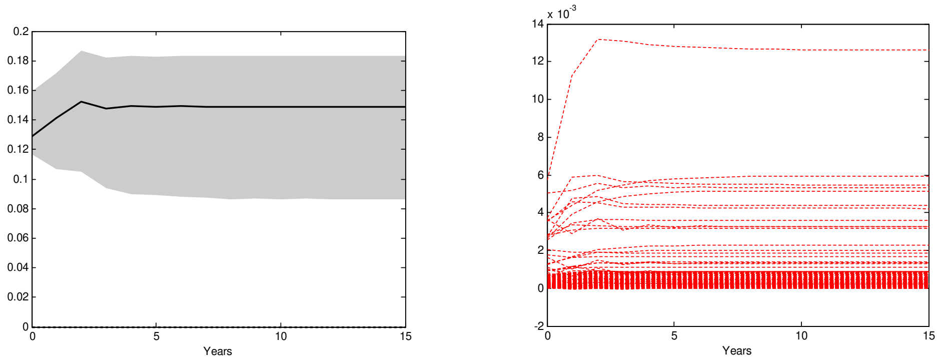
HOURS



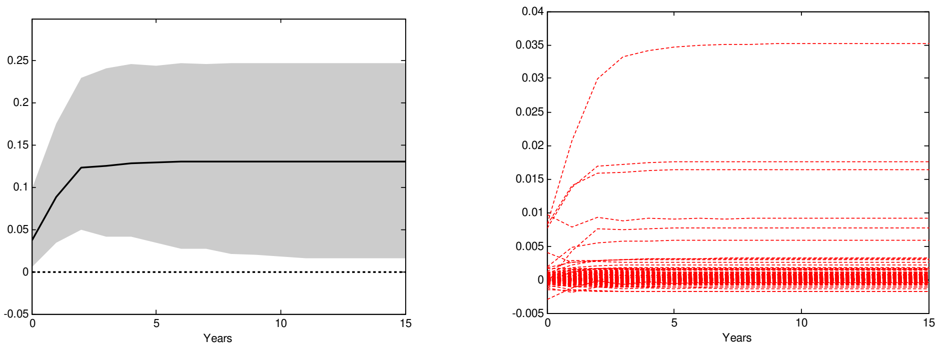
Notes: The figure shows impulse responses of labor productivity and hours to a contemporaneous shock, where no interaction between sectors is allowed. The left hand panel provides the aggregate response, the shaded area represents the 90-percent confidence intervals (Hall's "percentile interval", see 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 2 - RESPONSES TO AN AGGREGATE TECHNOLOGY SHOCK
(WITH SECTORAL INTERACTIONS)

PRODUCTIVITY



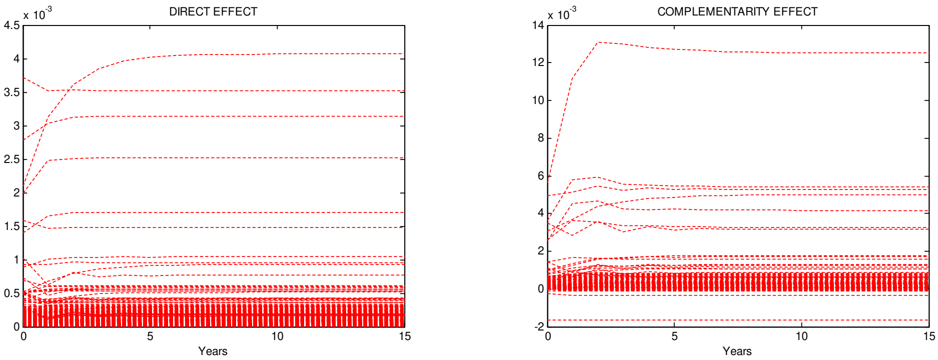
HOURS



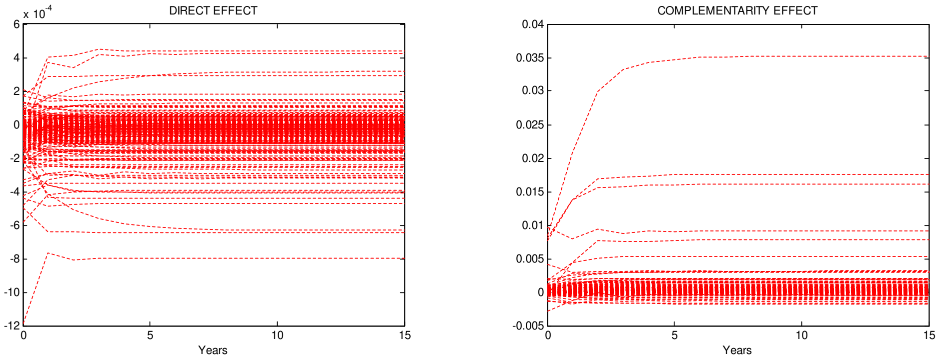
Notes: The figure shows impulse responses of labor productivity and hours to a contemporaneous change to the idiosyncratic sectoral technology shock when sectoral interactions are at work. The left hand panel provides the aggregate response, the shaded area represents the 90-percent confidence intervals (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, such that the sum of these corresponds to the figure on the left hand side.

FIGURE 3 - DECOMPOSITION OF THE DYNAMIC RESPONSE TO A TECHNOLOGY SHOCK

PRODUCTIVITY



HOURS



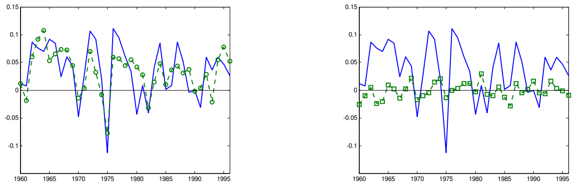
Notes: The figure shows the response of hours to an idiosyncratic technology shock at the sectoral level. The original impulse responses are weighted according to industry size, measured by the real value of shipments; in this way the sum of the sectoral impulse responses exactly match the aggregate response reported in Figure 2.

FIGURE 4 - BUSINESS CYCLE, HISTORICAL DECOMPOSITION

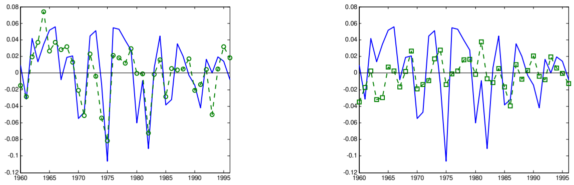
Sectoral vs aggregate shocks

SECTORAL SHOCKS	AGGREGATE TECH. SHOCK	MONETARY POLICY SHOCK

OUTPUT



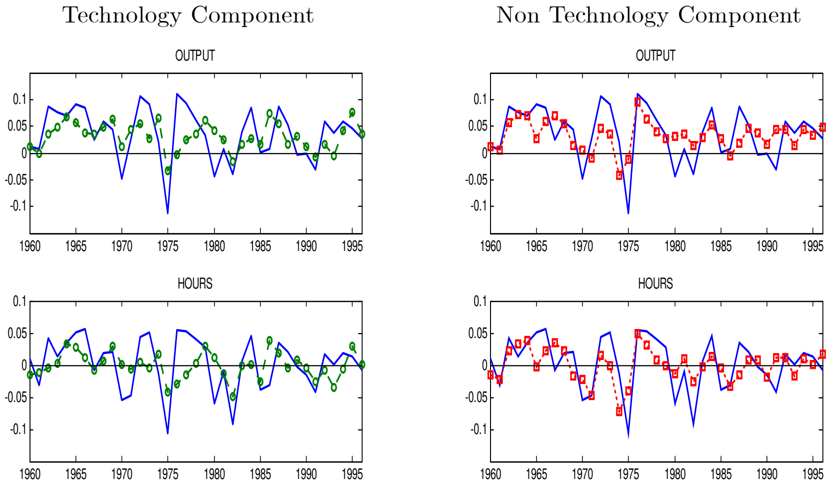
HOURS



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 $(-\square-\square-)$ the aggregate technology shock and the green dashed line with triangles $(-\triangle-\triangle-)$ is the component associated with monetary policy shocks.

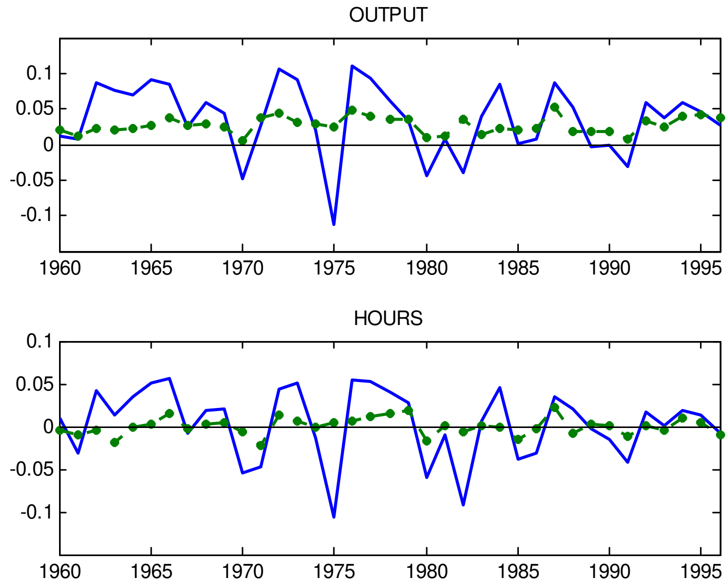
FIGURE 5 - BUSINESS CYCLE, HISTORICAL DECOMPOSITION

Technology vs non-technology shocks



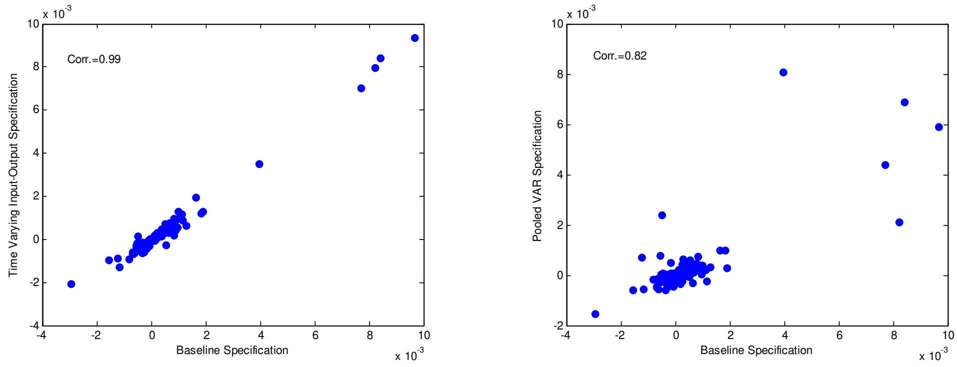
Notes: The figure shows a historical decomposition of the aggregate growth rate of manufacturing output and hours into that which is attributable to technology (left panel) and non-technology shocks (right panel). The blue continuous (—-) line represents actual data, the green dashed line with circles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

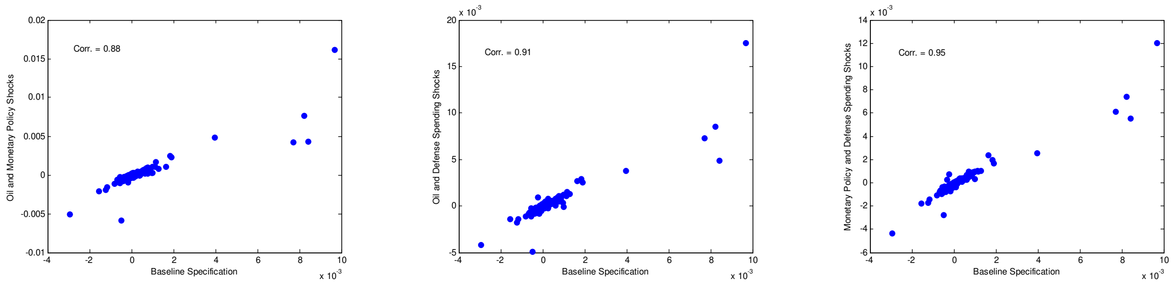
FIGURE 7 - ROBUSTNESS TO VAR SPECIFICATION



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 matrices (left panel) and pooling sectors to the 3 digit SIC level (right panel).

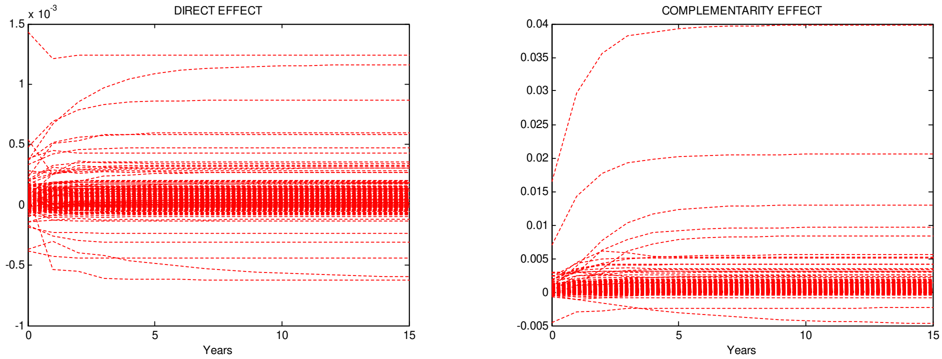
FIGURE 8 - ROBUSTNESS TO THE CHOICE OF AGGREGATE SHOCKS

OIL AND MON. POL. | OIL AND DEF. SPEND. | DEF. SPEND. AND MON. POL.



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 different choices of the aggregate shocks.

FIGURE 9 - Dynamic Response of Total Hours Worked to a permanent shock to TFP



Notes: The figure 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.

Appendix A: Labor productivity and TFP

Chang and Hong (2006) have argued that total factor productivity (TFP) and 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, both integrated of order 1, are not cointegrated. Therefore, the long run component of labor productivity does not truly identify technology shocks. In the top panel of Table A we report tests for cointegration between TFP and labor productivity using both the IPS test and the CIPS test. In both cases, as with Chang and Hong (2006), the null cannot be rejected at the conventional level. In the bottom panel, instead, 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, where those reflect the role played by the relative prices in line with what would be implied by the multi-sectoral model of section 2, specifically equation (3). Thus, we are now able to reject the null of a unit root, which implies that shocks that affect labor productivity in the long run reflect changes in TFP in some sector, which are propagated though the input-output linkages of the economy.

The simple sectoral bivariate VAR for TFP and labor input employed by Chang and Hong (2006) cannot fully capture 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 analyzing 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.

TABLE A - 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 productivity and TFP. All series are entered in log form, x_{it} is labor productivity, z_{it} is total factor productivity, $x^*_{it} = \sum_{j=1}^{N} \omega_{ij} x_{jt}$, 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. Underneath 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 10% level.

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 we estimate 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, and (abstracting from the presence of the aggregate shocks) $\mathbf{u}_t$ is a vector of the same size corresponding to 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 clearly appears 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

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

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

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

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

$$\mathbf{G}_0^{21} = \begin{bmatrix} \mathbf{io}_2^{[1]} \otimes (-\mathbf{C}_{20}) \\ \dots \\ \mathbf{io}_N^{[1]} \otimes (-\mathbf{C}_{N0}) \end{bmatrix},$$

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, 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 VAR for the all industries (11) is inverted to give

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

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)[33] 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 $\mathbf{s}_{11}$

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

implicitly selects the first n column of $\mathbf{G}_0^{-1}$, specifically

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

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. 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, captured by $\mathbf{G}_0^{21}$. These effects are further amplified by the interconnectivity 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 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[34].

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 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 $\boldsymbol{\psi}(0) = \left[\begin{array}{cc} \left(\mathbf{A}_{10}^{-1}\boldsymbol{\varrho}_1\right)', & \underbrace{\mathbf{0}'}_{1\times[(N-1)2]} \end{array}\right]'$.

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

Appendix C: 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 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

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

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 $A^{12}_{i0} = -A^{12}_{i1}$. A similar restriction for technology shocks to other sectors is also imposed, i.e. $C^{12}_{i0} = -C^{12}_{i1}$. It follows that the technology shock for sector i, ε^z_{it}, can be recovered from

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

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 hours 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[35]. 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[36]. Rewriting the expression as a 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 hours, 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 labor input is not zero. This condition corresponds to the long run neutrality of aggregate shocks to the labor input, as considered in Campbell

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

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

el al. (1996). However, as they also recognize, this restriction is quite restrictive and not entirely innocuous[37]. In the light of this we include Δh^*_{it-1} as an additional instrument for the identification of A_i^{12} above.

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

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

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

[37]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 D: Aggregation

Here we explain how to obtain the aggregate series and impulse responses for output and hours[38]. Small capitals indicate the logarithms of the variables, aggregate variables are denoted with a tilda. By definition aggregate hours is

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

and 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

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

[38] Note that in the text we defined log of hours as h_{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 $q_{it} = x_{it} + h_{it}$.

Additional results: Unit root versus stationary hours

There is an issue in literature concerning how the labor input (hours) should be modeled when extracting the technology shock.[39] 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, Smith, and Yamagata (2007)[40]. 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 B. Specifically, the null hypotheses cannot be rejected for the level of log labor productivity (x_{it}) and hours (h_{it}), 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 analyze (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.[41] Nevertheless, the 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 labor input. Indeed, the forcing variables will be acting to balance the distortionary effect of any low frequency components of the labor input, as well as possible breaks or nonlinearity in the variable.

[39] The empirical evidence on the stationarity of aggregate hours worked is mixed (see e.g. Shapiro and Watson, Shapiro and Watson (1988)). Christiano, Eichenbaum, and Vigfusson (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, more specifically, the mistreatment of labor input in the empirical model. Indeed, they find that the effect of a technology shock on the labor input clearly depends on the treatment of the labor input; if this is included in levels the puzzling result disappears.

[40] 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.

[41] 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.

TABLE B - UNIT ROOT TEST

	$CADF(0)$	$CADF(1)$	$CADF(2)$	$CADF(3)$
With intercept and linear trend				
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 depend 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.