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# FACTOR DEMAND LINKAGES, TECHNOLOGY SHOCKS, AND THE BUSINESS CYCLE

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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 the business cycle.

## I. 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 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 levels and 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, modeling aggregate time series directly implies that sectors are relatively homogeneous and, most important, that interactions among sectors are of second-order importance for aggregate fluctuations.<sup>1</sup>

Following the pioneering work of Long and Plosser (1983), real business cycle (RBC) models have been generalized into a multisectoral environment where industry-specific shocks

are propagated through sectoral interdependencies 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 multisectoral 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 nontechnology 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 nontechnology 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 a positive correlation between hours 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. Galí (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 Galí & Rabanal, 2004, 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 & Ramey, 2005). Galí (1999) suggests that the paradigm needs to be changed in favor of a business cycle

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<sup>1</sup> 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.

model driven by nontechnology 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 rest of the literature. The input-output channel can be both qualitatively and 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 significant, shocks to other sectors (transmitted through sectoral interactions) are fundamental for tracking individual sectoral cycles. Our analysis suggests that once sectoral interactions are accounted for, technology and nontechnology shocks seem to be equally important in explaining aggregate economic fluctuations in U.S. 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 II, we employ a basic multisectoral RBC model to derive long-run restrictions, which we then use in the empirical analysis. In section III, we show how to identify technology and nontechnology shocks in a way consistent with the restrictions of the multisectoral model, employing a structural VAR but applied to industrial sectors. We describe the data in section IV. In section V, we report our findings. In section VI, we consider some robustness checks. Section VII contains concluding remarks.

## II. A Simple Multisectoral 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 buffeted only 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,

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

subject to the usual intertemporal budget constraint. Here,  $E_0$  is the expectation operator conditional on time  $t = 0$ ,  $\beta$  is the discount factor, and  $V(L_t)$  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  $C_t = \prod_i \xi_i^{-\xi_i} \tilde{C}_{it}^{\xi_i}$ , 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

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

The shocks to preferences are exogenous and are assumed to follow an autoregressive process of the form  $Z_{it}^P = (Z_{it-1}^P)^\rho \exp[\Phi_i^P(L)\varepsilon_{it}^P]$  where  $|\rho| \leq 1$ ,  $\Phi_i^P(L) = (1 - \phi_i L)^{-1}$  is a square summable polynomial in the lag operator ( $|\phi_i| < 1$ ) and  $\varepsilon_{it}^P$  is white noise.<sup>2</sup>

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

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

$M_{ijt}$  is the intermediate input  $j$  used in the production of good  $i$ ,  $S_i$  is the set of supplier sectors of sector  $i$ ,  $\gamma_{ij}$  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  $Z_{it} = (Z_{it-1}) \exp[\mu_i^z + \Phi_i^z(L)\varepsilon_{it}^z]$ , where  $\mu_i^z$  is a constant drift and  $\Phi_i^z(L) = (1 - \rho_i L)^{-1}$  is a square summable polynomial in the lag operator (i.e.,  $|\rho_i| < 1$ ) and  $\varepsilon_{it}^z$  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, that is,  $\text{Cov}(\varepsilon_{it}^z, \varepsilon_{jt}^z) = 0, \forall i \neq j$ . Given the

<sup>2</sup>It is convenient to assume that the shocks are normalized such that  $\prod_i (Z_{it}^P)^{\xi_i} = 1$ , that is, idiosyncratic shocks do not directly affect aggregates (see also Franco & Philippon, 2007).

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:  $W_{it} = W_{jt} = W_t \forall i, j$ . The latter implies that the relative price of two goods is inversely related to relative (labor) productivity,

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

where  $\kappa_{ij}$  reflects differences in the labor intensity of the production functions.<sup>3</sup> From the definition of the price index for intermediate goods, the relative price of intermediate goods is

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

The relative prices act as an important conduit for the transmission of technology shocks. A positive technology shock to the  $j$ th sector lowers the price in the same sector. Since part of the production of the  $j$ th sector is supplied to the  $i$ th 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

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

where  $\phi_i$  is a convolution of the production parameters. Expression (3) makes it clear that in a multisectoral model, the long-run level of labor productivity is driven only by technology shocks, originating in either the same sector or other sectors through the intermediate inputs channel. Defining  $x_{it}$  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

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

where  $\mathbf{I}$  is the identity matrix,  $\mathbf{A} = \text{diag}(\alpha_1, \dots, \alpha_N)$ ,  $\boldsymbol{\phi} = [\log \phi_1, \dots, \log \phi_N]'$ , and  $\mathbf{G}$  is the “use” input-output matrix

<sup>3</sup>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 & Samaniego, 2008).

whose generic elements are the parameters  $\gamma_{ij}$  introduced above. The long-run response of labor productivity in sector  $i$  to the innovation to technology is then

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

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

where  $\mathbf{D} = \text{diag}(\rho_1, \dots, \rho_N)$  and  $\mathbf{v}_k$  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

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

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

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

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

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

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

$$H_{it} = \frac{(1 - \alpha_i) \xi_i Z_{it}^p Y_{it}}{\chi C_{it}} \frac{\partial V(L_t)}{\partial L_t} \quad (9)$$

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:

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

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

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 Horvath, 2000; Kim and Kim, 2006; Foerster, Sarte, & Watson, 2008).

### III. 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 nontechnology shocks.

Following Galí (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.<sup>4</sup> 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  $i$ th sector in the long run is also affected by labor productivity in the sectors that supply intermediate goods to the  $i$ th sector, through changes in relative prices as in equation (3). Therefore, to identify technology and nontechnology 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 multisectoral model with factor demand linkages. Specifically for each industry, we estimate the model<sup>5</sup>

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

where  $\boldsymbol{\varkappa}_{it} = [\Delta x_{it}, \Delta h_{it}]'$  and  $\Delta x_{it}$  and  $\Delta h_{it}$  denote, respectively, the growth rate of labor productivity and labor input<sup>6</sup> and  $\boldsymbol{\varkappa}_{it}^*$  are appropriate industry-specific weighted cross-sectional averages of the original variables in the system that 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,  $\boldsymbol{\varkappa}_{it}^* = [\sum_{j=1}^N \omega_{ij} \Delta x_{jt}, \sum_{j=1}^N \omega_{ij} \Delta h_{jt}]'$ , where the weights,  $\omega_{ij}$ , correspond to the (possibly time-varying) share of commodities  $j$  used as an intermediate input in sector  $i$  (i.e.,  $\omega_{ij} \approx \gamma_{ij}$ ). The specification includes a set of  $k$  exogenous aggregate variables,  $\mathbf{d}_t$ , which are meant to control for the effect of aggregate (nominal and real) shocks hitting the economy.<sup>7</sup> The sectoral idiosyncratic shocks  $\boldsymbol{\varepsilon}_t = [\boldsymbol{\varepsilon}'_{1t}, \dots, \boldsymbol{\varepsilon}'_{Nt}]'$  are such that for each industry  $\boldsymbol{\varepsilon}_{it} = [\boldsymbol{\varepsilon}'_{it}, \boldsymbol{\varepsilon}'_{it}]'$ , where  $\boldsymbol{\varepsilon}'_{it}$  denotes the technology shock and  $\boldsymbol{\varepsilon}''_{it}$  denotes the nontechnology shock for the  $i$ th sector. The key identifying assumption is that  $E(\boldsymbol{\varepsilon}'_{it}\boldsymbol{\varepsilon}_{it}) = \boldsymbol{\Omega}_{ie} \forall i$  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  $i$ th sector, this restriction has to be imposed on shocks originating in the  $i$ th sector and on shocks originating in other sectors that supply inputs to the  $i$ th sector. The equilibrium relation for labor productivity in equation (4) states that labor productivity in the long run in the  $i$ th sector is affected only by direct technology shocks to the 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  $A_{i0}^{12} = -A_{i1}^{12}$ . The second restriction, which is nonstandard, is derived from equation (8) and requires that  $C_{i0}^{12} = -C_{i1}^{12}$ .

It is possible to recover the SecVAR specification by stacking the sector-specific models in equation (10). The model can be rewritten as

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

<sup>4</sup> See, for example, King, Plosser, and Rebelo (1988), King et al. (1991), and Christiano and Eichenbaum (1992). Notice that increasing returns, capital taxes, and some models of endogenous growth would all imply that nontechnology shocks can change long-run labor productivity, thus invalidating the identifying assumption. Francis and Ramey (2005) 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.

<sup>5</sup> 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 terms (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.

<sup>6</sup> 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 (Campbell & Kuttner, 1996; Phelan & Trejos, 2000). Evidence that labor productivity and labor input follow unit root processes is provided in Holly and Petrella (2010).

<sup>7</sup> Foerster et al. (2008) emphasize that a factor error structure at the industry level can arise from both the presence of aggregate shocks and input-output linkages.

where  $\kappa_t = [\kappa'_{1t}, \dots, \kappa'_{Nt}]'$  and the matrices of coefficients are

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

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 equation (10), as outlined in Pesaran et al. (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 equation (11), more specifically,

$$\kappa_t = \mathbf{B}(L)\mathbf{u}_t. \quad (12)$$

The transmission mechanism is captured by  $\mathbf{B}(L)$ , a matrix polynomial in the lag operator,  $L$ , and the innovations are such that  $E(\mathbf{u}'_t \mathbf{u}_t) = \mathbf{\Omega}_t$  and  $E(\mathbf{u}'_t \mathbf{u}_s) = \mathbf{0} \forall t \neq s$ .<sup>8</sup> The specification in equation (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-specific component ( $\mathbf{u}_{it} = \lambda_i \mathbf{d}_t + \varepsilon_{it}$ ).

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, equation (12), with each sector analyzed in isolation (i.e., the matrix polynomial  $\mathbf{B}(L)$  is composed of block diagonal matrices). The specification in equation (10) encompasses the specification of Kiley (1998) and Chang and Hong (2006) by setting the coefficients reflecting factor-demand linkages to 0 ( $\mathbf{C}_{il} = \mathbf{0}, \forall i, l$ ). However, the model in the previous section makes it clear that this would be appropriate only 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 on only aggregate shocks. The specification in equation (10) instead allows us to 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 et al. (2004) but at the industry level. The difference is that we consider a fully structural model: 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.

## IV. Data and Estimation Results

### A. Data Description

The data used are collected from the NBER-CES Manufacturing Industry Database (Bartelsman & Wayne, 1996). The database covers all four-digit manufacturing industries from 1958 to 1996 (39 annual observations) ordered by 1987 SIC codes (458 industries).<sup>9</sup> Labor input is measured as total hours worked, while productivity is measured as real output divided by hours.<sup>10</sup> Each variable is included as a log difference, where this choice is supported by panel unit root tests.

We match the data set with the standard input-output matrix at the highest disaggregation, provided by the Bureau of Economic Activity (BEA).<sup>11</sup> 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 1.

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 equation (4). In the empirical analysis, however, we use the average of the input-output matrix in 1977 and 1987.<sup>12</sup> In the robustness section, we investigate whether the results are affected by changes in the IO structure.

<sup>9</sup> As in other studies we exclude the Asbestos Product industry (SIC 3292) because the time series ends in 1993.

<sup>10</sup> 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 of Holly and Petrella (2010), we address this question. Furthermore, in section VI, we show that our results are robust to whether we use TFP or labor productivity.

<sup>11</sup> The data are available at [http://www.bea.gov/industry/io\\_benchmark.htm](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 (four-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 among the SIC sectors. The original IO matrix also includes within-sectors trade, we exclude this from the calculation of the standardized weighting matrix.

<sup>12</sup> 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 on request.

<sup>8</sup> Appendix B in Holly and Petrella (2010) provides more details on the construction of equation (11) and how to recover the MA moving average representation, as well as some detailed discussion of the transmission mechanism of idiosyncratic shocks.

TABLE 1.—PRELIMINARY ANALYSIS OF COMOVEMENT

	Labor Productivity	Hours
$\bar{\rho}$	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	Technology	Nontechnology
$\bar{\rho}$	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	Nontechnology
$\bar{\rho}$	0.009	0.010
CD	19.04	20.94
Onatski		
( $H_0: r = 0$ )	2.683	2.274

The first part of the table reports measures of the strength of the cross-sectional dependence between sectors.  $\bar{\rho}$  is the simple average of the pair-wise cross-section correlation coefficients,  $\bar{\rho} = [2/N(N-1)] \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}$  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 (2007). 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  $\kappa = 3$ . \* Significant at the 5% level.

### B. 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, and the second row reports the associated cross-section dependence (CD) test of Pesaran (2004). 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 takes the residuals recovered from the SecVAR described by equation (10) but without allowing for the input-output channel (so for each  $i$ ,  $C_{i0} = C_{i1} = 0$ ). Again the residuals, corresponding to technology and nontechnology shocks, exhibit considerable cross-section dependence, especially for the nontechnology shocks.

In the 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 nontechnology shocks, whereas it identifies no aggregate factors for the labor productivity series and the technology shocks.<sup>13</sup> 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

<sup>13</sup> These results are consistent with Bai and Ng (2002)  $IC_{P1}$  and  $BIC_3$  criteria with a maximum number of factors set to 5. The  $BIC_3$  criteria are reported given that they perform well in the presence of pervasive weak cross-sectional dependence (see Bai & Ng, 2002; Onatski, 2005).

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 nontechnology shocks.<sup>14</sup>

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, equation (10). Specifically, we include the aggregate technology shock constructed by Basu, Fernald, and Kimball (2006) and a monetary policy shock derived from an exactly identified VAR, estimated on quarterly data averaged for each year, following the procedure adopted by Christiano, Eichenbaum, and Evans (1999).<sup>15</sup> The bottom panel of table 1 shows that the shocks identified by the sectoral model, equation (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 although 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, that is, the covariance matrix of the idiosyncratic shocks in equation (12),  $\Omega_\varepsilon$ , 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 equation (10) is not able to capture.<sup>16</sup>

In order to quantify how widespread the rejection of orthogonality is, we computed the number of significant correlations between sectors. The number of rejections varies

<sup>14</sup> The information criteria of Bai and Ng (2002) and the test introduced by Onatski (2007) determine the number of common static factors. As Stock and Watson (2002b) observed, the number of static factors imposes an upper bound on the possible number of dynamic common factors. Foerster et al. (2008) also find evidence consistent with 1 or 2 static common factors in their analysis of sectoral industrial production.

<sup>15</sup> The data are provided by Basu et al. (2006) and are available at the AER Web site (<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.

<sup>16</sup> 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  $\Omega_\varepsilon$ . Here the issue is complicated as we identify not one but two types of shock.

from a minimum of 11 to a maximum of 67 (median 36) for technology shocks and 17 and 73 (median 39) for nontechnology 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 & Tosetti, 2007, and Carvalho, 2009), and (c) the importance of a sector as an input user (measured by the number of supplying sectors and the size of the input material bill). Overall, for considerations a and c, there seems to be no relation (the correlations are rather small and are all insignificant). For consideration b, even though there is no relation for technology shocks, there seems to be a significant correlation for nontechnology 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 assuming that  $\Omega_\varepsilon$  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 of little importance for explaining aggregate fluctuations in manufacturing. Therefore, in the rest of the paper, we proceed as if  $\Omega_\varepsilon$  is diagonal.

### C. The Exogeneity of Cross-Sectional Averages

An important issue for the consistent estimation of equation (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 equation 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

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

and

$$\Delta h_{it} = (A_{i0}^{21} + A_{i1}^{21} L) \Delta x_{it} + (C_{i0}^{21} + C_{i1}^{21} L) \Delta x_{it}^* + A_{i1}^{22} \Delta h_{it-1} + (C_{i0}^{22} + C_{i1}^{22} L) \Delta h_{it}^* + \lambda_{hi} \mathbf{d}_t + \varepsilon_{it}^p. \quad (14)$$

Estimation of equations (13) and (14) requires three instruments in each equation. The long-run restrictions on the effect of nontechnology shocks allow the use of the lagged (growth) of hours and the associated cross-sectional average,  $\Delta h_{it-1}$  and  $\Delta h_{it-1}^*$ , among the instruments in the equation for labor

productivity. Furthermore, the identified technology shock from equation (13) can be used to identify the contemporaneous relation between labor productivity and hours in equation (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.<sup>17</sup> 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 (Eichenbaum, Hansen, & Singleton, 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 two industries for productivity and in only seven industries for hours (out of 458).<sup>18</sup> 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 equation (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 part of equation (10), thus partially addressing some of the concerns of Christiano et al. (2003) about possible biases arising from the use of weak instruments.<sup>19</sup>

## V. Technology Shocks and the Business Cycle

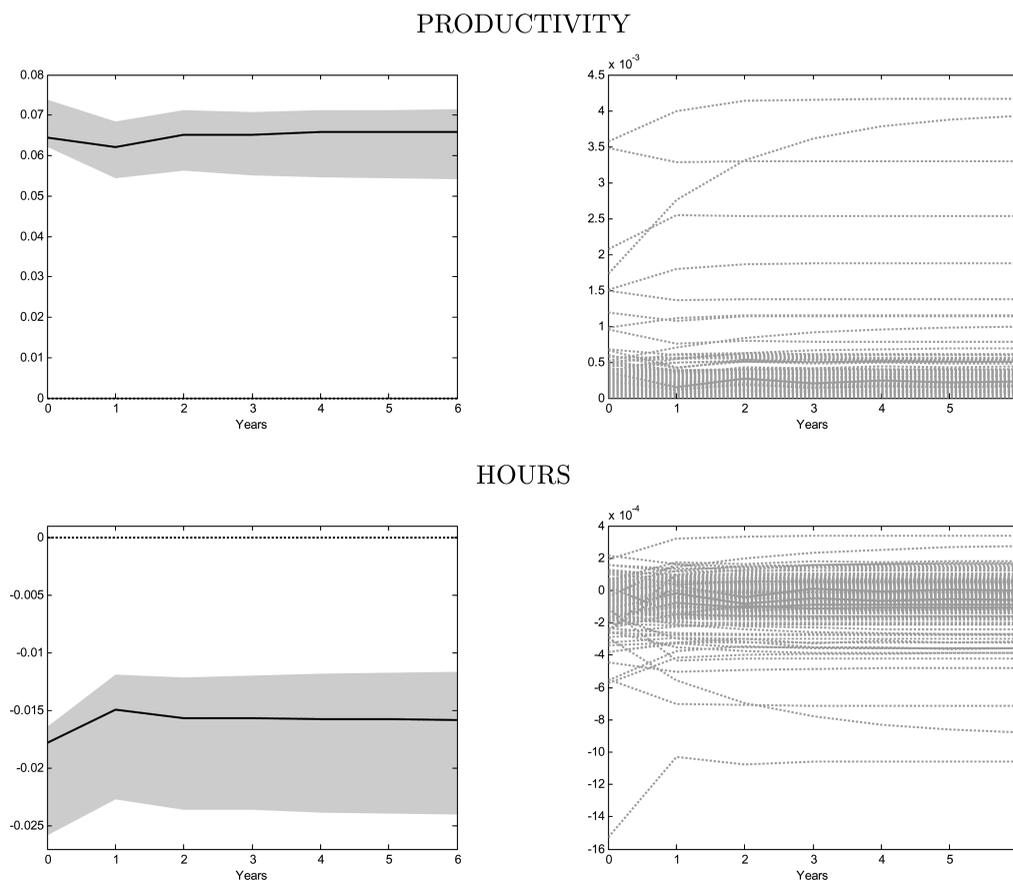
Real business cycle theory assigns a central role to technology shocks as a source of aggregate fluctuations. Moreover, positive technology shocks should lead to positive comovement of output, hours and productivity. However, Galí (1999) finds that positive technology shocks appear to lead to a decline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

<sup>17</sup> Shea (1997) partial  $R^2$  suggest that those are relevant instruments.

<sup>18</sup> None of the sectors where we reject the null is a large input supplier.

<sup>19</sup> In appendix C of Holly and Petrella (2010), we show that  $\Delta h_{it-1}^*$  can be used as an additional instrument in the productivity equation and that, under fairly general conditions, should improve the identification in equation (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.

FIGURE 1.—IMPULSE RESPONSES TO TECHNOLOGY SHOCKS WITHOUT SECTORAL INTERACTIONS



The figure shows impulse responses of labor productivity and hours to a contemporaneous technology shock to all sectors, where no interaction between sectors is allowed. The left panels provide the aggregate response, and the shaded area represents the 90% confidence intervals (Hall's "percentile interval"; see Hall, 1992) based on bootstrapping 500 draws. The right panels show the sectoral responses weighted by sectoral average real shipment value, such that the sum of these corresponds to the panels on the left.

A. *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.<sup>20</sup> The panel on the left displays the aggregate response of manufacturing to a contemporaneous shock to all sectors, and the panel on the right displays the aggregate response to each of the  $N$  sectoral shocks.<sup>21</sup> 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 affects only the sector from which the shock originates. The aggregate response for hours is negative, and the effect persists in the long run. The right 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 & Hong, 2006, when they use labor productivity) and confirm previous findings in the literature (see, e.g., Galí, 1999; Francis & Ramey, 2005).<sup>22</sup>

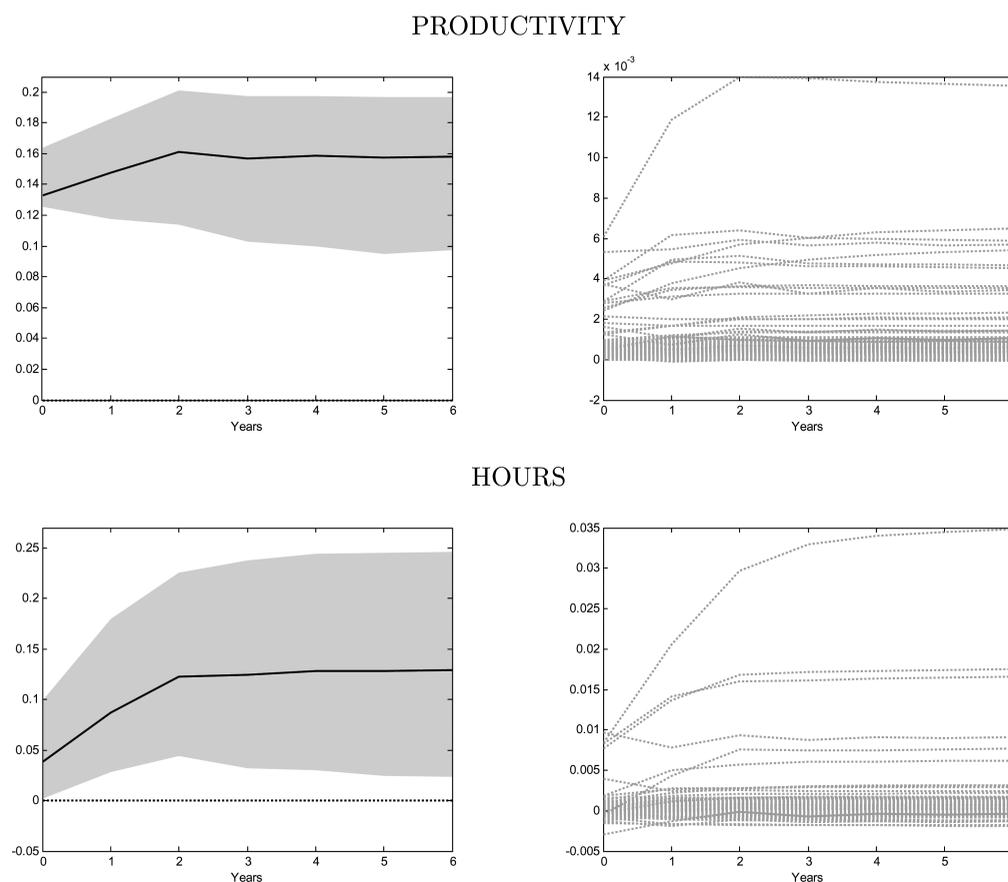
When we allow sectoral interactions, we obtain a very different outcome. Figure 2 shows that technology shock to all sectors now has a positive (short- and long-run) aggregate impact on total hours in manufacturing. Although the confidence intervals on the impulse responses are wide, the effect of technology on hours is always significant. The impact of the shock is generally also much larger in magnitude, highlighting the importance of sectoral interactions as an amplifier of sectoral shocks (Cooper & Haltiwanger, 1996). The right 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

<sup>20</sup> Pesaran and Tosetti (2007) and Chudik and Pesaran (2007) show that neglecting cross-section dependence, that is, estimating equation (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 equation (10) and then set  $C_{il}$  ( $\forall i$  and  $l = 0, 1$ ) arbitrarily equal to  $\mathbf{0}$ . Estimating the bivariate model without including the cross-sectional averages (as in Kiley, 1998, and Chang & Hong, 2006) would give similar results.

<sup>21</sup> The aggregation weights are proportional to the average shipment value of each sector. Although some sectors have a bigger share in total shipments, the unweighted average of the impulse responses would be very similar.

<sup>22</sup> Basu et al. (2006) reach the same conclusion identifying the shocks from a completely different perspective. They also identify the shocks at the sectoral level (two-digit SIC) but do not consider sectoral interactions.

FIGURE 2.—IMPULSE RESPONSES TO TECHNOLOGY SHOCKS WITH SECTORAL INTERACTIONS



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 panels provides the aggregate response; the shaded area represents the 90% confidence intervals (Hall's "percentile interval"; see Hall, 1992) based on bootstrapping 500 draws. The right panels show the sectoral responses weighted by sectoral average real shipment value, such that the sum of these corresponds to the panels on the left.

sectors; interestingly, these are also the largest supplier sectors.<sup>23</sup> 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.

*The role of the factor demand linkages.* In the reduced-form model (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

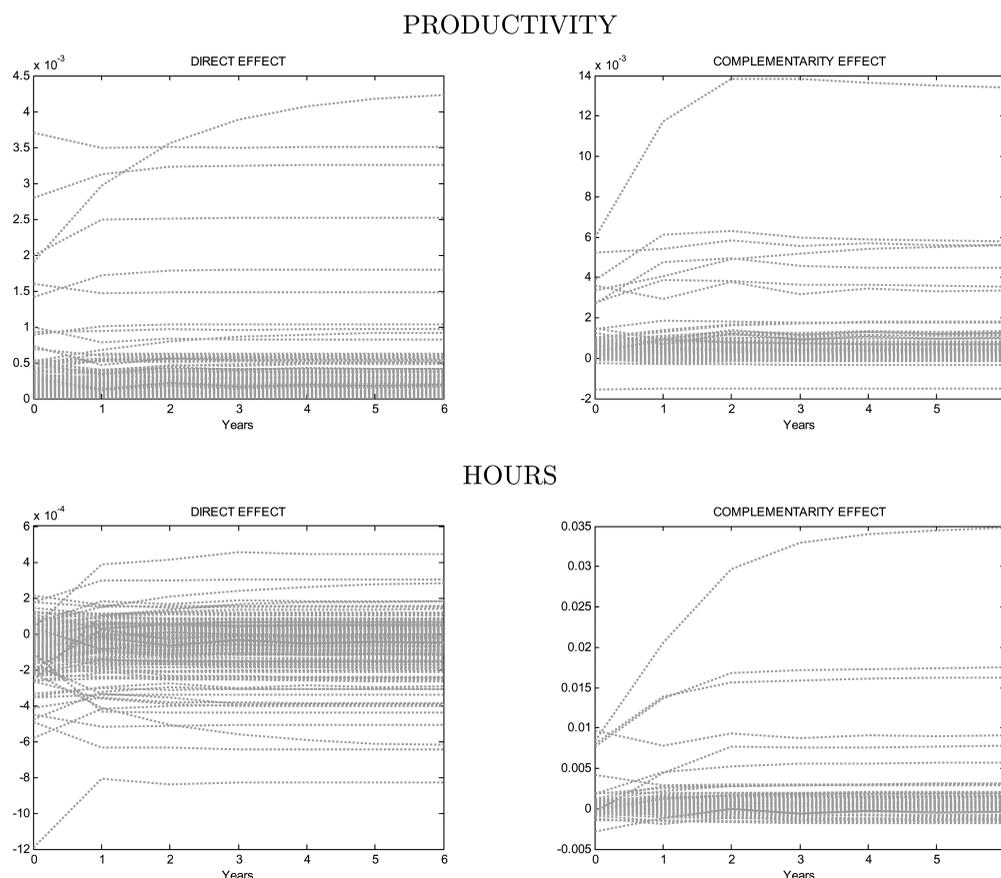
a rich set of short-run dynamics. The first effect from sector  $i$  to all the other sectors in the economy is a downstream propagation from supplier to user (Shea, 2002). At the same time, we have the second-round effect, a reflex response, as the original sector is also a user of other sectors' supplies. In figure 3 we separate out the two components: the direct component (the effect of a shock to sector  $i$  on the same  $i$ th sector) and the complementary component (the effect of this shock on all other sectors).<sup>24</sup> There is considerable heterogeneity in the dynamic response to a technology shock, the direct effects on hours are generally negative, being positive for only 96 sectors. However, the direct effect is also relatively small. The complementary effect usually overwhelms the effect of the shock to the same sector. This is especially true for the dynamic response of hours.

Sectoral interactions appear to be key to reestablishing 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

<sup>23</sup> The most important five sectors are all part of 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.

<sup>24</sup> In appendix B of Holly and Petrella (2010), 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.

FIGURE 3.—DECOMPOSITION OF THE DYNAMIC RESPONSES TO A TECHNOLOGY SHOCK



The figure shows the decomposition of the responses of labor productivity and 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 matches the aggregate response reported in figure 2.

by it. Positive shocks to sectors that 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 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 utility of leisure.<sup>25</sup> 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 most connected through input-output linkages.<sup>26</sup>

Moreover, figure 3 makes clear that the dynamic response following a technology shock to a particular sector is indeed different depending on whether the shock originates in the sector itself or is a shock to other sectors transmitted through factor demand linkages. According to the aggregation theorem in Blanchard and Quah (1989), 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

<sup>25</sup> 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 (2005) 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.

<sup>26</sup> 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 equation (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).

TABLE 2.—FORECAST VARIANCE DECOMPOSITION

HORIZON	Sector Technology		Sector Nontechnology		Aggregate Technology	Monetary Policy
	Same Sector	Other sectors	Same Sector	Other sectors		
Labor Productivity						
1	74.11 (69.7–79.1)	12.33 (6.5–16.0)	2.40 (1.6–2.9)	2.12 (0–3.4)	3.62 (0.3–5.5)	5.38 (1.8–8.2)
2	72.35 (66.7–79.5)	21.49 (13.6–27.1)	0.24 (0.09–0.3)	0.82 (0–1.5)	3.47 (0–6.3)	1.60 (0–3.1)
3	73.66 (67.2–81.3)	22.52 (13.9–28.7)	0.04 (0–0.08)	0.15 (0–0.4)	3.39 (0–6.2)	0.20 (0–0.5)
5	73.76 (66.6–82.3)	22.91 (14.0–29.7)	0.003 (0–0.01)	0.01 (0–0.06)	3.28 (0–6.2)	0.01 (0–0.06)
10	73.83 (66.6–83.0)	22.86 (13.3–29.2)	0.0 (0–0)	0.0 (0–0.003)	3.29 (0–6.1)	0.0 (0–0.001)
Hours						
1	12.76 (11.0–14.7)	9.69 (2.6–14.3)	41.80 (37.0–46.6)	19.79 (10.4–26.5)	8.83 (1.2–14.4)	7.11 (3.9–9.1)
2	11.42 (9.4–13.4)	20.14 (9.9–27.8)	32.10 (28.0–35.9)	22.81 (13.2–30.6)	7.67 (0–13.6)	5.82 (2.4–8.1)
3	10.96 (8.6–13.1)	26.44 (14.9–36.6)	31.92 (27.0–36.6)	20.11 (9.7–27.8)	5.76 (0–9.6)	4.78 (0.5–7.6)
5	10.97 (8.4–13.3)	28.73 (15.5–40.4)	31.43 (26.2–36.4)	19.95 (10.1–28.0)	4.09 (0–6.9)	4.81 (0–7.5)
10	10.97 (8.2–13.5)	29.12 (14.3–41.1)	31.18 (25.8–36.6)	19.86 (9.6–27.9)	4.01 (0–6.6)	4.82 (0–7.5)

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.

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.

### B. 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 nontechnology 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  $j$ th 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%. 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 nontechnology shocks; nevertheless, technology shocks coming from other sectors are also important. On impact, technology shocks account for roughly 20% of the variation

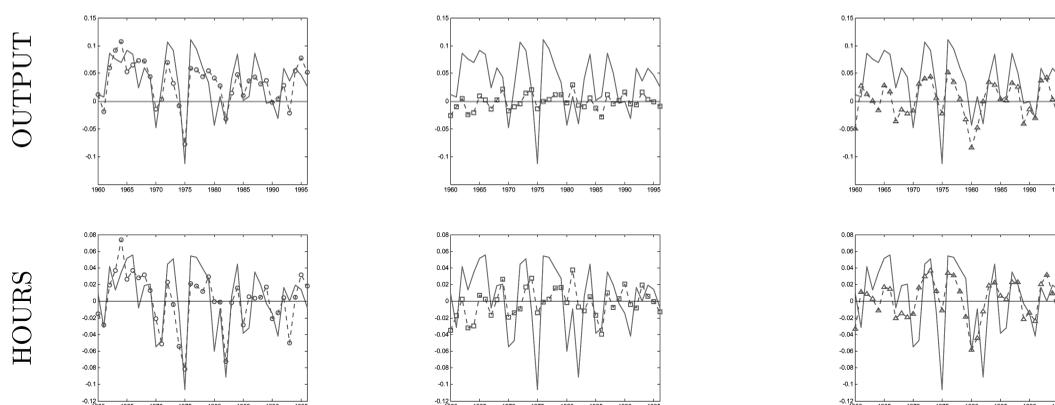
in hours, with its role rising steadily to roughly 40%, though this increase is entirely due to the role of technology shocks to other sectors. This reflects the fact that the complementary effect dominates the direct effect in the aggregate response of hours to a technology shock. Sectoral interactions, 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 account for only 15% to 20% of the variation.

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

### C. 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 originate from aggregate or sectoral shocks amplified by sectoral interactions or a combination of the two is not clear a priori (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 that can be attributed to the aggregate

FIGURE 4.—BUSINESS CYCLE, HISTORICAL DECOMPOSITION: SECTORAL VERSUS AGGREGATE SHOCKS



The figure shows a historical decomposition of the aggregate growth rate of output and hours into sector-specific and aggregate shocks. The continuous line represents the actual data, the dashed line with circles the simulated data with only sector-specific shocks, the dashed line with squares the aggregate technology shock, and the dashed line with triangles is the component associated with monetary policy shocks.

shocks,  $\lambda_i d_i$ . The average partial  $R^2$  is approximately just 8% for both labor productivity and hours.<sup>27</sup> Furthermore, the aggregate component is able to explain only a small part of the comovement (see the 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.<sup>28</sup> The figure clearly shows that the bulk of aggregate volatility is to be attributed to sectoral shocks.<sup>29</sup> The aggregate technology shock plays a very limited role. However, a bigger role can be assigned to monetary policy shocks. Interestingly, monetary policy seems to account for the recession in the early 1980s, corresponding to the Volcker disinflation. 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 nontechnology 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 nontechnology shocks seem to be equally important for explaining aggregate fluctuations. Nevertheless, some differences 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, nontechnology shocks appear to be more important in the earlier period, from 1960 to 1980. Furthermore, the slowdown at the beginning of the 1990s seems to be largely the result of technology shocks (Hansen & 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 (Galí & Gambetti, 2009). Interestingly the latest period also corresponds to a steady decrease in aggregate volatility, the so-called great moderation (see Stock & Watson, 2002a).

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 idiosyncratic 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 the 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.

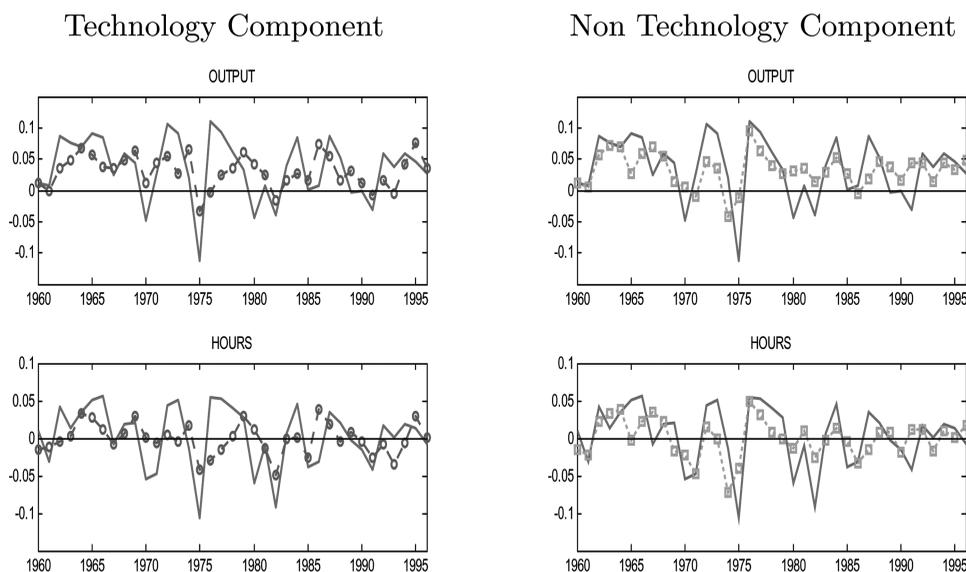
The results above underline the role of factor demand linkages in reproducing aggregate fluctuations. In figure 6 we show a decomposition of the business cycle that is directly attributable to shocks, both aggregate and sector specific, and plot them against the actual data (the difference can be attributed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

<sup>27</sup> The fit of the whole SVARX, equation (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.

<sup>28</sup> 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 of Holly and Petrella (2010).

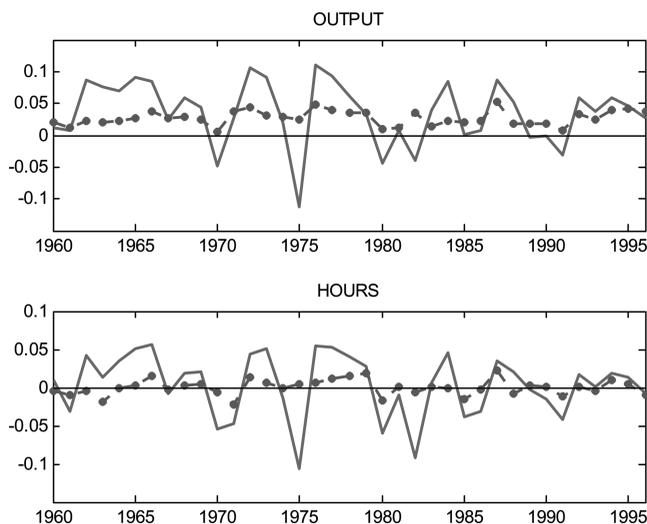
<sup>29</sup> On empirical grounds, Long and Plosser (1987) first investigated whether the source of business cycle fluctuations is aggregate or sector specific. Their analysis is consistent with the existence of a single aggregate disturbance whose explanatory power is, however, limited. Similar results are reported by Cooper and Haltiwanger (1996). Conley and Dupor (2003) also support the sectoral origin of the business cycle. On the other hand, Foerster et al. (2008) report evidence that most of the variance of industrial production at the sectoral level is explained by the presence of two aggregate factors, even after controlling for the role of factor demand linkages.

FIGURE 5.—BUSINESS CYCLE, HISTORICAL DECOMPOSITION: TECHNOLOGY VERSUS NONTECHNOLOGY SHOCKS



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

FIGURE 6.—BUSINESS CYCLE, HISTORICAL DECOMPOSITION: THE ROLE OF FACTOR-DEMAND LINKAGES



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 continuous line represents the actual data and the broken line with dots the simulated data with aggregate and idiosyncratic shocks but excluding sectoral interactions.

channel). 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.

### VI. Some Robustness Checks

In order to test the robustness of our results, we have performed a number of checks. First, we replicated our

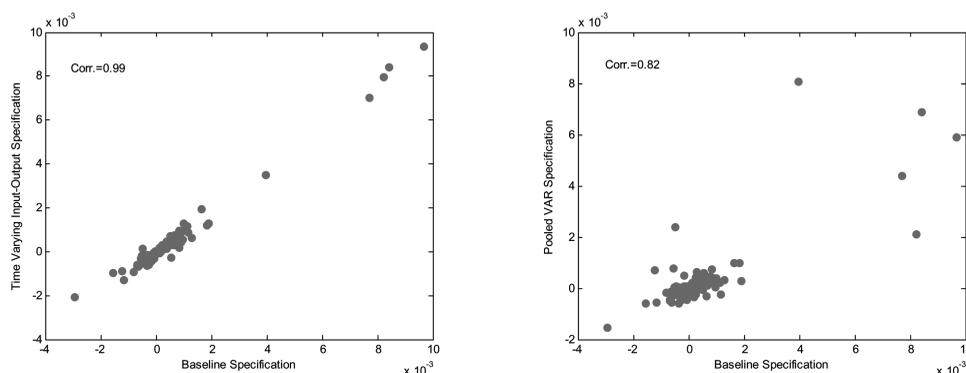
results using different measures of hours, employment, hours worked, and labor productivity. The results, not reported here, confirm the previous analysis.

Second, 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 in relation to 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.

Third, to address possible problems with only 37 annual observations for each industry, we repeated the analysis by pooling sectors at the three-digit SIC level; each more aggregated sector is estimated as a pooled VAR (as in Chang & Hong, 2006). This implicitly assumes that heterogeneity among industries in the same three-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 four-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 itself might be a source of amplification for shocks hitting the economy.

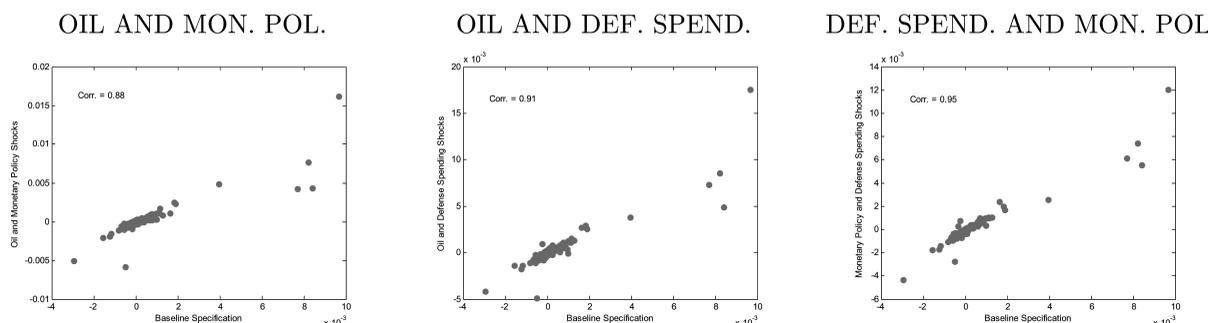
Next we examined the robustness of our results to the choice of conditioning aggregate shocks. Which shocks or factors to include is not uncontroversial. Earlier we used a measure of aggregate technology so as not to attribute all the effect of technology shocks to the sector-specific shocks.

FIGURE 7.—ROBUSTNESS TO VAR SPECIFICATION



x-axis: short-run responses of hours to permanent shocks to labor productivity from the baseline specification. y-axis: short-run response of hours to permanent shocks to labor productivity, controlling for time-varying input-output matrices (left) and pooling sectors to the three-digit SIC level (right).

FIGURE 8.—ROBUSTNESS TO THE CHOICE OF AGGREGATE SHOCKS



x-axis: short-run responses of hours to permanent shocks to labor productivity from the baseline specification. y-axis: short-run response of hours to permanent shocks to labor productivity, controlling for different choices of the aggregate 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, an exogenous oil production shock<sup>30</sup> as well as the spread between six-month commercial paper and the Treasury Bill interest rate, which is intended to proxy for monetary policy (Friedman & Kuttner, 1992).<sup>31</sup> 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.<sup>32</sup> In the last panel, we use the growth rate of real government defense spending and the monetary policy shock.

<sup>30</sup> The data for the oil production shock are 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 the sum of the quarterly shocks.

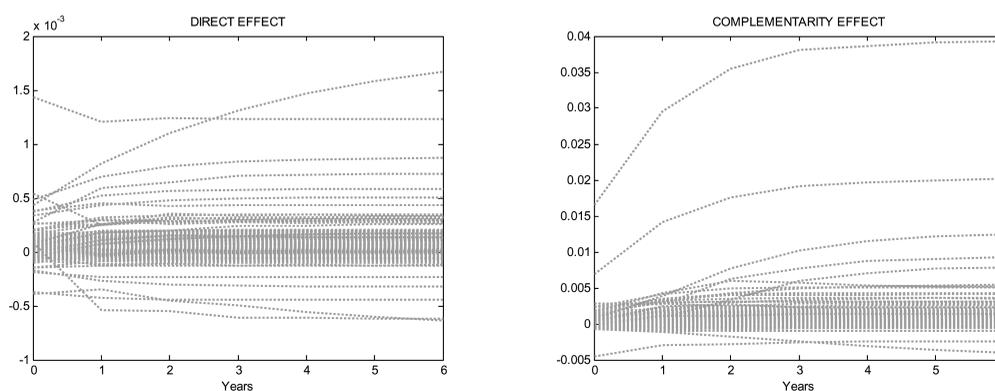
<sup>31</sup> The inclusion of the commercial paper spread as a measure of monetary policy produces results that are quantitatively and qualitatively very similar to those with a monetary policy shock measured as in Christiano et al. (1999) and reported in the previous sections.

<sup>32</sup> 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.

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.

As a final robustness check, following Chang and Hong (2006), we replicated the results using total factor productivity (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 equation (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. Similar 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, although

FIGURE 9.—DYNAMIC RESPONSE OF TOTAL HOURS WORKED TO A PERMANENT SHOCK TO TFP



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 equation (10), which uses the cross-sectional average computed from the input-output matrix to proxy for sectoral interactions.

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.

## VII. Conclusion

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 structural sectoral 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 important, we show that the contraction in hours worked in response to a technology shock found in many other studies remains if sectoral interactions via the input-output matrix are ignored. 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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