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COMPLEMENTARITIES AND COMOVEMENTS

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COMPLEMENTARITIES AND COMOVEMENTS

ABSTRACT

Short-run interindustry comovement may be due either to common shocks or to complementarities that propagate shocks across sectors. This paper assesses the importance of input-output linkages, aggregate activity spillovers, and local activity spillovers to comovement in postwar US manufacturing. I find that input-output linkages and local activity spillovers are important to comovement, while aggregate activity spillovers are not important. I find that complementarities are important to aggregate volatility, even after I remove observable aggregate shocks from the data. Local spillovers are particularly important, explaining between 15 and 36 percent of manufacturing employment volatility.

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I. INTRODUCTION

Positive comovement between different sectors of the economy is a salient feature of business cycles. Over the period 1959-1986, for instance, the average pairwise correlation of annual employment growth for the 126 three-digit US manufacturing industries listed in the Appendix is 0.341. For gross output and value added, the corresponding figures over 1960-1986 are 0.284 and 0.228. Similar evidence is presented in Long and Plosser (1987), Murphy, Shleifer and Vishny (1989 a), and Cooper and Haltiwanger (1990).

Interindustry comovement is essential to aggregate output and employment volatility. To see this, suppose we approximate the growth rate of some aggregate activity measure, denoted q , as a weighted average of disaggregated industry growth rates:

$$(1) \quad q_t \cong \sum_{i=1}^M \text{SHARE}_i q_{it},$$

where M is the number of sectors and SHARE_i equals sector i 's steady-state share of aggregate activity. Then the variance of q is approximately

$$(2) \quad \text{SHARE} * \Psi * \text{SHARE}',$$

where SHARE is a 1-by- M vector of industry shares and Ψ is the M -by- M variance-covariance matrix of disaggregated industry activity.

From (2), one can decompose the approximate variance of q into a term due to the diagonal elements of Ψ , and a "comovement" term due to the off-diagonal elements of Ψ . Table 1 presents this decomposition for manufacturing employment, gross output and value added growth, using

annual data over 1959-86 for employment and over 1960-86 for output and value added. The matrix Ψ and the vector SHARE are estimated using 126 three-digit manufacturing industries; the data are described in the appendix.

The results suggest that most aggregate volatility is due to interindustry comovement. For instance, the actual standard deviation of annual manufacturing employment growth over the sample period is 4.31 percent. The approximate standard deviation implied by (2) is 4.42 percent. The standard deviation implied by the diagonal elements of Ψ is just 0.99 percent, while the standard deviation implied by the off-diagonal elements of Ψ is 4.31 percent; comovement thus accounts for almost 95 percent of the variance of manufacturing employment. Qualitatively similar results hold for output and value added.

In principle, interindustry comovement could be due entirely to the direct effects of common shocks. For instance, monetary policy may directly affect the demand for all durable goods. However, comovement may also be caused by *complementarities* that propagate shocks across sectors. For instance, monetary policy may generate comovement between cars and steel not because money affects steel directly, but because money affects cars and because shocks to cars are transmitted to steel. Recent research has suggested several potential sources of interindustry linkage, including the input-output table (Long and Plosser (1983)), trading externalities (Diamond (1982)), and aggregate demand spillovers (Murphy, Shleifer and Vishny (1989 b)). Some of these linkages, such as input-output, are consistent with frictionless models; others inherently rely on frictions such as imperfect competition or externalities.¹ The common implication of such theories is that the interindustry *pattern* of

comovement depends on the interindustry pattern of linkage. Complementarities do not merely imply that A should comove with B; they imply that the amount of comovement between A and B should depend on the strength of the linkages between A and B.

This paper assesses the importance of complementarities for short-run comovement. Using postwar US data for disaggregated industries, I examine the relationship between the observed pattern of comovement and observable measures of complementarity suggested by three simple models. In Model One, shocks are propagated by factor demand linkages. The model implies that the effect of a shock to industry A on industry B depends on the strength of upstream and downstream linkages between A and B. In Model Two, shocks are propagated by an aggregate spillover, as in Baxter and King (1991); increases in aggregate output raise optimal output in each industry. The model implies that the effect of a shock to A on B depends on A's size: shocks to large industries have a larger aggregate impact than shocks to small industries, and are thus transmitted more strongly to other sectors. In Model Three, shocks are propagated by a local spillover; increases in overall city output raise optimal output in each local industry. The model implies that at the national level, the effect of a shock to industry A on industry B depends both on A's size and on whether A and B cluster in the same cities. Industries with a strong "spatial correlation" should exhibit strong temporal comovement.

The models imply that industry fluctuations result from the propagation of shocks through a matrix whose elements depend on observable measures of potential complementarity and on parameters governing the strength of different linkage mechanisms. Given sufficient restrictions on the covariance matrix of underlying shocks, I can estimate the

complementarity parameters using data on disaggregated industry fluctuations. My empirical work examines the pattern of comovement among 126 disaggregated US manufacturing industries, using annual data covering 1958-1986. I assess the importance of complementarities in two ways: first, I examine whether the complementarity parameters are statistically significant and of the correct sign; second, I measure the contributions of complementarities to aggregate volatility.

The rest of this paper proceeds as follows. Section II outlines the three models. Section III describes data sources and presents empirical results. Section IV compares my work to previous literature, and Section V concludes. My main results are as follows. I find that input-output linkages are important to short-run comovement, with significant linkages running both from downstream users to upstream suppliers and vice-versa. I find little support for aggregate activity spillovers. However, I find strong support for local activity spillovers; even after controlling for input-output linkages, industries clustered in the same cities tend to comove over the business cycle. I find that complementarities are important to aggregate volatility, even after removing observable aggregate shocks from the data. Local spillovers are especially important; for instance, I estimate that local spillovers are responsible for between 15 and 36 percent of employment volatility in manufacturing, depending on my treatment of aggregate shocks.

II. THREE MODELS OF INTERINDUSTRY COMPLEMENTARITY

This section presents three models of interindustry linkage. The models are simple, for the sake of analytic and empirical tractability. Nevertheless, I believe the models capture the essential implications of

their respective linkage mechanisms for the pattern of interindustry comovement, and that the models' qualitative predictions would thus remain true in richer models; exceptions are duly noted.

Model One: Factor Demand Linkages

This subsection presents a multisectoral general equilibrium model in which shocks are propagated by input-output linkages, as in Long and Plosser (1983). There is a representative agent with preferences

$$(3) \quad U = \sum_{i=1}^N \alpha_i \log(C_i) - L \quad ; \quad \alpha_i = a_i \exp(d_i) \quad ; \quad \sum_{i=1}^N a_i = 1.$$

Utility depends on consumption C_i of N goods, and on hours worked L . The goods have stochastic preference weights α_i . Some goods receive more weight than others on average; this is reflected in the fixed a_i parameters. The d_i are mean-zero taste (demand) shocks.

Each good is produced using both labor and intermediate inputs, where each of the N goods is potentially used as an input by every other good:

$$(4) \quad Q_i = \lambda_i * \left[\prod_{k=1}^N (X_{ki})^{\beta_{ki}} \right] * L_i^{\gamma_i} \quad ; \quad \gamma_i + \sum_{k=1}^N \beta_{ki} = 1.$$

Here, Q_i is output of good i ; X_{ki} represents the amount of k used as an input for i ; and

$$(5) \quad \lambda_i = \exp(s_i),$$

where the s_i are mean-zero technology (supply) shocks. Finally, market clearing requires

$$(6) \quad Q_i = \sum_{k=1}^N X_{ik} + C_i \quad ; \quad L = \sum_{i=1}^N L_i.$$

A log-linear approximation to the competitive equilibrium yields

$$(7) \quad q_i = K_i + \sum_{k=1}^N \text{COST}_{ik} s_k + \sum_{k=1}^N \text{DEM}_{ik} d_k,$$

where K_i is a constant. According to (7), fluctuations in industry i depend on technology and taste shocks in every industry. The effect of the technology shock s_k on q_i depends on COST_{ik} , equal to the ultimate dollar requirement of good k per dollar sold of good i , incorporating direct and indirect linkages. For instance, COST_{ik} could be high because i uses k as an input, or because i uses h while h uses k , and so on. The effect of the taste shock d_k on q_i , meanwhile, depends on DEM_{ik} , equal to the steady-state share of demand for i ultimately embodied in final purchases of k . DEM and COST are in turn functions of the taste and production parameters; details are provided in the appendix.

Notice that this model is oversimplified in that supply and demand shocks propagate in only one direction each. Technology shocks to industry A propagate downstream, affecting costs in sectors using A as an input, but do not affect upstream sectors supplying inputs to A . This is because utility and production functions are Cobb-Douglas. In general, (neutral) technology shocks have two competing effects on upstream demand: they reduce the amount of input needed to produce any given level of industry output, but they also raise industry output. Under Cobb-Douglas, these two effects cancel exactly; under alternative specifications, technology shocks could have upstream effects. Conversely, in this model taste shocks to industry A shift upstream demand curves, but do not affect downstream sectors using A as an input. This is because supply curves are flat. If A 's supply curve sloped up, then favorable taste shocks would raise A 's price, raising costs to downstream sectors. On the other hand, if A 's supply curve sloped down, then taste shocks would lower costs to

downstream sectors.

In the empirical work below, I assess the roles of upstream versus downstream linkages for comovement, using input-output matrices modelled on DEM and COST. While it is sometimes useful to refer to upstream propagation of shocks from users to suppliers as a "demand-side linkage", and downstream propagation from suppliers to users as a "supply-side linkage", the reader should keep in mind that the empirical results will reveal only the direction in which shocks propagate; the results will not in general reveal whether the fundamental shocks driving the economy are demand or supply shocks.

Model Two: Aggregate Activity Spillovers

This subsection presents a model in which shocks are propagated by an aggregate activity spillover. The representative agent's utility is

$$(8) \quad U = \sum_{i=1}^N \alpha_i \log(Q_i) - L \quad ; \quad \sum_{i=1}^N \alpha_i = 1.$$

As in Model One, utility depends on consumption Q_i of N final goods, and on hours worked L . The goods have nonstochastic preference weights; sectors with a high α are larger on average than sectors with low α .

Final goods are produced according to

$$(9) \quad Q_i = \lambda_i L_i (Q_A)^\beta \quad ; \quad \lambda_i = \exp(s_i),$$

where

$$(10) \quad Q_A = \sum_{i=1}^N Q_i \quad ; \quad L = \sum_{i=1}^N L_i.$$

Output of good i depends on labor, on productivity λ_i , and on aggregate activity Q_A , where β lies in the interval $[0,1)$. Assume that Q_A

is an externality; firms make decisions taking Q_A as given. Then a log-linear approximation to the competitive equilibrium yields

$$(11) \quad q_i = \log(\alpha_i) + s_i + \mu \sum_{z=1}^N \alpha_z s_z,$$

where μ equals $(\beta/1-\beta)$. From (11), fluctuations in industry i depend on i 's technology shock and on the aggregate activity index, which is a size-weighted average of all technology shocks. For simplicity, I have assumed that the aggregate spillover is an external economy of scale, as in Baxter and King (1991). However, an equation similar to (11) would presumably hold under other types of aggregate spillovers; the key feature of (11) is that shocks to large sectors have larger aggregate impacts, and thus larger effects on other sectors, than shocks to small sectors.² Notice that the effect of size on comovement in this model does not merely follow from the fact that large industries comprise a higher fraction of aggregate output than small industries. While it is true that the effect of industry shocks on *aggregate output* would trivially tend to increase with size in virtually any model, the effect of industry shocks on *other industries* increases with size only if aggregate spillovers are present.³

Model Three: Local Activity Spillovers

This subsection presents a model in which goods are produced in a large number of spatially distinct locations. Shocks are propagated by a symmetric local spillover, in which productivity in a particular industry-city depends on overall city output. The chief implication of the model is that the interindustry patterns of temporal comovement and spatial location should be similar.

The representative agent's utility at time t is

$$(12) \quad U_t = \sum_{i=1}^N C_{it} - L_t$$

Utility depends on the consumption C_{it} of N final goods, and on hours worked. Each final good, in turn, can be produced in a large number M of cities. In order to avoid complete concentration of industries in one city, I assume that different cities produce differentiated versions of each final good, which are imperfect substitutes in utility. Thus,

$$(13) \quad C_{it} = \sum_{j=1}^M \log(Q_{ijt}),$$

where Q_{ijt} is production of good i in city j at time t , given by

$$(14) \quad Q_{ijt} = u_{ijt} * L_{ijt} * (Q_{jt})^\beta,$$

where

$$(15) \quad u_{ijt} = \exp(s_{it}) * \exp(w_{ij})$$

and

$$(16) \quad Q_{jt} = \sum_{i=1}^N Q_{ijt}.$$

Production in an industry-city depends on labor; on the overall level of city activity Q_{jt} ; and on the productivity shifter u_{ijt} , which in turn depends on two terms: s_{it} , which varies over industries and time but not cities; and w_{ij} , which varies across industry-cities but not time. One can think of s as an industry-specific technology shock and w as a Ricardian parameter reflecting long-run attributes that give particular cities a comparative advantage in hosting certain industries.

Assume that agents regard local activity spillovers as an externality. Let Q_{it} denote industry i 's total output at time t , equal to

the sum of Q_{ijt} over M cities. Then a log-linear approximation to this economy's competitive equilibrium yields

$$(17) \quad q_{it} = K_i + s_{it} + \mu \sum_{k=1}^N \text{CITY}_{ik} s_{kt},$$

where the K 's are constants, μ equals $(\beta/1-\beta)$, and

$$(18) \quad \text{CITY}_{ik} = \sum_{j=1}^M \text{SHARE1}_{ji} * \text{SHARE2}_{kj},$$

where SHARE1_{ji} equals city j 's steady-state share of industry i 's activity, and where SHARE2_{kj} equals industry k 's steady-state share of city j 's activity; SHARE1 and SHARE2 in turn depend on the w parameters.

According to (17), fluctuations in industry i depend on technology shocks in all industries. The effect of a shock to industry k on industry i is proportional to CITY_{ik} , which is an average of k 's share of steady-state activity in the M cities, weighted according to each city's steady-state share of i 's activity. CITY_{ik} thus measures the extent to which i is concentrated in cities where k is important. Intuitively, if CITY_{ik} is large, then shocks to k have a large impact on activity in cities where i is clustered, and therefore propagate to i .

Notice that this model predicts that industries that cluster together in space should also comove through time. From (17), comovement between i and k increases in CITY_{ik} , which in turn increases in k 's size and in the degree to which i and k cluster in the same cities. The predictions of this model are thus at odds with a Marshallian "labor market pooling" story, in which industries with negatively correlated fluctuations optimally cluster together to stabilize local labor demand.⁴

I must point out that symmetric local spillovers are not the only mechanism that could generate a correspondance between the interindustry

patterns of spatial and temporal comovement. For instance, if city-specific shocks such as weather or taxes are important to fluctuations, then industries clustered in the same cities will tend to comove over time by virtue of experiencing a similar mix of local shocks. Alternatively, there may be asymmetric local spillovers, in which the degree of synergy varies across industry pairs; in this case, pairs with particularly strong linkages will comove over time and will optimally cluster together in space to maximize the synergy. Thus, while I frame the empirical findings below as evidence for symmetric local spillovers, one could also interpret the results as evidence for asymmetric spillovers or local shocks. These stories are difficult to distinguish using national data alone. However, in Shea (1995), I show that the three stories have sharply different implications for the pattern of interindustry comovement *within cities*, and can thus be distinguished using data on fluctuations at the city-industry level.

III. EMPIRICAL EVIDENCE

The models presented above imply that comovement results from the propagation of industry shocks through complementarities. This section presents empirical evidence on complementarities. I first describe my empirical framework. I assume that fluctuations obey

$$(19) \quad q_t = \mu + A * \varepsilon_t,$$

where q_t is an observable N-by-1 vector of industry fluctuations at time t; μ is an N-by-1 vector of constants; ε_t is a vector of mean-zero industry-level shocks, with covariance matrix Ω ; and A is an N-by-N matrix governing how shocks are propagated across sectors. The models outlined

in Section II suggest that A depends on observable measures of interindustry linkage and on parameters governing the strength of different propagation mechanisms. I specify A as follows:

$$(20) \quad A = \beta_1 * \text{COST} + \beta_2 * \text{DEM} + \beta_3 * \text{SIZE} + \beta_4 * \text{CITY}.$$

Here, COST is an N-by-N matrix whose [i,k] element equals the ultimate dollar requirement of good k per dollar sold of good i; DEM is a matrix whose [i,k] element equals the share of demand for i ultimately embodied in final purchases of k; SIZE is a matrix whose [i,k] element is proportional to k's size; and CITY is a matrix whose [i,k] element equals a weighted average of k's steady-state share of activity over a group of cities, weighted by each city's steady-state share of i's activity. From Section II, COST represents downstream propagation of shocks, from suppliers to users, while DEM represents upstream propagation of shocks, from users to suppliers; SIZE represents aggregate activity spillovers, while CITY represents local spillovers. COST and DEM are measured using 1977 US input-output data; SIZE is measured using industries' long-run average share of nominal manufacturing value added; and CITY is measured using 1977 disaggregated employment data for 273 cities.⁵ Details on data construction are provided in the appendix.

I estimate (19)-(20) using annual data from 1958-1986 on 126 US three-digit manufacturing industries. I experiment with three measures of q: the growth rate of employment, the growth rate of real gross output, and the growth rate of real value added. These series are constructed using the Penn-Census-SRI Productivity Database used in Bartlesman, Caballero and Lyons (1994); details are provided in the appendix.

Identification and Estimation

My objective is to use the pattern of interindustry comovement to identify the β parameters, along with the elements of the shock covariance matrix Ω . However, I cannot from (19)-(20) estimate both the β 's and an unrestricted Ω matrix. My identifying assumption in this paper is that industry shocks consist of two orthogonal components: an unobserved industry-specific component, assumed orthogonal across industries, and a component driven by observable aggregate disturbances. Specifically, I assume that

$$(21) \quad \varepsilon_t = v_t + F * a_t.$$

Here, v_t is an N-by-1 vector of industry shocks, with diagonal covariance matrix Σ ; a_t is a P-by-1 vector of observable aggregate shocks orthogonal to v_t ; and F is an N-by-P matrix of factor loadings, indexing each industry's sensitivity to aggregate shocks. I assume that a_t consists of two elements: the growth rate of the real Producer Price Index for fuels and power (OIL) and the spread between the commercial paper and Treasury-Bill interest rates (SPREAD), intended to proxy for monetary policy.⁶ Under these assumptions, I can rewrite (19) as

$$(22) \quad q_t = \mu + G * a_t + A * v_t,$$

where

$$(23) \quad G = A * F.$$

In addition to these identifying restrictions, I must choose a normalization; as currently specified, the absolute levels of β and Ω are not separately identified. One possible normalization would be to set β_1

and/or $\beta_2 = 1$; this is unappealing because it imposes a restriction that either upstream or downstream input-output linkages must be important to comovement. I instead normalize the own effect of an industry shock to one, and let β_1 through β_4 govern only the cross-industry effects of shocks. In other words, I assume

$$(24) \quad A = ID + \beta_1 * COST + \beta_2 * DEM + \beta_3 * SIZE + \beta_4 * CITY,$$

where ID is an N-by-N identity matrix and the diagonals of COST, DEM, SIZE and CITY are set to zero.

I estimate the model using a two-step procedure. First, I estimate μ and G by running industry-by-industry OLS regressions of q_t on a constant, OIL and SPREAD; these regressions fit best when I lag OIL and SPREAD one year.⁷ These estimates are consistent under the assumption that a_t is orthogonal to v_t .⁸ I then use the residuals from these regressions to estimate β and Σ using Gaussian maximum likelihood. Details on the log likelihood function and its gradient are given in the appendix. Given estimates of G and β , I can use (23) to back out estimates of the factor loading matrix F, which allows me to distinguish the direct effects of aggregate shocks on comovement from the indirect effects resulting from the propagation of aggregate shocks through complementarities. Of course, this decomposition depends on the assumption that aggregate and industry-specific shocks are propagated through the same matrix A.

Before proceeding to the results, I must must acknowledge two important gaps between the models outlined in Section II and the empirical framework described above. First, while Section II consists of three separate models, I estimate a single system which nests all three models' implications. Allowing for all three linkages simultaneously is essential

for proper inference; for instance, if I tested Model Two without controlling for input-output linkages, I might find a positive association between industry size and comovement even if aggregate spillovers did not exist, because large industries have stronger input-output links to other sectors than small industries. Unfortunately, nesting the three models limits the structural interpretability of the estimates. For instance, the estimated coefficients on SIZE and CITY can be used to test the null that aggregate and local spillovers do not exist, but cannot be used to infer the aggregate and local spillover parameters in Models Two and Three. Ideally, Section II would consist of a single model nesting all three linkages, so that the empirical estimates would have unambiguous structural interpretations. Unfortunately, I have been unable to find a tractable model incorporating all three linkages.

Second, while Model One shows that demand and supply shocks may have different propagation mechanisms, the empirical work assumes that all shocks propagate in the same way. Attempts to estimate models allowing for both supply and demand shocks proved unsuccessful, although perhaps future work could have more success by incorporating price data. As mentioned above, the empirical work thus cannot answer the question of whether supply or demand shocks are more important to business cycles; the estimates reveal only the relative importance of upstream versus downstream propagation of shocks.

Estimates of β

Table 2 presents estimates of β for the three measures of industry activity. Estimates of G and Σ are omitted to save space, but are available from the author. Standard errors are in parentheses and are estimated by numerical computation of the Hessian at the maximum

likelihood estimates.

Results are as follows. First, input-output linkages are significant sources of short-run comovement. The coefficients on DEM and COST are positive and significant in all cases, suggesting that shocks propagate both upstream (from users to suppliers) and downstream (from suppliers to users). Second, aggregate activity spillovers receive little support; the coefficient on SIZE is positive in all cases, but statistically insignificant. Third, local activity spillovers receive strong support; the coefficient on CITY is positive and highly significant in all specifications. Finally, the results for employment and output are similar to each other, but different from the results for value added, which show smaller coefficients on DEM and COST and larger coefficients on SIZE and CITY. Since measuring value added requires both more information and more assumptions about the production function than measuring employment or output, value added is likely to contain more measurement error than employment or output; therefore, the employment and output results should perhaps carry more weight than the value added results.

Table 3 presents statistics describing the fit of the models. For each activity measure, the column "Implied Volatility" presents the standard deviation of manufacturing activity implied by the formula

$$(25) \quad \text{Var}(q) = \text{SHARE}' * \Psi * \text{SHARE}.$$

Here, SHARE is a 126-by-1 vector of steady-state industry activity shares, estimated as described in the appendix. In rows labelled "Data", Ψ is set equal to the covariance matrix of the original data; in rows labelled "Residuals", Ψ is the covariance matrix of the residuals from projecting the data on aggregate shocks. In the remaining rows, Ψ equals the fitted covariance matrix, either including or excluding the effects of

aggregate shocks. In the former case, Ψ equals $\hat{A} * \hat{\Sigma} * \hat{A}'$ plus $\hat{G} * \hat{\phi} * \hat{G}'$, where $\hat{\phi}$ is the estimated covariance matrix of aggregate shocks; in the latter case, Ψ equals $\hat{A} * \hat{\Sigma} * \hat{A}'$. The last three columns, meanwhile, report statistics for the pairwise correlations implied by the data and the empirical estimates; the fourth and fifth columns show the mean and standard deviation of the pairwise correlations over the 7875 possible pairs of sample industries, while the sixth column presents the correlation between the fitted and observed pairwise correlations.⁹

The results of Table 3 suggest that the fitted model can account for most of the volatility and comovement features of the data. For employment, the fitted model including the effects of aggregate shocks explains 96 percent of the variance and 89 percent of the mean pairwise correlation found in the data; for gross output, the model explains over 100 percent of aggregate variance and 99 percent of average comovement; for value added, the model explains over 100 percent of both aggregate variance and average comovement. Removing aggregate shocks from both the model and the data has little effect on these results. For all three activity measures, the pairwise correlations in the original data themselves exhibit a correlation of around 0.78 with the correlations implied by the fitted model including aggregate shocks; this suggests that the model including aggregate shocks can account for why some pairs of industries comove more strongly than others. The model without aggregate shocks is not as successful at explaining cross-sectional variation in the degree of comovement; the correlation between the residual correlations and the fitted correlations excluding aggregate shocks ranges from 0.286 for employment to 0.386 for gross output. The fitted models tend to understate somewhat the standard deviation of observed pairwise

correlations, especially when aggregate shocks are excluded; the fitted models thus do not account especially well for the magnitude of variation in the degree of comovement across industry pairs.

Variance Decompositions

While the estimates of the β 's are interesting, they do not prove that complementarities are economically important. Table 4 assesses economic significance by decomposing the aggregate variance implied by the fitted model into components due to aggregate shocks, input-output linkages, local spillovers, and other factors. The variance decomposition results depend crucially on how one measures the impact of aggregate shocks. The third column measures this impact as \hat{G} , the matrix of coefficients from projecting y on aggregate shocks industry-by-industry. This measure assigns to aggregate shocks both their direct effects and the indirect effects resulting from their propagation through complementarities. The final column measures the impact of aggregate shocks as $\hat{F} = \hat{A}^{-1} * \hat{G}$. This measure includes only direct effects, and is based on the assumption that aggregate shocks are propagated by the same complementarities as idiosyncratic shocks. For each activity measure, the first row presents the fraction of fitted variance attributable to aggregate shocks, setting Ψ either to $\hat{G} * \hat{\Phi} * \hat{G}'$ (third column) or $\hat{F} * \hat{\Phi} * \hat{F}'$ (fourth column). The row "Diagonals" presents the fraction of fitted variance due to idiosyncratic shocks, setting Ψ to $\hat{\Sigma}$. The row COST presents the fraction of volatility due to cost-side linkages; this row is constructed by first defining $\hat{A}_{COST} = ID + \hat{\beta}_1^{COST}$ and $\hat{G}_{COST} = \hat{A}_{COST} * \hat{F}$, then setting Ψ equal to either $\hat{A}_{COST} * \hat{\Sigma} * \hat{A}_{COST}'$ (third column), or to $\hat{A}_{COST} * \hat{\Sigma} * \hat{A}_{COST}' + \hat{G}_{COST} * \hat{\Phi} * \hat{G}_{COST}$ (fourth column); one can think of

\hat{G}_{COST} as an estimate of what the overall impact of aggregate shocks would be if cost linkages were the only complementarity in the economy. The third column of row COST subtracts the variance due to idiosyncratic shocks, while the fourth column subtracts the variance due to idiosyncratic shocks and to the direct impact of aggregate shocks. The rows DEM, SIZE, and CITY are constructed in the same way as COST, while the row "Interactions" reports the fraction of variance due to interactions between COST, DEM, SIZE and CITY.

The results of Table 4 suggest that both aggregate shocks and complementarities are important to aggregate volatility. If we measure the impact of common shocks using \hat{G} , then aggregate shocks explain over half of manufacturing employment volatility, 45 percent of output volatility, and almost 40 percent of value added volatility. The importance of aggregate shocks falls substantially, however, if we measure their impact using \hat{F} instead of \hat{G} ; for each activity measure, the share of volatility attributable to the direct effects of aggregate shocks is less than five percent. This suggests that complementarities play an important role in transmitting oil and monetary shocks across sectors, provided one assumes that aggregate and idiosyncratic shocks are propagated through the same channels. Interestingly, local spillovers appear to be the most economically important complementarity. If we ignore the role of complementarities in propagating common shocks, local spillovers explain between 15 and 19 percent of aggregate volatility, depending on the measure of activity; these figures rise to around 35 percent if we allow local spillovers to propagate aggregate as well as idiosyncratic shocks. Regardless of the treatment of aggregate shocks, then, local spillovers have non-trivial consequences for volatility in manufacturing.

Input-output linkages are nearly as important as local spillovers for gross output volatility, but are not as important for employment or value added volatility.

IV. COMPARISON WITH PREVIOUS WORK

In contrast to the large theoretical literature, there is relatively little existing empirical work on complementarities.¹⁰ There is a literature that analyzes comovements among disaggregated industries using latent factor models; examples include Long and Plosser (1987), Cooper and Haltiwanger (1990) and Norrbin and Schlagenhauf (1990). Papers in this tradition typically focus on questions concerning the economy's underlying shocks, such as the number of common factors or the relative importance of aggregate and sectoral disturbances. In terms of my notation, this literature is thus interested primarily in Ω rather than A . Complementarities are usually assumed to operate only with lags; these papers thus typically decompose fluctuations into predictable and unpredictable components, and assume that the unpredictable component depends only on the underlying shocks. Moreover, complementarities are usually not modelled in terms of observable variables.¹¹

My work differs from this literature in several respects. First, I do not decompose fluctuations into predictable and unpredictable components. This is because I do not agree with the assumption that complementarities operate only with lags; this assumption seems especially unrealistic when applied to annual data. Second, I focus primarily on the structure of interindustry complementarities rather than the structure of common shocks. Finally, I model both complementarities and aggregate shocks in terms of observable variables, rather than relying on

unobservable common factors or principal components to explain the data.

Bartlesman, Caballero and Lyons (1994) is perhaps the closest antecedant of the present paper. These authors find that a demand-share weighted aggregate of other sectors' activity raises an industry's productivity in the short run, while a cost-share weighted aggregate is unimportant to short-run productivity but important to long-run productivity growth. My work differs from Bartlesman *et al* in the following ways. First, I estimate a model of the interindustry covariance matrix, rather than a system of production function regressions; my framework is harder to estimate, but is perhaps more readily adaptable to alternative specifications of spillovers or common shocks. Second, I examine output and employment rather than productivity; I believe that productivity data is too clouded by factor utilization to be useful for measuring short-run fluctuations in true productivity. Finally, I analyze a richer set of complementarity measures, including local spillovers.

IV. CONCLUSION

This paper has investigated the role of complementarities in the short-run propagation of shocks. Using data on disaggregated manufacturing industries in the postwar United States, I find that input-output linkages are important to short-run comovement, with significant links running both from users to upstream suppliers and from suppliers to downstream users. I also find that aggregate activity spillovers are not important to short-run comovement.

The most important finding of this paper is that industries that cluster together in space also tend to comove through time, and that the comovement associated with this correspondance accounts for a large

fraction of aggregate volatility. In this paper, I interpret this phenomenon as evidence for symmetric local activity spillovers. However, as mentioned in Section II, a link between spatial and temporal correlation could also result from city-specific shocks or asymmetric local spillovers that vary across industry pairs. Distinguishing among these stories using national-level data alone would be difficult, since all three stories have broadly similar implications for interindustry comovement at the national level. In parallel work (Shea (1995)), however, I show that city-specific shocks, symmetric local activity spillovers and asymmetric local spillovers have sharply different implications for the pattern of interindustry comovement *within cities*. I test these implications using time-series employment data for 387 city-industries taken from seven large US metropolitan areas, and find evidence for both symmetric and asymmetric local spillovers.¹²

There are a number of ways in which this paper could be extended. First, one could examine higher-frequency data and allow shocks to propagate dynamically; for instance, it might be interesting to know how quickly shocks travel through the input-output table, or whether direct linkages are realized more quickly than indirect linkages. Second, one could examine other linkage mechanisms, by adding additional elements to the matrices A or Ω . Third, one could apply this paper's methodology to analyze comovements among other vector time series, such as international outputs or asset prices. With suitable modifications, the framework employed here should be applicable to any problem where one wants to test competing theories of how shocks are propagated across agents, provided theory expresses linkages as a function of observable data and a small number of parameters.

APPENDIX

Maximum Likelihood Estimation

Let \tilde{q} denote the residuals from projecting industry growth rates on a constant and aggregate shocks. Then from (22), we have

$$(A.1) \quad \tilde{q}_t = A * v_t,$$

where A is given by (24) in the text, and where $\Sigma = \text{Var}(v)$ is diagonal. Assuming that v is Gaussian, the log likelihood function for T observations on the vector \tilde{q}_t is given by

$$(A.2) \quad \log L = -(T * 126)/2 - (T/2) * \log|\Psi| - (1/2) \sum_{t=1}^T (\tilde{q}_t' \Psi^{-1} \tilde{q}_t),$$

where $\Psi = A * \Sigma * A'$. From Greene (1990, p. 517-18), one can rewrite the log likelihood function (A.2) as

$$(A.3) \quad \log L = -(T * 126)/2 - (T/2) * \log|\Psi| - (T/2) * \text{tr}(\Psi^{-1}S),$$

where tr denotes trace, and where

$$(A.4) \quad S = (1/T) \sum_{t=1}^T \tilde{q}_t * \tilde{q}_t'$$

is the moment matrix of the data. From Greene (1990, p. 518), one can show that

$$(A.5) \quad \partial(\log L)/\partial\Psi \equiv B = -(T/2) * [\Psi^{-1} - \Psi^{-1} * S * \Psi^{-1}].$$

Furthermore, one can show that

$$(A.6) \quad \partial\Psi/\partial\beta_1 \equiv C_1 = A * \Sigma * \text{COST}' + \text{COST} * \Sigma * A'.$$

It thus follows that the gradient of $\log(L)$ with respect to β_1 is

$$(A.7) \quad \partial(\log L)/\partial\beta_1 = \text{tr}(B * C_1');$$

in other words, the effect of β_1 on the log likelihood is equal to

the effect of β_1 on the [1,1] element of Ψ times the effect of the [1,1] element of Ψ on $\log(L)$, plus the effect of β_1 on the [1,2] element of Ψ times the effect of the [1,2] element of Ψ on $\log(L)$, and so on. One can similarly compute the gradient of $\log(L)$ with respect to β_2 through β_4 .

Next, for the covariance matrix Σ , one can show that

$$(A.8) \quad \partial\Psi/d\Sigma_{ii} \equiv D_i = A[.,i] * A[.,i]',$$

where $A[.,i]$ is the i th column of A . Combining (A.5) and (A.8), one can show that the gradient of the log likelihood with respect to the element $[i,i]$ of the diagonal matrix Σ is given by

$$(A.9) \quad \partial(\log L)/d\Sigma_{ii} = \text{tr}(B * D_i').$$

Data Description

I estimate the model using annual data on 126 disaggregated manufacturing industries. These industries cover the entire manufacturing sector, and generally correspond to the three-digit Standard Industrial Classification; in some cases, I combine two or more industries to conform to available input-output data. A complete list of sample industries can be found at the end of this appendix.

I use three measures of industry activity: the growth rate of employment; the growth rate of gross output, defined as real shipments plus the change in real inventories; and the growth rate of real value added. Following Basu and Fernald (1993), I measure value added growth as the Tornquist approximation to a divisia index; real value added growth between $t-1$ and t is thus

$$(A.10) \quad 1/SVA * GOUT_t - (1-SVA)/SVA * GMAT_t,$$

where $GOUT$ equals the growth rate of gross output, $GMAT$ equals the

growth rate of materials, and SVA is the average share of nominal value added in nominal gross output over $t-1$ and t .

All three measures of q_t are constructed by aggregating annual four-digit data from the Penn-SRI-Census Productivity Database (described in Bartlesman, Caballero and Lyons (1994)) to the three-digit level. Real output and real materials are expressed in 1972 dollars. The data cover the period 1958-1986; after converting to growth rates and measuring inventory change, the employment measure runs from 1959-1986 while the output and value added measures run from 1960-1986. These are the sample periods for subsequent estimation.

Equation (5) in Model One expresses output fluctuations as a function of taste shocks, technology shocks, and elements of the matrices COST and DEM. In terms of model parameters, these matrices in turn satisfy

$$(A.11) \quad \text{COST} = [(\text{ID} - \beta)^{-1}]'$$

and

$$(A.12) \quad \text{DEM}_{ik} = \text{COST}_{ki} a_k / \left(\sum_{z=1}^N \text{COST}_{zi} a_z \right),$$

where ID is an N-by-N identity matrix; β is an N-by-N matrix whose $[k,i]$ element equals β_{ki} ; and a_k is the steady-state share of good k in overall consumption.

I construct the matrices COST and DEM using data from the 1977 detailed US input-output study. To begin, I construct a 158-by-158 matrix β , whose $[k,i]$ element equals the share of industry i 's cost directly attributable to good k. I construct β from raw input-output data using methods described in Shea (1991 and 1993); in terms of terminology introduced in these papers, β_{ki} is the Direct Cost Share of k in i . As in this previous work, β_{ki} includes both i 's purchases of k as a material

input and an imputed service flow from i 's use of k as capital. The 158 industries consist of the 126 sample manufacturing industries, plus 32 nonmanufacturing industries listed below. Next, following (A.11), I construct a 158-by-158 "total requirements" matrix TOTAL by computing the transpose of the Leontief inverse of β . I then construct COST by taking the rows and columns of TOTAL corresponding to the 126 sample industries. Given COST, I construct DEM following (A.12). I define industry k 's final demand a_k as the sum of purchases from consumption, government, and the 32 nonmanufacturing industries.

Following Model Two, I construct the matrix SIZE using the Penn-Census-SRI database described above. I define industry size as the industry's share of nominal value added in manufacturing in year t , averaged over the period 1959-1986.

Following Model Three, I construct the matrix CITY using County Business Patterns (CBP) data from the Department of Commerce. The CBP provides employment by disaggregated industry for every county in the United States. I aggregate counties into the 273 standard metropolitan statistical areas (SMSAs) defined by the 1980 Census of Population. While CBP data is available annually since 1958, I use 1977 data only; this is reasonable provided the spatial distribution of industries is stable over time. To preserve confidentiality, employment in county-industries with a small number of establishments is reported in the CBP as a range (e.g. 100-250; 250-499); in these cases, I take midpoints. I construct the elements of CITY following (18), where $SHARE1_{ji}$ is defined as the share of industry i 's total 1977 employment in the 273 SMSAs accounted for by SMSA j , while $SHARE2_{kj}$ is defined as the share of SMSA j 's total manufacturing employment in 1977 accounted for by industry k .

Finally, I construct the vector SHARE for employment as the mean over 1958-1986 of annual industry shares of manufacturing employment; for value added, SHARE is the mean over 1959-1986 of annual industry shares of double deflated real value added in 1972 dollars; for gross output, SHARE is the mean over 1959-86 of annual industry shares of real gross output in 1972 dollars.

Manufacturing Industries Used In Estimation:

1. SIC 201: Meat Products
2. SIC 202: Dairy Products
3. SIC 203: Prepared Foods
4. SIC 204: Grain Mill Products
5. SIC 205: Baked Goods
6. SIC 206: Confectionary
7. SIC 207: Fats and Oils
8. SIC 208: Beverages
9. SIC 209: Miscellaneous Food
10. SIC 21: Tobacco Products
11. SIC 221-223 and 226: Broadwoven Fabrics
12. SIC 224: Narrow Fabrics
13. SIC 225: Knit Goods
14. SIC 227: Floor Coverings
15. SIC 228: Yarn and Thread
16. SIC 229: Miscellaneous Textiles
17. SIC 231-238: Clothing
18. SIC 239: Miscellaneous Apparel
19. SIC 241: Logging
20. SIC 242: Sawmills
21. SIC 243: Millwork and Plywood
22. SIC 244: Wood Containers
23. SIC 245: Manufactured Homes
24. SIC 249: Miscellaneous Wood
25. SIC 251: Household Furniture
26. SIC 252: Office Furniture
27. SIC 253: Public Building Furniture
28. SIC 254: Partitions
29. SIC 259: Miscellaneous Furniture
30. SIC 261: Pulp Mills
31. SIC 262: Paper Mills
32. SIC 263: Paperboard Mills
33. SIC 264: Converted Paper Products
34. SIC 265: Paperboard Boxes
35. SIC 266: Building Paper and Board
36. SIC 271: Newspapers
37. SIC 272: Periodicals
38. SIC 273: Books
39. SIC 274: Miscellaneous Publishing
40. SIC 275: Commercial Printing

41. SIC 276: Manifold Business Forms
42. SIC 277: Greeting Cards
43. SIC 278: Bookbinding and Related Services
44. SIC 279: Printing Trade Services
45. SIC 281, 286: Industrial Chemicals
46. SIC 282: Synthetic Materials
47. SIC 283: Drugs
48. SIC 284: Toiletries
49. SIC 285: Paints
50. SIC 287: Agricultural Chemicals
51. SIC 289: Miscellaneous Chemicals
52. SIC 291: Refined Petroleum
53. SIC 295: Building Materials
54. SIC 299: Miscellaneous Petroleum Products
55. SIC 301: Tires
56. SIC 302: Rubber Footwear
57. SIC 303: Reclaimed Rubber
58. SIC 304: Rubber and Plastic Hose
59. SIC 306: Miscellaneous Rubber Products
60. SIC 307: Miscellaneous Plastic Products
61. SIC 311: Leather Tanning and Finishing
62. SIC 313: Boot and Shoe Cut Stock
63. SIC 314: Leather Footwear
64. SIC 315: Gloves
65. SIC 316: Luggage
66. SIC 317: Personal Leather Goods
67. SIC 319: Miscellaneous Leather Goods
68. SIC 321-3: Glass Products
69. SIC 324: Cement
70. SIC 325: Clay Products
71. SIC 326: Pottery Products
72. SIC 327: Concrete
73. SIC 328: Cut Stone Products
74. SIC 329: Miscellaneous Nonmetallic Mineral Products
75. SIC 331: Iron and Steel Mills
76. SIC 332: Iron and Steel Foundries
77. SIC 333: Primary Nonferrous Metals
78. SIC 334: Secondary Nonferrous Metals
79. SIC 335: Nonferrous Metal Mills
80. SIC 336: Nonferrous Metal Foundries
81. SIC 339: Primary Metals Services
82. SIC 341: Metal Containers
83. SIC 342: Cutlery and Hand Tools
84. SIC 343: Plumbing and Heating Equipment
85. SIC 344: Structural Metal
86. SIC 345: Screw Machine Products
87. SIC 346: Forgings and Stampings
88. SIC 347: Fabricated Metals Services
89. SIC 348: Ordnance
90. SIC 349: Miscellaneous Fabricated Metals
91. SIC 351: Engines and Turbines
92. SIC 352: Agricultural Machinery
93. SIC 353: Construction and Mining Machinery
94. SIC 354: Metalworking Machinery

- 95. SIC 355: Special Industrial Machinery
- 96. SIC 356: General Industrial Machinery
- 97. SIC 357: Office Machinery and Computers
- 98. SIC 358: Service Industry Machinery
- 99. SIC 359: Miscellaneous Nonelectric Machinery
- 100. SIC 361: Electrical Distribution Equipment
- 101. SIC 362: Electrical Industrial Machinery
- 102. SIC 363: Household Appliances
- 103. SIC 364: Lighting and Wiring Fixtures
- 104. SIC 365: Household Radio and TV Equipment
- 105. SIC 366: Communications Equipment
- 106. SIC 367: Electronic Components
- 107. SIC 369: Miscellaneous Electrical Equipment
- 108. SIC 371: Motor Vehicles
- 109. SIC 372, 376: Aerospace Equipment
- 110. SIC 373: Ships and Boats
- 111. SIC 374: Railroad Equipment
- 112. SIC 375: Bicycles and Motorcycles
- 113. SIC 379: Miscellaneous Transportation Equipment
- 114. SIC 381: Scientific Instruments
- 115. SIC 382: Measuring Instruments
- 116. SIC 383: Optical Instruments
- 117. SIC 384: Medical Instruments
- 118. SIC 385: Ophthalmic Instruments
- 119. SIC 386: Photographic Equipment
- 120. SIC 387: Watches and Clocks
- 121. SIC 391: Jewelry
- 122. SIC 392: Musical Instruments
- 123. SIC 393: Games and Toys
- 124. SIC 394: Office Supplies
- 125. SIC 395: Clothing Accessories
- 126. SIC 399: Miscellaneous Manufacturing Not Elsewhere Classified

Additional Nonmanufacturing Sectors Used to Compute DEM and COST

- 127. Various SIC 01-09: Livestock Farming
- 128. Various SIC 01-09: Other Agriculture
- 129. SIC 10-14: Mining
- 130. Various SIC 15-17: Residential Construction
- 131. Various SIC 15-17: Nonresidential Construction
- 132. Various SIC 15-17: Maintenance Construction
- 133. SIC 40: Railroads
- 134. SIC 42: Trucking
- 135. SIC 44: Shipping
- 136. SIC 45: Airlines
- 137. SIC 41, 43, 46-7: Other Transportation
- 138. SIC 483: Radio and TV Communication
- 139. Other SIC 48: Other Communications
- 140. SIC 491: Electric Utilities
- 141. SIC 492: Gas Utilities
- 142. Other SIC 49: Other Utilities
- 143. SIC 50, 51: Wholesale Trade
- 144. SIC 52-57, 59: Retail Trade
- 145. SIC 58: Bars and Restaurants

- 146. SIC 60-66: Finance, Insurance, Real Estate
- 147. SIC 70: Hotels
- 148. SIC 72: Personal Services
- 149. SIC 73: Business Services
- 150. SIC 75: Automotive Services
- 151. SIC 76: Repair Services
- 152. SIC 78-79: Amusements
- 153. SIC 80: Health Care
- 154. SIC 81, 89: Legal and Professional Services
- 155. SIC 82: Education
- 156. SIC 83: Social Services
- 157. SIC 84, 86: Membership Organizations
- 158. Various SIC: Government Enterprise

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FOOTNOTES

¹Cooper and John (1988) use the phrase "strategic complementarity" to refer to linkages that inherently depend on market imperfections.

²Miller (1992) adopts a similar strategy in a different context; he tests whether international activity spillovers are an important source of endogenous growth by examining whether large countries have more persistent income innovations than small countries, exploiting the fact that transitory shocks to large countries should have more impact on international activity than transitory shocks to small countries.

³Notice that even if aggregate activity spillovers are present, industry size will be an economically important determinant of comovement variation across industry pairs only to the extent that the available data classification system divides economic activity into meaningful aggregates. Suppose, for instance, that the underlying economy consists of a large number of equally-sized independent sectors, and that the data authority arbitrarily groups these sectors into industries of varying size. Then a given-sized shock to a "large" industry will still propagate more strongly than a similar-sized shock to a "small" industry; however, the large industry will have a smaller standard deviation of shocks than the smaller industry, since the large industry's shock will be the average over a larger number of uncorrelated shocks.

⁴Marshall (1949, p.273) writes: "A district which is dependent chiefly on one industry is liable to extreme depression, in case of a

falling-off in the demand for its produce, or of a failure in the supply of the raw material which it uses. This evil again is in a great measure avoided by those large towns...in which several distinct industries are strongly developed. If one of them fails for a time, the others are likely to support it indirectly..." Neumann and Topel (1991) find that cities with a poorly diversified employment base indeed have higher average rates of unemployment than cities with a well-diversified base.

⁵I also experimented with measuring SIZE using the period average shares of employment, real gross output, and real value added. Estimates of β_1 and β_2 (cost and demand linkages) were not sensitive to the choice of SIZE. Using employment shares tended to raise the estimates of β_3 (aggregate spillovers), to the point of statistical significance in some cases, and reduce the estimates of β_4 (local spillovers), although local spillovers were still statistically significant. Using real gross output or real value added shares tended to make estimates of β_3 negative, and tended to increase the estimates of β_4 .

⁶Friedman and Kuttner (1992) and others have found the paper-bill spread to be a highly informative indicator of monetary policy, with more predictive power for aggregate output than other commonly used indicators such as M1 or the T-bill rate alone.

⁷For output, the average R-squared from these regressions is 0.34. For employment and value added, the average R-squared is 0.30 and 0.31.

⁸Notice that these industry-by-industry estimates of μ and G, while

consistent, are not efficient due to the correlation of shocks across industries.

⁹For the fitted model including the effects of aggregate shocks, the sixth column reports the correlation between the pairwise correlations in the original data and the correlations implied by the fitted Ψ matrix including $\hat{G} * \hat{\phi} * \hat{G}'$. For the fitted model excluding aggregate shocks, the sixth column reports the correlation between the pairwise correlation in the data residuals and the correlations implied by the fitted Ψ matrix excluding $\hat{G} * \hat{\phi} * \hat{G}'$.

¹⁰Cooper and Haltiwanger (1993) survey evidence on complementarities.

¹¹Norrbin and Schlagenhauf (1990) allow for lagged averages of other industries' outputs to affect current industry output. However, their weighting scheme is not based on any underlying theory of complementarities, and they do not allow for any contemporaneous propagation of shocks across sectors.

¹²In Shea (1995) I also attempt to put some structure on the concept of "local spillovers" by examining one of the most promising microeconomic foundations for local spillovers: limited intercity tradeability of certain goods due to high transportation costs. Empirically, nontraded goods do not seem capable of explaining the phenomenon of local spillovers.

TABLE 1

Comovement and Aggregate Volatility

$$\text{Var}(q) \cong \text{SHARE} * \Psi * \text{SHARE}'$$

-----Standard Deviations-----

<u>Activity Measure</u>	<u>Actual</u>	<u>Implied</u>	<u>Diagonal</u>	<u>Off-Diagonal</u>	<u>% Due To Comovement</u>
Employment	4.31	4.42	0.99	4.31	94.9
Gross Output	5.61	5.42	2.08	5.00	85.4
Value Added	7.37	6.67	2.99	5.97	80.0

NOTES: the second column presents the standard deviation of annual employment, gross output, and value added growth in US manufacturing over 1959-86 for employment and 1960-86 for output and value added. The third column presents the standard deviation implied by equation (2) in the text, where SHARE and Ψ are constructed using 126 three-digit manufacturing industries. The fourth and fifth columns report the standard deviation implied by the diagonal and off-diagonal elements of Ψ , while the sixth column reports the share of aggregate variance due to the off-diagonal "comovement" term.

TABLE 2

Empirical Estimates

$$q_t = \mu + G * a_t + A * v_t$$

$$A = ID + \beta_1 \text{COST} + \beta_2 \text{DEM} + \beta_3 \text{SIZE} + \beta_4 \text{CITY}$$

$$\text{Var}(v_t) = \Sigma$$

Activity Measure	β_1	β_2	β_3	β_4
Employment	0.325 **(0.104)	0.857 **(0.103)	0.385 (0.401)	1.451 **(0.282)
Gross Output	0.402 **(0.090)	1.029 **(0.101)	0.043 (0.358)	1.274 **(0.273)
Value Added	0.304 **(0.055)	0.242 **(0.090)	0.655 (0.487)	1.582 **(0.295)

NOTES: this table presents maximum likelihood estimates of the β parameters. Standard errors are in parentheses and are estimated by numerical computation of the Hessian matrix at the maximum likelihood estimates. A (**) denotes significance at 5 percent. See text for further details.

TABLE 3

Goodness of Fit

Activity Measure	Case	Implied Volatility	-Pairwise Correlations-		
			Mean	Stan Dev	Corr
Employment	Data	4.42	0.341	0.423	1
	Fitted, including aggregate shocks	4.32	0.305	0.353	0.782
	Residuals	3.09	0.254	0.350	1
	Fitted, excluding aggregate shocks	2.95	0.198	0.226	0.286
Output	Data	5.42	0.284	0.394	1
	Fitted, including aggregate shocks	5.83	0.280	0.338	0.779
	Residuals	3.70	0.185	0.316	1
	Fitted, excluding aggregate shocks	4.33	0.177	0.207	0.386
Value Added	Data	6.67	0.228	0.364	1
	Fitted, including aggregate shocks	7.81	0.263	0.323	0.782
	Residuals	4.45	0.142	0.292	1
	Fitted, excluding aggregate shocks	6.08	0.194	0.219	0.358

NOTES: This table presents goodness-of-fit statistics for the fitted model. For each activity measure, the column "Implied Volatility" presents the standard deviation of aggregate manufacturing activity implied by the formula $\text{Var}(q) = \text{SHARE}' * \Psi * \text{SHARE}$, setting Ψ either to the observed covariance matrix of the original data, the covariance matrix of the residuals from projecting the data on aggregate shocks, or to fitted Ψ including or excluding the effects of aggregate shocks. The remaining three columns present statistics for the pairwise correlations implied by each case. See the text for further discussion.

TABLE 4
Variance Decomposition

Activity Measure	Component	Impact of Agg Shocks	
		\hat{G}	\hat{F}
Employment	Agg Shocks	53.4	4.6
	Diagonals	3.5	3.5
	COST	2.5	6.9
	DEM	6.5	10.1
	SIZE	3.3	6.8
	CITY	15.1	35.9
	Interactions	15.7	32.1
Gross Output	Agg Shocks	44.8	3.7
	Diagonals	10.9	10.9
	COST	5.3	12.1
	DEM	10.6	13.4
	SIZE	0.5	0.9
	CITY	16.4	34.5
	Interactions	11.5	24.5
Value Added	Agg Shocks	39.3	2.9
	Diagonals	13.2	13.2
	COST	4.0	7.1
	DEM	1.9	2.3
	SIZE	8.1	13.0
	CITY	18.6	34.3
	Interactions	14.8	27.1

NOTES: This table presents the decomposition of the variance implied by the fitted model into components attributable to aggregate shocks, shock variances, individual complementarities, and interactions among complementarities. The third column reports results using the OLS estimates from regressing activity on OIL and SPREAD to measure the impact of aggregate shocks. The fourth column reports results using the estimated direct effects matrix F to measure the impact of aggregate shocks. See the text for further information.