A Spatial Analysis of Sectoral Complementarity

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This paper presents a spatial econometric method for characterizing productivity comovement across sectors of the U.S. economy. Input-output relations provide an economic distance measure that is used to characterize interactions between sectors, as well as conduct estimation and inference. We construct two different economic distance measures. One metric implies that two sectors are close to one another if they use inputs of other industrial sectors in nearly the same proportion, and the other metric implies that sectors are close if their outputs are used by the same sectors. Our model holds that covariance in productivity growth across sectors is a function of economic distance. We find that (1) positive cross-sector covariance of productivity growth generates a substantial fraction of the variance in aggregate productivity, (2) cross-sector productivity covariance tends to be greatest between sectors with similar input relations, and (3) there are constant to modest increasing returns to scale. We test and reject the hypothesis that these correlations are due to a common shock.

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I. Introduction

The comovement of output across sectors has long been considered a prominent feature of the business cycle (see, e.g., Burns and Mitchell 1946). The majority of theoretical work on business cycles studies single-sector aggregative models. Many of these models, such as Kydland and Prescott (1982), use exogenous fluctuations in the rate of technological innovation to the single sector's production function to drive aggregate movements. Empirical work on business cycles has also traditionally avoided studying multisectoral models. Typical empirical work has focused on aggregate data such as output and total factor productivity. Even if the ultimate goal is to understand aggregate phenomena, this empirical strategy ignores information in disaggregate data that may be useful in explaining economywide fluctuations.

A number of researchers, including Summers (1986), have argued against the single-sector technological shock explanation of business cycles. First, they point out a lack of independent, corroborating evidence that the pace of technological innovation dramatically increases during booms. Second, they argue that single-sector models provide a poor framework for discussing technological innovation. True technological innovation occurs at a more disaggregated level. Since different sectors' production processes vary greatly, we should not expect innovations to be correlated across sectors to form "aggregate" productivity shocks. Other researchers have noticed these deficiencies of aggregative theoretical and empirical work and have pursued a disaggregate approach.[1]

Blanchard and Fischer (1989, p. 337) concisely state the challenge facing the technology shock explanation: "One obvious question at this stage is whether shocks in aggregate productivity are sufficiently large to explain short-run fluctuations in output. … Whether there is enough variance in sectoral productivity or enough correlation across sectors to explain substantial aggregate fluctuations is at this stage an open issue."

This paper measures the cross-sector correlation properties of sectoral productivity. Our estimation strategy is general enough to allow for alternative explanations of procyclical productivity. In addition, we go beyond characterizing the comovement of sector productivities and consider whether sector-specific observable variables can capture the co-

[1] Empirical work that studies aggregate fluctuations using disaggregate evidence includes Lilien (1982), Cooper and Haltiwanger (1990, 1992, 1996), and Caballero, Engel, and Haltiwanger (1997). Theoretical work on aggregate fluctuations from disaggregate shocks includes Long and Plosser (1983), Jovanovic (1987), Cooper and Haltiwanger (1990), Bak et al. (1993), Horvath (1998), and Dupor (1999). Costello (1993), Bartelsman, Caballero, and Lyons (1994), and Shea (2002), most closely related to this paper, are discussed in Sec. V.

variance patterns of estimated sector productivities.[2] We use a spatial model of covariance structure, where an *economic distance* between sectors is defined by the degree to which different sectors have a common input-output structure. A burgeoning line of research suggests that factor demand linkages provide a strong synchronization mechanism for sector output and productivity growth.

Long and Plosser (1983) construct a multisector model with an input-output structure that smooths shocks over time and across sectors. The model generates comovement of sector outputs by assuming that each sector depends on the output of other sectors for materials. When there is a positive technology shock to sector i, there is an incentive to transmit the benefit to all sectors. Sector i increases the flow of materials to all other sectors, leading to increased output in sectors that use i intensively. In brief, the Long and Plosser model suggests that the degree of output comovement should be most intense between sectors that share input-output relations. Long and Plosser's model, however, does not explain why sector productivities should comove.

We employ two distinct measures of economic distance between sectors. The first measure implies that two sectors are close if they sell to similar industries. This measure is motivated by Dupor's (1996) multisector model in which factor demand relations generate comovement of sector productivity growth. In his model, there is a cost of adopting new technologies. Factor demand spillovers create an incentive for firms with similar downstream purchasers to adopt new technologies simultaneously, leading to comovement in sectoral productivity growth.[3] This model suggests that the degree of productivity growth comovement should be most intense between sectors that share input-output relations.

Our second metric is motivated by the simple argument that sectors with similar technology will likely have similar productivity growth. We use similarity in sectors' input requirements to measure their proximity with respect to technology. This measure will also capture similarity in upstream factor demand relations across sectors, another potential source of comovement.

We measure sectoral productivity by estimating production functions rather than calculating Solow residuals. This approach has several advantages. First, we impose orthogonality of our productivity measures

[2] Costello (1993), e.g., documents the comovement of sector productivities but does not attempt to link correlations to observed sector-specific variables.

[3] Dupor's model does not require coordination failures to generate productivity comovement, as is stressed in other complementarity models (see, e.g., Shleifer 1986). Fixed costs of technology adoption imply that sectors that sell their output as materials to similar sectors should have highly correlated productivity growth, even if the arrival times of ideas or innovations are uncorrelated.

to industry-specific demand shocks using instrumental variables. Second, we control for cyclical capital utilization.[4] Finally, we allow for potentially nonconstant returns to scale that differ across sectors in a way determined by data. Since we wish to interpret our estimated productivity measures as true technology shocks, it is essential that our strategy admits alternative possible explanations for procyclical productivity.

We estimate production functions and measure comovement using methods based on the spatial generalized method of moments (GMM) approach in Conley (1999) and the dynamic spatial model in Chen and Conley (2001). The key feature of the model is that our two measures of economic distances are used to characterize the dependence structure in our data. In particular, covariances across sectors are modeled as functions of our economic distances. Modeling covariances as functions of distance puts structure on the covariance matrices needed for inference and for use as weighting matrices in efficient GMM. This is particularly helpful when these covariance matrices have a very large dimension: the situation we face because of our large panel of sectors.[5] Our estimation method is potentially very useful in other applications in which large-dimension covariance matrices need to be estimated. Examples include applications in finance requiring estimates of covariances between large numbers of asset returns as in Jagannathan and Ma (2001) and in international trade using data from many countries as in Taylor (in press). In addition to facilitating GMM estimation and inference, modeling covariance as a function of distance(s) allows us to easily investigate the relationship between our metrics and productivity comovement.

We use nonparametric estimates of covariance as functions of economic distances to investigate the relationship between comovement patterns in productivity and input-output relationships without the need for restrictive assumptions.[6] Flexible data description is fundamentally important here because of the scarcity of prior work on these comovement patterns. We present measures of comovement across sectors as functions of each of our metrics individually and of both together. To investigate the statistical significance of our results, we present a simple test for independence. In addition, our framework allows a simple test of the hypothesis that comovement is caused by a common aggregate shock.

[4] Burnside, Eichenbaum, and Rebelo (1995) show that unmeasured cyclical capital utilization leads to mismeasured total factor productivity in U.S. two-digit manufacturing data.

[5] We use data on 17 sectors with typically two and sometimes as many as five instruments for a given sector. This results in upward of 30 moment conditions in most specifications, and we have 83 time-series observations.

[6] Our nonparametric approach is a departure from typical spatial econometric models in which a parametric form of dependence is assumed; see, e.g., Anselin and Griffith (1988) or Case (1991).

Our spatial model puts restrictions on comovement across sectors that are different from those of typical factor models, the most common method for characterizing large numbers of time series. Covariance across variables in factor models is mediated by a relatively low-dimensional set of factors as in, for example, Quah and Sargent (1993) and Forni and Reichlin (1998). Our model does not require the existence of a low-dimensional source of covariation; it instead relies on replications in covariance patterns across sectors as functions of their economic distances. Moreover, our approach explicitly models comovement as a function of the economic relationship between sectors, providing a decisive advantage over atheoretic factor models in addressing our question of interest.

We present estimates of returns to scale utilizing a variety of instrument sets. Overall, we find constant to mild increasing returns to scale in sectoral production functions. However, our results are clearly sensitive to the instrument set chosen and, to a lesser extent, to the particular regression specification.

We find strong evidence of significant comovement of short-run productivity growth as a positive and decreasing function of our measure of input distance. This evidence of comovement depending on input distance is robust across variation in instrument sets and regression specifications. We test and reject the hypothesis that these correlations are due to a common aggregate shock. Furthermore, we show that sectoral productivity correlations explained by factor demand relations play a quantitatively significant role in explaining measured aggregate productivity volatility. We argue that our results demonstrate that factor demand relations may provide a strong synchronization mechanism for sector-specific technology shocks.

In Section II, we present our spatial model and define distances using the input-output table. In Section III, we describe the estimation procedure. Section IV presents our results. In Section V, we discuss related research and present conclusions.

II. Spatial Econometric Model

Our characterization of comovement in sectors' productivities is based on constructed measures of economic distance between them. These metrics are formed from an observed input-output table $\mathbf{\Gamma}$, whose (i, j)th element is the value of goods from sector i used in sector j. Observations of $\mathbf{\Gamma}$ for a given year enable us to construct input and output shares for each sector. We index sectors by their input and output share vectors. This results in a spatial model in which sectors' positions correspond to their share vectors. Thus sectors with similar share vectors are close and those with dissimilar shares are far apart. Covariances between variables from different sectors are modeled as functions of these indices. Because of the large number of sectors, we model covariances between sectors as being functions of the Euclidean distances between their share vectors. We use estimates of these covariance functions to characterize comovement in productivities across sectors and also to estimate covariance matrices used in efficient GMM estimation and inference.

Our sample includes observations on both random variables for each sector, say $X_{i,t}$, and locations (shares), $\mathbf{s}_{i,t} \in \Re^k$. We assume that the entire vector of sector variables and locations $\{(X_{i,t}, \mathbf{s}_{i,t})\}_{i=1}^N$ is a Markov process. Let $\text{Cov}_t(X_{i,t+1}, X_{j,t+1})$ denote the covariance of $X_{i,t+1}$ and $X_{j,t+1}$ conditional on information at time t. We assume that $\text{Cov}_t(X_{i,t+1}, X_{j,t+1})$ is a smooth function of $\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|$. Thus, if two sets of locations are the same distance apart, then the conditional covariance of variables associated with those locations is the same. In this way, economic distances between sectors add considerable structure to the covariance patterns across them. Locations and distances may vary over time; however, we are forced to treat them as exogenous because, as described below, our data do not have adequate variation to allow for their endogeneity.[7]

We use a local average method to estimate conditional covariances as a function of economic distance. Consider variables $X_{i,t+1}$ and $X_{j,t+1}$ that have conditional mean zero for simplicity. Our model implies that

$$E_t(X_{i,t+1}X_{j,t+1}) = \text{Cov}_t(X_{i,t+1}, X_{j,t+1}) = c(\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|).$$

Here, $c(\cdot)$ is a smooth function that we call the spatial covariance function. We can estimate $c(\cdot)$ by running a nonparametric regression of cross products of variables, $X_{i,t+1}X_{j,t+1}$, on economic distances, $\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|$. We utilize such nonparametric regressions to generate covariance estimates used to characterize comovement in productivities across sectors and to estimate GMM covariance matrices.

In addition to providing a basis for characterizing comovement properties across sectors, our constructed economic distances can provide a graphical representation of interindustry factor demand linkages. The remainder of this section details the construction of quarterly economic distances from benchmark input-output tables and describes a graphical method for conveying the information in them.

A. *Construction of Economic Distances*

Input-output accounts document purchases and sales of intermediate goods between all industries. We use this input-output information to

[7] This econometric model is a special case of that in Chen and Conley (2001). That paper contains a complete description of required regularity conditions.

construct measures of economic distance. The Bureau of Economic Analysis prepares highly detailed benchmark input-output use tables for the U.S. economy every five years. Our input-output data set consists of benchmark use tables for 1972, 1977, 1982, and 1987.[8] In 1987, the input-output table is presented at the 95- and 480-industry detail, corresponding to roughly the two- and six-digit standard industrial classification (SIC) code. Let $\mathbf{\Gamma}_t$ denote the input-output table in year t. Then the typical element $\Gamma_t(i, j)$ is the dollar value of compensation to sector i for goods used in industry j in year t.

Our two economic distance measures hold that two industries are close if they either buy or sell goods from similar industries. One difficulty is that the panel we use to estimate total factor productivity is manufacturing sectors, whereas the input-output table contains other industries besides manufacturing. Manufacturing does make up a large portion of the input-output table. For example, in 1987, at a 95-industry detail, 51 of the industries are manufacturing. To address this difference between the input-output data and the value-added panel, we aggregate all nonmanufacturing productive sectors into one industry group.[9]

Next, the input-output table includes rows (suppliers of commodities) and columns (purchasers of commodities) that do not correspond to any SIC industry. On the column side, besides intermediate users of commodities such as manufacturing, mining, and construction, the input-output table contains columns for other components of gross domestic product: personal consumption expenditure, investment, change in business inventories, and government purchases. On the row side, the input-output table contains rows for compensation to nonindustries, such as wages and business taxes. We address these components of the input-output table by (*a*) removing all the final-use columns of the input-output tables and (*b*) dropping all additional rows of the table except compensation to employees. With these modifications in place, $\mathbf{\Gamma}_t$ is a 22×21 nonnegative matrix with elements defined as above. Columns of $\mathbf{\Gamma}_t$ correspond to the 20 two-digit SIC manufacturing sectors and one additional sector that sums all nonmanufacturing industries. Rows of $\mathbf{\Gamma}_t$ correspond to the compensation to the 21 sectors above as well as to labor. Table 1 lists the shares of manufacturing GDP for sectors used in our analysis.

As stated above, we use two measures of economic distance. First, we

[8] Lawson and Teske (1994) provide a detailed discussion of the construction of benchmark input-output accounts for the U.S. economy.

[9] Another issue arises in attempting to match input-output data with our quarterly manufacturing panel. The input-output industry classification system does not correspond exactly to the SIC classification. Fortunately, Lawson and Teske (1994, app. B) provide a concordance between industry codes used in the input-output accounts and SIC codes. Using the concordance, we aggregated industries in the input-output data in order to construct sectors that match, as closely as possible, SIC sectors in our manufacturing panel.

TABLE 1
Two-Digit SIC Manufacturing Industries

Industry	Manufacturing GDP Share 1972	Manufacturing GDP Share 1992
20 Food	.11	.11
22 Textiles	.04	.02
23 Apparel	.07	.03
24 Lumber	.03	.02
25 Furniture	.02	.02
26 Paper	.04	.04
27 Printing	.03	.08
28 Chemicals	.06	.11
31 Leather	.01	.00
32 Stone, glass, and clay	.02	.03
33 Primary metals	.08	.04
34 Fabricated metals	.07	.06
35 Nonelectrical machinery	.09	.10
36 Electrical machinery	.07	.10
37 Transportation	.17	.11
38 Instruments	.01	.04
39 Miscellaneous	.02	.02

Note.—Excluded sectors are tobacco (SIC 21), petroleum (SIC 29), and plastics and rubber(SIC 30).

measure the BUY distance between sectors i and j at time t in terms of factor demand, denoted $D_t^b(i, j)$. Letting $B_t(i, j) = \Gamma_t(i, j)/[\sum_{k=1}^{22} \Gamma_t(k, j)]$, we define

$$D_t^b(i, j) = \left\{\sum_{k=1}^{22} [B_t(k, i) - B_t(k, j)]^2\right\}^{1/2}$$

for $i, j = 1, \ldots, 21$. To construct our second distance measure, let $\Psi_t(i, j) = \Gamma_t(i, j)/[\sum_{k=1}^{21} \Gamma_t(i, k)]$. Then, SELL distance, with typical element $D_t^s(i, j)$, is defined by

$$D_t^s(i, j) = \left\{\sum_{k=1}^{21} [\Psi_t(i, k) - \Psi_t(j, k)]^2\right\}^{1/2}$$

for $i, j = 1, \ldots, 21$. These two measures define typical elements of two alternative distance matrices $\mathbf{D}_t^b$ and $\mathbf{D}_t^s$. Both are nonnegative, symmetric about the main diagonal, and zero along the main diagonal.

To construct quarterly economic distances, we identify the benchmark input-output matrices with configurations of sectors in the first quarters of 1972, 1977, 1982, and 1987. Observations for quarters prior to 1972:1 and after 1987:1 are the 1972 and 1987 benchmarks, respectively. Configurations for intermediate quarters are imputed as linear interpolations of the benchmarks. Table 2 tabulates BUY and SELL distances using the 1987 input-output table for the 17 two-digit manufacturing sectors. Although table 2 contains a large amount of detailed information on factor demand relations between sectors, patterns may be obscured by the sheer amount of data. In the next section, we describe a graphical representation of these distance measures.

B. Description of BUY and SELL Configurations

In order to describe BUY and SELL distances succinctly, we plot configurations of points in two dimensions whose interpoint distances approximate those given by $\mathbf{D}_t^b$ and $\mathbf{D}_t^s$ using classical multidimensional scaling (CMDS). This is useful because it allows us to visualize a high-dimensional object on a plane. In particular, it facilitates identification of clusters of sectors with either similar upstream or downstream factor demand relations. Note that we use the actual distances between shares in 22 and 21 dimensions as described above in estimation; the CMDS representations are used only for illustration of patterns. Histograms of BUY and SELL distances are reported in Appendix B (figs. B1 and B2).

Here, we briefly describe the procedure, closely following Mardia, Kent, and Bibby (1979).[10] Consider, for example, BUY share vectors for N sectors at time t. For convenience we shall suppress the time subscript for the remainder of this section. We arrange these vectors as rows of an $N \times 22$ matrix $\mathbf{B}$. Define $\mathbf{U}$ to be the centered inner product matrix for $\mathbf{B}$ with typical element

$$u_{j,k} = (\mathbf{b}_j - \bar{\mathbf{b}})'(\mathbf{b}_k - \bar{\mathbf{b}}),$$

where $\mathbf{b}_j$ is the jth column of the BUY share configuration in $\mathbf{B}$ and $\bar{\mathbf{b}}$ is the average of $\mathbf{b}_j$ across sectors. The matrix $\mathbf{U}$ is positive semidefinite with rank equal to the dimension of the Euclidean space in which the locations (shares) reside. Then, let $\mathbf{v}_i$ be the ith eigenvector (normalized to have norm one) of $\mathbf{U}$ with associated eigenvalue λ_i. Without loss of generality, let $\lambda_1 \geq \cdots \geq \lambda_N$. Using its spectral representation, we can write $\mathbf{U}$ as a matrix of renormalized eigenvectors $\lambda_i^{1/2}\mathbf{v}_i$ times its transpose:

$$\mathbf{U} = [\lambda_1^{1/2}\mathbf{v}_1 \quad \lambda_2^{1/2}\mathbf{v}_2 \quad \cdots][\lambda_1^{1/2}\mathbf{v}_1 \quad \lambda_2^{1/2}\mathbf{v}_2 \quad \cdots]'.$$

A vector of ones is an eigenvector of $\mathbf{U}$ (with a zero eigenvalue) because it is a centered inner product matrix. Since the $\mathbf{v}_i$ are orthogonal, the others sum to zero. Thus, if the elements of $\lambda_i^{1/2}\mathbf{v}_i$ are viewed as coordinates, this configuration will be centered at the origin and will have the same inner products and hence distances as the locations in $\mathbf{B}$. The CMDS approximation of the configuration $\mathbf{B}$ on a plane is that given by using the elements of $\lambda_1^{1/2}\mathbf{v}_1$ and $\lambda_2^{1/2}\mathbf{v}_2$, the first two (normalized)

[10] Their book contains a complete description of CMDS.

TABLE 2
BUY and SELL Distances

SIC	20	22	23	24	25	26	27	28	31	32	33	34	35	36	37	38	39
									A. BUY Distances								
20	0	.51	.56	.46	.43	.45	.47	.44	.45	.34	.39	.51	.49	.46	.47	.50	.37
22		0	.30	.49	.36	.44	.45	.33	.40	.42	.47	.49	.45	.44	.45	.45	.38
23			0	.50	.33	.46	.42	.48	.38	.44	.49	.46	.41	.40	.43	.40	.37
24				0	.28	.41	.43	.45	.44	.38	.44	.46	.42	.41	.43	.42	.34
25					0	.32	.26	.37	.29	.25	.30	.26	.22	.20	.30	.21	.14
26						0	.22	.38	.40	.35	.43	.44	.39	.38	.41	.38	.31
27							0	.41	.36	.30	.41	.38	.31	.29	.38	.26	.25
28								0	.41	.34	.42	.46	.43	.40	.43	.42	.33
31									0	.37	.43	.40	.34	.33	.37	.33	.30
32										0	.32	.37	.31	.28	.37	.29	.20
33											0	.19	.31	.33	.38	.38	.22
34												0	.24	.28	.35	.31	.23
35													0	.18	.30	.19	.21
36														0	.30	.09	.18
37															0	.33	.29
38																0	.21
39																	0

B. SELL Distances

20	0	.84	.83	.54	.68	.58	.48	.63	.67	.40	.71	.41	.60	.54	.90	.48	.49
22		0	.44	.77	.75	.66	.86	.62	.67	.79	.66	.69	.70	.70	.92	.80	.84
23			0	.77	.69	.72	.82	.70	.67	.76	.71	.66	.69	.70	.83	.75	.79
24				0	.58	.54	.42	.55	.60	.35	.63	.36	.50	.43	.84	.38	.39
25					0	.61	.63	.58	.67	.54	.54	.35	.43	.40	.32	.46	.61
26						0	.54	.45	.61	.55	.53	.45	.52	.50	.82	.56	.62
27							0	.60	.60	.26	.71	.38	.54	.45	.88	.26	.24
28								0	.60	.53	.51	.43	.50	.48	.80	.56	.61
31									0	.58	.64	.53	.60	.56	.88	.60	.61
32										0	.61	.26	.45	.35	.80	.20	.21
33											0	.44	.41	.46	.74	.62	.70
34												0	.29	.23	.62	.24	.36
35													0	.30	.65	.43	.53
36														0	.70	.31	.42
37															0	.72	.88
38																0	.23
39																	0

NOTE.—BUY and SELL distance configurations were tabulated from the 1987 U.S. benchmark input-output table. Row and column headings correspond to two-digit SIC manufacturing codes.

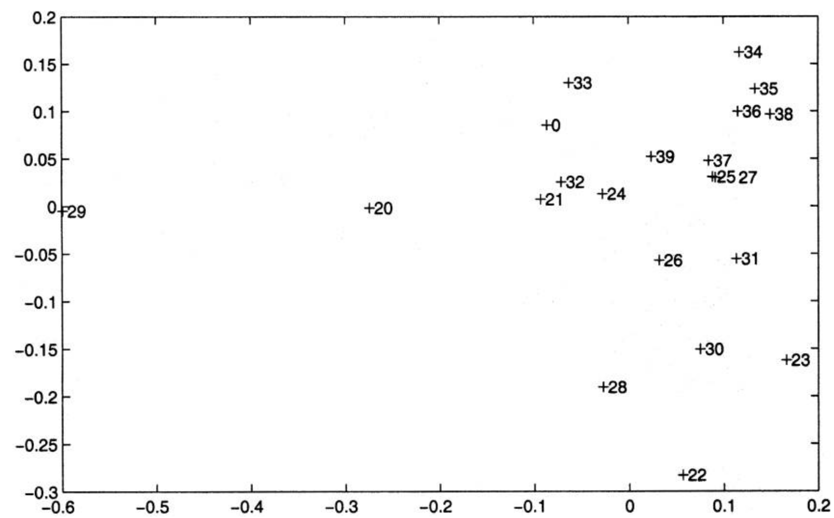

FIG. 1.—BUY distance configuration. CMDS representation of two-digit SIC manufacturing sectors' relative distances using BUY measure. Constructed from the 1987 input-output table. Nonzero numbers correspond to SIC codes. The "all other goods" sector is labeled zero.

principal components of **U**, as coordinates. This corresponds to an optimal projection of the original configuration onto a plane. Even if the original distances were not Euclidean, the CMDS solution minimizes the sum of least-squares distances between the elements of a centered inner product matrix for N points on a plane and its analogue for the original locations.[11]

As a goodness-of-fit statistic, we use the ratio of the sum of the two largest eigenvalues of **U** to the sum of all its eigenvalues. If the distance information in $\mathbf{D}_t^b$ is perfectly represented by a configuration on the plane, then this ratio will be one. The goodness-of-fit statistics for $\hat{\mathbf{D}}_t^b$ and $\hat{\mathbf{D}}_t^s$ for 1987 are 50 percent and 55 percent, respectively. These goodness-of-fit measures can be roughly interpreted as the proportion of variation in distances that is captured by the CMDS configurations. They indicate that a good deal of the distance information is represented by the two-dimensional CMDS configurations, even though the share vectors are of much higher dimension.

Figures 1 and 2 present our CMDS configurations for BUY and SELL distances, respectively, in 1987. The location for each sector is labeled with its SIC code. All two-digit manufacturing sectors are represented in figure 1. Figure 2 contains all sectors except tobacco. With SELL

[11] See, e.g., Mardia et al. (1979) for proofs of these optimality properties.

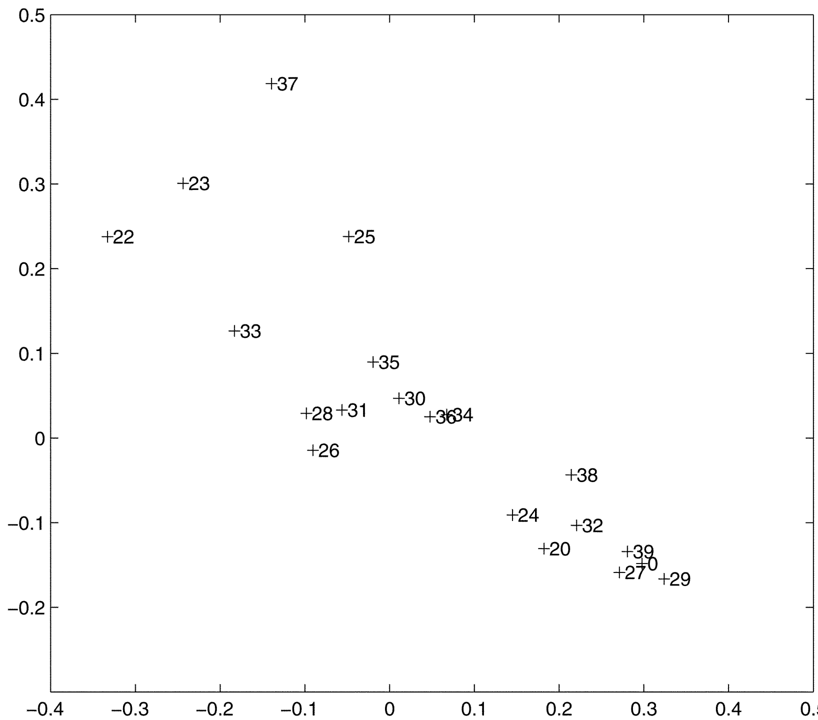

FIG. 2.—SELL distance configuration. CMDS representation of two-digit SIC manufacturing sectors' relative distances using SELL measure. Constructed from the 1987 input-output table. Nonzero numbers correspond to SIC codes. The "all other goods" sector is labeled zero. Tobacco (SIC 21) not included.

distance, tobacco (SIC 21) is very far away from the other industrial sectors, and its inclusion in the picture would eliminate all other detail.

Figures 1 and 2 have several notable clusters. For example, durable-goods sectors are close together in BUY distance. In SELL distance, leather (SIC 31) is close to paper (SIC 26) and chemicals (SIC 28). Textiles (SIC 22) and apparel (SIC 23) are relatively distant from other sectors and close to each other in both metrics. In addition to such clusters, there are distinct outliers. As mentioned above, tobacco (SIC 21) is such an outlier in SELL distance that it cannot be included in figure 2 without a change in scale, and oil (SIC 29) is a distinct outlier in BUY distance.

Some sectors' relative distances are substantially different under the two metrics. Consider the relative locations of two durable-goods industries: transportation (SIC 37) and instruments (SIC 38). These sectors have relatively similar input shares and hence are close to each other under BUY distance; however, the output from these two sectors goes to different customers. Thus they are relatively far apart in SELL distance. Transportation is in fact relatively far in SELL distance from most of the other sectors largely because of the relatively high share of transportation output going to transportation. This is in sharp contrast to the position of transportation in the BUY configuration near other durable-goods sectors, resulting from their similar input mixes.

III. Sectoral Productivity and Output

A. *Production Function Specification*

The important features of our production specification are that (*a*) gross output is a fixed coefficient function of materials and value-added, (*b*) value-added depends on capital services and labor, and (*c*) electricity usage measures capital services.

Let $V_{j,t}$ denote value-added output for sector j at time t. Gross output is produced by combining material inputs $M_{j,t}$ and value-added using a Leontief production function.[12] Value-added is created according to a Cobb-Douglas production function that depends on capital services $K_{j,t}$ and labor input $L_{j,t}$ in sector j at time t:

$$V_{j,t} = A_{j,t}(K_{j,t})^{\alpha}(L_{j,t})^{\beta}, \tag{1}$$

where $A_{j,t}$ represents exogenous total factor productivity. We place no restrictions on α and β, allowing for nonconstant returns to scale. Initially, we restrict production functions to be identical across sectors. Later, we relax this assumption to allow α and β to differ across sectors.

Value-added data are the quarterly average of the seasonally adjusted Federal Reserve Board industrial production index.[13] Labor hours are seasonally adjusted total employee hours on nonagricultural payrolls, from the Bureau of Labor Statistics. Our measure of capital services is

[12] We assume that materials and value-added enter into gross output production in fixed coefficients for two reasons. First, the assumption allows us to estimate production function regressions using quarterly data. Quarterly data on material usage for manufacturing industries are not available. Second, some evidence suggests that the Leontief assumption is reasonable in manufacturing. Basu (1996) contains a careful discussion of this issue.

[13] The Federal Reserve Board uses measures of physical product, kilowatt hours of electricity, and production worker hours to construct sectoral, monthly industrial production indices. The fact that output indices are created in part using input data, which are in turn used to estimate production functions, should cause some concern. Approximately 43 percent of the output index, however, is based on physical product measures. In addition, at the end of the year, the monthly estimates are benchmarked to match annual data for which various censuses provide physical production data. Burnside et al. (1995) estimate production function regressions using Federal Reserve Board industrial production indices. They discuss and assess the robustness of their results by using alternative data sources, including annual data and quarterly data for industries in which the production index is based entirely on physical output. We do not, however, conduct those robustness checks here.

slightly nonstandard. Following Burnside et al. (1995), we assume that total electricity consumption is proportional to capital services. We use electricity because standard capital stock measures fail to reflect capital utilization, which has a strong cyclical component.[14] Complete value-added and input data were available for 17 of the 20 two-digit manufacturing sectors. Our sample period is 1972:2–1992:4. We are forced to exclude tobacco, petroleum, and plastics and rubber (SIC 21, 29, and 30) for lack of labor data. We also exclude one quarter (1988:1) for instruments and electrical machinery (SIC 38 and 36) because of an apparent data error detailed in Appendix A.

Equation (1) implies a linear production function regression in growth rates. We allow for industry fixed effects by demeaning our variables and estimate

$$v_{j,t} = \alpha k_{j,t} + \beta l_{j,t} + a_{j,t}, \tag{2}$$

where $v_{j,t}$ denotes the deviation of the one-quarter growth rate of $V_{j,t}$ from its mean, and $k_{j,t}$ and $l_{j,t}$ are similarly defined.

We estimate α and β in (2) via GMM and then back out the implied productivity growth rates. Our moment conditions for each sector are

$$E(a_{j,t} z_{j,t}) = 0, \tag{3}$$

where $z_{j,t}$ are instruments, described in the next subsection.

B. *Moment Conditions and Instrument Selection*

We estimate the model employing several different instrument sets. One popular set of instruments, used by Hall (1988, 1990) and Ramey (1989), consists of the political party of the president, federal defense expenditures, and current and lagged oil prices. Hall (1988) provides a rationale for using these instruments. Two criticisms of these instruments have been leveled and are worth reviewing.

First, Shea (1993*b*) argues that the president's political party and defense expenditure have *low relevance*, or are nearly uncorrelated with aggregate economic activity. In large samples, instruments with low relevance generate consistent parameter estimates as long as the moment condition holds; however, Nelson and Startz (1990) document poor small-sample properties resulting from low relevance instruments. Nelson and Startz argue that poor small-sample properties are capable of explaining Hall's finding of large increasing returns. Low relevance arises, in part, because the same instruments are used in every sector. The Hall-Ramey instruments are aggregate variables, containing no sec-

[14] Electricity usage by two-digit industry is collected monthly by the Federal Reserve Board.

tor-specific component.[15] Instead, Shea argues that particular instruments may be relevant for some industries and not others. For example, defense expenditure may be a good instrument for sectors that produce tanks and ammunition. For sectors that produce goods not used in the military, defense expenditure may be a poor instrument; therefore, failing to use a priori information to include or exclude certain instruments from certain industries may lead to poor finite-sample properties of the estimators. Because of this criticism, we do not estimate (3) using only Hall-Ramey type instruments.

The second criticism concerns the final Hall-Ramey instrument, the price of oil. Oil prices are negatively correlated with the business cycle (see Hamilton 1983) and thus do not suffer from low relevance. Yet, the price of oil may be an inappropriate instrument for a different reason. If oil is a factor of production in a sector, then the oil price should be a right-hand-side variable and is not a valid instrument. Given our assumption of Leontief production between materials (including energy) and value-added, this is not a problem in our specification. In some cases, described below, we use oil prices.

Our main strategy for choosing instruments is a simplified version of Shea's (1993*a*, 1993*b*) approach. Sector j's instruments are the output growth rates of industry, government, or foreign sectors that are large customers of sector j. Industry-specific instruments are created using prior information contained in the input-output table. Intuitively, output movements of a downstream purchaser of a sector's goods generate a pure demand shift for the upstream supplier of that good. Shea also requires instrument sectors to have a small cost share for industry j, making it more plausible that the instrument is an exogenous shock. Because of our level of aggregation, we are unable to ensure instrument exogeneity with this technique.

According to our procedure, if sector j makes at least 10 percent of its sales, outside of sector j, to sector i, then sector i output growth is an instrument for the sector j regression.[16] This procedure does not restrict instruments to be expenditures by manufacturing industries used in our regression since input-output data as well as value-added data are available for nonmanufacturing industries and nonproductive sectors, such as government purchases.[17]

[15] Aggregate instruments are commonly used for sectoral production function estimation. Examples include Domowitz, Hubbard, and Petersen (1988), Burnside (1996), and Basu and Fernald (1997*b*).

[16] More specifically, we require this relationship to hold in at least two of the four observations of the input-output use table in order for sector i output to instrument the sector j regression.

[17] Finding exogenous but relevant instruments is a challenging task if technology adoption decisions are endogenous, as in Shleifer (1986) and Dupor (1996). For example, a demand shock may spur firms to adopt an unexecuted blueprint for productivity im-

TABLE 3
CUSTOM INSTRUMENTS

SIC	Industry	Instrument
24	Lumber	Printing
		Construction
26	Paper	Food
27	Printing	Banking and wholesale trade
		Health care
28	Chemicals	Plastics and rubber
32	Stone, clay, and glass	Construction
33	Primary metals	Construction
		Fabricated metals
		Electrical machinery
		Nonelectrical machinery
		Transportation equipment
34	Fabricated metals	Construction
		Transportation equipment
35	Nonelectrical machinery	Exports
36	Electrical machinery	Construction
		Defense
37	Transportation equipment	Defense
		Exports
38	Instruments	Health care

NOTE.—Custom instruments are output growth rates of industry, government, or foreign sectors that are large purchasers of the respective sector's goods. SIC 20, 22, 23, 25, 31, and 39 had no industry-specific instruments.

Table 3 lists the instrument(s) and corresponding sectors constructed by this algorithm. Note that federal defense expenditure is an instrument for electrical machinery and transportation equipment (SIC 36 and 37) according to our procedure. For sectors that supply a large fraction of their output to national defense, we contend that this is a relevant instrument. The procedure finds at least one sector-specific or custom instrument for 11 of the 17 sectors. Sectors without custom instruments are food, textiles, apparel, furniture, leather, and miscellaneous.

We employ three different instrument sets. First, we estimate (3) only for sectors that have custom instruments (IS1). Second, we estimate the model including the six sectors without custom instruments (IS2). In this case, the instruments for these six sectors are the contemporaneous and a four-quarter-lagged oil price growth rate. Finally, for comparison with previous studies that use the Hall-Ramey instruments, IS3 contains only the current and four-quarter-lagged oil price growth rate and federal defense expenditure. In the next subsection, we describe our spatial GMM framework.

provement. In this context, demand-side instruments may not be exogenous to true productivity growth. Basu and Fernald (1997*b*) note a similar problem concerning reallocation effects and finding exogenous instruments.

C. GMM Estimation

We estimate two baseline specifications. First, we use the moment condition in (3) for each of our sector-instrument pairs to obtain GMM estimators of the parameters α and β. Next, we allow α and β to differ for durable and nondurable sectors. For ease of exposition, we describe only the specification in which α and β are common across sectors. For notational simplicity, let the stacked $a_{j,t}z_{j,t}$ terms for each sector-instrument pair be denoted by a vector $\mathbf{g}_t(\alpha, \beta)$. Then the moment condition becomes $E\{\mathbf{g}_t(\alpha, \beta)\} = 0$. We estimate α and β via a two-step procedure. First, we obtain consistent estimates, using an identity matrix as a weighting matrix. We use them to estimate the asymptotic covariance matrix of the moment conditions, which is used as a second-stage weighting matrix to obtain efficient GMM estimates (see Hansen 1982). Following Burnside et al. (1995), we assume that $\mathbf{g}_t(\alpha, \beta)$ is serially uncorrelated. Thus we need to estimate the covariance matrix $\mathbf{\Omega} \equiv E\{\mathbf{g}_t(\alpha, \beta)\mathbf{g}_t(\alpha, \beta)'\}$. Note that $\mathbf{\Omega}$ would still have to be estimated to conduct inference, even if we were not interested in efficient GMM.

Unconstrained estimation of $\mathbf{\Omega}$ is not feasible because the dimension of $\mathbf{g}_t(\alpha, \beta)$ is too large relative to the number of time-series observations; therefore, we adopt two strategies to reduce the dimensionality of this estimation problem. First, we make an assumption about the dependence of instruments and productivities. The element of $\mathbf{\Omega}$ corresponding to the covariances between variables of sector i, instrument z, and sector j, instrument $\tilde{z}$, is $E\{[a_{i,t}z_{i,t}][a_{j,t}\tilde{z}_{j,t}]\}$. We follow Burnside et al. and assume that our instruments are second-moment independent of productivity shocks, so that we can write $E\{[a_{i,t}z_{i,t}][a_{j,t}\tilde{z}_{j,t}]\} = E\{a_{i,t}a_{j,t}\}E\{z_{i,t}\tilde{z}_{j,t}\}$. We estimate the $E\{z_{i,t}\tilde{z}_{j,t}\}$ terms without constraints. The second dimension-reducing strategy is to utilize our spatial model of productivity comovement to obtain estimates of the $E\{a_{i,t}a_{j,t}\}$ terms. Using the simple model described below, we model covariances between productivity growth rates as functions of economic distances between sectors. We use nonparametric estimates of these spatial covariances to estimate $E\{a_{i,t}a_{j,t}\}$. Moreover, these nonparametric estimates of spatial covariances also provide us with a simple way to characterize productivity comovement across sectors.

1. Model of Productivity Covariances

We model $a_{j,t}$ as having two components: $a_{j,t} = \mu_{j,t} + \epsilon_{j,t}$. First, the idiosyncratic component, $\mu_{j,t}$, is serially uncorrelated, has expectation zero, and is independent across sectors with a sector-specific variance σ_j^2. The second component, $\epsilon_{j,t}$, is independent of $\mu_{j,t}$ and also has expectation zero and is serially uncorrelated. The $\epsilon_{j,t}$ are correlated across sectors as a function of economic distance with a conditional covariance function, $c(\|\mathbf{s}_{i,t-1} - \mathbf{s}_{j,t-1}\|)$, that depends on the distance between sectors. Thus we model all the comovement of productivities across sectors as arising from the spatially correlated component $\epsilon_{j,t}$ that is described by the function $c(\cdot)$. Letting $\boldsymbol{\Sigma}_t$ denote the conditional covariance of sectoral productivity growth rates at time $t+1$ given information at time t, we have

$$\boldsymbol{\Sigma}_t = \begin{bmatrix} \sigma_1^2 + c(0) & c(\|\mathbf{s}_{1,t} - \mathbf{s}_{2,t}\|) & \cdots & c(\|\mathbf{s}_{1,t} - \mathbf{s}_{N,t}\|) \\ c(\|\mathbf{s}_{1,t} - \mathbf{s}_{2,t}\|) & \sigma_2^2 + c(0) & \cdots & c(\|\mathbf{s}_{2,t} - \mathbf{s}_{N,t}\|) \\ \cdots & \cdots & \cdots & \cdots \\ c(\|\mathbf{s}_{1,t} - \mathbf{s}_{N,t}\|) & c(\|\mathbf{s}_{2,t} - \mathbf{s}_{N,t}\|) & \cdots & \sigma_N^2 + c(0) \end{bmatrix}.$$

We characterize comovement of our estimated productivity shocks across industries by estimating $c(\cdot)$. Armed with our estimates $\hat{\alpha}$ and $\hat{\beta}$, we can form estimates of productivities:

$$\hat{a}_{j,t} = v_{j,t} - \hat{\alpha} k_{j,t} - \hat{\beta} l_{j,t}.$$

Using these productivity estimates, $\{\hat{a}_{j,t}\}$, we follow Hall and Patil (1994) and estimate $c(r)$ for $r > 0$ by a local average method. We estimate $c(r)$ by a weighted average of all the cross products of data with the same time index, giving a large weight to those observations whose distance is close to r and a small weight to those whose distance is far from r. In other words, we run a nonparametric regression of $\hat{a}_{i,t}\hat{a}_{j,t}$ on $\|\mathbf{s}_{i,t-1} - \mathbf{s}_{j,t-1}\|$. This results in the following estimator of $c(r)$ for $r > 0$:

$$\hat{c}(r) = \sum_t \sum_i \sum_{j \neq i} W_T(r - \|\mathbf{s}_{i,t-1} - \mathbf{s}_{j,t-1}\|)[\hat{a}_{i,t}\hat{a}_{j,t}] \quad \text{for } r > 0. \tag{4}$$

The term $W_T(\cdot)$ is a weight function that adds to one and that will concentrate its mass at zero as $T \to \infty$. This strategy works because the idiosyncratic components are uncorrelated across sectors. Our estimates of sectors' variances are the corresponding sample moments of $\hat{a}$: $(1/T)\sum_t \hat{a}_{j,t}^2$. Thus we do not attempt to separately estimate $c(0)$ and $\{\sigma_j^2\}$.[18]

In Section IV, we present estimates of the contemporaneous productivity covariance across sectors: $\hat{c}(r)$. For presentation, we normalize $\hat{c}(r)$ by dividing it by the arithmetic average of the sample variances of sectoral productivities. We plot $\hat{\rho}(r)$ defined as

$$\hat{\rho}(r) = \frac{\hat{c}(r)}{(1/N)\sum_j [(1/T)\sum_t \hat{a}_{j,t}^2]}. \tag{5}$$

[18] In principle, we could identify $c(0)$ from the idiosyncratic variances σ_i^2 if $c(\cdot)$ were sufficiently smooth. However, we remain agnostic about whether $c(\cdot)$ is continuous at zero.

If there are no idiosyncratic shocks, all $\sigma_i^2 = 0$, $\hat{\rho}(r)$ will be the sample spatial autocorrelation function of ϵ. With idiosyncratic shocks, it remains a useful comparison of whether the estimated covariance across industries, $\hat{c}(r)$, is large relative to the variation within industries.

Note that our local average estimates of these covariance functions are not constrained to be valid covariance functions. It is possible for our estimates not to be positive definite because of sampling error. This is not important when they are used to examine comovement properties and our bootstrap tests of spatial independence are unaffected. It is a potential problem for estimation of $\mathbf{\Omega}$ described below. In all our results, the relevant covariance matrix estimates were positive definite, even though we did not impose this constraint. See Chen and Conley (2001) for a method of estimating spatial covariances that imposes that the estimates be valid covariance functions.

2. Estimation of $\mathbf{\Omega}$

This subsection describes our strategy for estimating $\mathbf{\Omega}$. By assumption, its elements can be expressed as $E\{a_{i,t}a_{j,t}\}E\{z_{i,t}\tilde{z}_{j,t}\}$, and we separately estimate moments of productivities and instruments. Instrument moments $E\{z_{i,t}\tilde{z}_{j,t}\}$ are estimated using their sample analogues: $(1/T)\sum_t z_{i,t}\tilde{z}_{j,t}$. We use our spatial model of productivity covariances to estimate $E\{a_{i,t}a_{j,t}\}$ as follows. The basic idea is to write $E\{a_{i,t}a_{j,t}\}$ in terms of the conditional expectation of this product given the distance between sectors i and j. This conditional covariance function can be estimated nonparametrically and then time-averaged to get an estimate of $E\{a_{i,t}a_{j,t}\}$. As described above, our model implies that, for distinct locations i and j, the conditional expectation of $a_{i,t+1}a_{j,t+1}$ given information at time t can be written as a function of the distance between locations $\mathbf{s}_{i,t}$ and $\mathbf{s}_{j,t}$:

$$E_t\{a_{i,t+1}a_{j,t+1}\} = c(\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|).$$

Using an iterated expectations argument, we get

$$\begin{aligned} E\{a_{i,t}a_{j,t}\} &= E[E_t\{a_{i,t+1}a_{j,t+1}\}] \\ &= \int c(\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|)d\lambda(\mathbf{s}_{i,t}, \mathbf{s}_{j,t}), \end{aligned} \tag{6}$$

where $\lambda(\cdot, \cdot)$ is the measure induced by the process determining the time series of sectors' locations.

Having obtained an estimate of $\hat{c}(r)$ for all nonzero distances between the sectors i and j in our time span, $\{\|\mathbf{s}_{i,t} - \mathbf{s}_{j,t}\|\}_{t=1}^{T-1}$, we use the empirical distribution of relative distances to approximate $\lambda(\cdot, \cdot)$. In other words,

TABLE 4
Description of Instrument Sets

	IS1	IS2	IS3
Custom instrument sectors (11 total sectors)	Custom instruments	Custom instruments	Change in oil price plus one-year lag, defense expenditure
Noncustom sectors (6 total sectors)	Not included	Change in oil price plus one-year lag	Change in oil price plus one-year lag, defense expenditure
Number of moment conditions	20	32	51

Note.—Custom instruments are detailed in table 3. For comparison with existing research, instrument set 3 consists of only Hall-Ramey aggregate instruments.

we simply use a time average of $\hat{c}(r)$ to approximate the integral in (6). Thus our estimate of $E\{a_{i,t}a_{j,t}\}$ is

$$\hat{E}\{a_{i,t}a_{j,t}\} = \frac{1}{T-1}\sum_{t=1}^{T-1}\hat{c}(\|\mathbf{s}_{i,t}-\mathbf{s}_{j,t}\|).$$

As described above, idiosyncratic sector-specific shocks are allowed for by estimating the variances within each sector separately via its sample analogue, for example, $(1/T)\sum_{t=1}^{T}\hat{a}_{i,t}^2$ for sector i. Our estimate of $\mathbf{\Omega}$ consists of the compilation of the estimates $\hat{E}\{a_{i,t}a_{j,t}\}(1/T)\sum_t z_{i,t}\tilde{z}_{j,t}$ for all sector-instrument cross products.

IV. Empirical Results

We estimate production functions for both distance measures and three instrument sets. The three instrument sets are described in table 4. As noted in Section III*B*, output growth of sector i is an instrument for sector j if the value of purchases by sector i of sector j goods makes up a large portion of sector j's sales. Eleven industries have at least one industry-specific or custom instrument. These industries and associated instrument(s) appear in table 3 and define the first instrument set (IS1). Restricting attention only to sectors that have sector-specific demand shift instruments requires throwing out one-third of our sectors. The second instrument set (IS2) adds to IS1 the additional sectors by defining the current and four-quarter-lagged oil price growth rate as instruments for the remaining six sectors. The set IS2 is our benchmark specification since it uses both custom instruments and all industries. For comparison with existing studies that use Hall-Ramey instruments, we define a third instrument set (IS3). The set IS3 consists of current defense expenditure growth and current and four-quarter-lagged oil price growth for all 17 sectors.

First, we discuss our estimates of returns to scale (RTS) and aggregate productivity volatility and how they relate to previous studies' RTS es-

TABLE 5
Production Function Estimates: Equal Coefficients across All Sectors

	BUY			SELL		
	IS1	IS2	IS3	IS1	IS2	IS3
β	.53	.54	.84	.54	.53	.84
	(.18)	(.12)	(.11)	(.18)	(.12)	(.11)
α	.70	.62	.20	.70	.63	.19
	(.21)	(.15)	(.12)	(.21)	(.15)	(.12)
$\alpha+\beta$	1.23	1.16	1.04	1.24	1.16	1.03
	(.07)	(.06)	(.09)	(.07)	(.06)	(.09)
J-test	36.74	54.14	52.32	36.61	53.49	53.35
Degrees of freedom	18	30	49	18	30	49
r_h	1.90	2.37	2.38	1.90	2.35	2.37
r_y	1.71	2.14	2.24	1.69	2.10	2.21
Number of sectors	11	17	17	11	17	17

Note.—Sample period is 1972:2–1992:4. Equation (2) is estimated with identical coefficients across each sector using different instrument sets and distance measures. r_y and r_h report the relative contribution of off-diagonal covariance terms to GDP-weighted and raw average sectoral productivity growth variance.

timates. Then we present evidence that productivity comovement is significantly related to one measure of economic distance and that a substantial amount of aggregate productivity fluctuations are due to this spatially correlated component.

A. *Returns to Scale*

Table 5 presents estimates for both BUY and SELL distances for the three instrument sets assuming that production parameters are identical across sectors. The estimated matrices of derivatives have good condition, indicating that the instruments are clearly correlated with the regressors: they are relevant. Estimates of RTS are sensitive to instrument set choice, but they are not sensitive to bandwidth choice in our estimator of $\mathbf{\Omega}$.[19] For both distance measures and IS1 and IS2 in table 5, we find evidence of mild increasing returns. The point estimates of $\alpha + \beta$ range from 1.16 to 1.24. However, RTS appear approximately constant for IS3 across distance metrics. The test of overidentifying restrictions rejects the model for IS1 and IS2, but not for IS3.

Table 6 presents our estimates when α and β are allowed to differ across durable and nondurable sectors.[20] Our point estimates here also vary considerably across instrument sets.[21] The highest BUY distance

[19] The kernel used in calculating GMM weighting matrices via the spatial method described above is a normal density with standard deviation 0.08 for both distances and all specifications. The reported estimates are robust to changes in these bandwidths of doubling and halving them.

[20] The same kernels are used as for the previous specification in table 5.

[21] This is consistent with previous evidence, first documented by Burnside (1996), that sectoral production regressions can be sensitive to instrument selection.

TABLE 6
PRODUCTION FUNCTION ESTIMATES: DURABLES AND NONDURABLES

	IS1		IS2		IS3	
	Durables	Nondurables	Durables	Nondurables	Durables	Nondurables
	A. BUY Distance					
β	.61	1.24	.51	.84	.85	.60
	(.20)	(.60)	(.17)	(.27)	(.12)	(.23)
α	.56	.58	.64	.56	.24	.31
	(.23)	(.59)	(.21)	(.28)	(.13)	(.23)
$\alpha+\beta$	1.16	1.82	1.15	1.40	1.09	.91
	(.07)	(.22)	(.07)	(.13)	(.10)	(.15)
J-test	26.31		49.84		46.95	
Degrees of freedom	16		28		49	
r_h	2.17		2.37		2.42	
r_y	1.92		2.00		2.26	
	B. SELL Distance					
β	.61	1.25	.51	.80	.86	.60
	(.20)	(.60)	(.17)	(.27)	(.12)	(.22)
α	.55	.58	.65	.62	.22	.32
	(.23)	(.59)	(.21)	(.28)	(.13)	(.23)
$\alpha+\beta$	1.16	1.82	1.16	1.42	1.08	.91
	(.07)	(.22)	(.07)	(.13)	(.10)	(.15)
J-test	26.46		49.00		48.09	
Degrees of freedom	16		28		49	
r_h	2.20		2.40		2.40	
r_y	1.91		2.01		2.22	

NOTE.—Sample period is 1972:2–1992:4. Equation (2) is estimated with identical coefficients within durable and nondurable sectors using different instrument sets and distance measures. r_y and r_h report the relative contribution of off-diagonal covariance terms to GDP-weighted and raw average sectoral productivity growth variance.

point estimates of $\alpha + \beta$, 1.16 for durables (SIC 24, 25, and 32–39) and 1.82 for nondurables (SIC 20, 22, 23, and 26–31), obtain for IS1. Estimates are lower for IS2—1.15 for durables and 1.40 for nondurables—and still lower for IS3—1.09 and 0.91. Again, SELL estimates are very close to these BUY estimates for all instrument sets. Estimates for IS1 and IS2 remain consistent with the evidence of increasing returns in table 5 when durables/nondurables heterogeneity is allowed. Constant returns appears much more plausible with IS3 estimates, again consistent with the pattern in table 5. The outcome of tests of overidentifying restrictions mimics table 5: instrument sets IS1 and IS2 are rejected but IS3 is not.

1. Relation to Previous Work

There is a substantial body of work with which to compare our results. Basu and Fernald (1997*b*) use annual Jorgenson two-digit manufacturing data and the Hall-Ramey instruments. They estimate returns to value-added directly as well as recover value-added returns based on estimating gross production functions. Whereas in table 6 we require parameter coefficients to be identical within durable and nondurable groups, Basu and Fernald allow RTS to vary by sector. They then report value-added weighted averages. Their point estimate for instrumented, direct value-added returns to durables is 1.26, which is in line with our benchmark estimate; however, they find substantially lower returns in nondurables, 0.26.

Burnside (1996) uses several data and instrument sets to estimate various production function specifications. While he finds that the typical U.S. manufacturing industry displays constant returns to value added, there is significant heterogeneity across industries. This suggests that whether parameters are restricted to be identical across sectors may be important in explaining differences across studies. He also stresses that estimates are very sensitive to instrument selection. This is consistent with our finding as well.

Burnside et al. (1995) use quarterly input and output measures identical to ours, including a capital utilization correction, but a different instrument set and estimation strategy. They find evidence of higher returns to value-added in nondurables, 1.13, than durables, 1.04 (see table 4, cols. 3 and 4, of their study). The relative magnitude of returns in durables versus nondurables is consistent with our findings using IS1 and IS2 but inconsistent with those of Basu and Fernald (1997*b*). Burnside et al. are, however, unable to reject constant returns at conventional levels of statistical significance.

Harrison (1998) uses energy-corrected Jorgenson data to estimate value-added RTS in consumption and investment goods sectors. In the Harrison study, consumption sectors (which are close to nondurable goods) have diminishing to constant RTS, whereas investment sectors (which are close to durable goods) have constant to mildly increasing RTS. These findings are more closely aligned with Basu and Fernald's results than ours.

We examine three potential reasons for the difference between estimates in previous work and our baseline results above: using alternative instruments, using spatial GMM, and constraining parameters to be the same across sectors within durables and nondurables. We discuss these three reasons in turn.

First, instrument differences are clearly an important cause of variation in results. The above-mentioned studies all use aggregate instruments as opposed to our sector-specific instruments, IS1 and IS2. These studies typically find smaller returns to value-added than we obtain with IS1 and IS2. For comparison, our third set consists of only aggregate instruments applied to all 17 sectors. Estimates are generally lower using the aggregate instruments. For example, the point estimate of returns to value-added in nondurables using BUY distance falls from 1.40 to 0.91 when we switch from IS2 to IS3. Our IS3 results are substantially closer to those of Basu and Fernald, who also find diminishing returns to nondurables using a similar instrument set. As mentioned above, Burnside (1996) emphasizes that production function estimates are sensitive to the instrument choice.

Second, we assess the potential effect of our spatial GMM procedure on our results. We reestimate all the specifications in tables 5 and 6 imposing the restriction of zero correlation in productivity across sectors. This eliminates the influence of spatial covariances on GMM weighting matrices and hence estimates. Results are presented in Appendix tables B1 and B2. The main change resulting from this restriction is that estimated standard errors for RTS are somewhat smaller when zero correlation across sectors is imposed. However, the change in standard errors does not alter conclusions about RTS, nor the outcome of overidentifying restrictions tests. For the specification with α and β common across sectors, point estimates of α, β, and $\alpha + \beta$ are quite similar to those obtained for either BUY or SELL distances when this restriction is imposed. For the specification with α and β allowed to differ for durables and nondurables, α and β point estimates are more varied, but there does not appear to be a robust pattern across instrument sets. Returns to scale point estimates are still close to those for the baseline specifications. Therefore, we are confident that our estimates are not solely driven by our spatial GMM procedure.

Third, our relatively high estimates of RTS for IS1 and IS2 could be caused by our constraining parameters to be the same across sectors within durables and nondurables. Several other authors (e.g., Basu and Fernald) allow for sector-specific parameters and in this aspect are more flexible than our baseline estimators. It is possible that sector-specific α and β are required to properly fit the data; indeed, our IS1 and IS2 models are rejected on the basis of the overidentifying restrictions test. Unfortunately, we are unable to identify sector-specific α and β with our custom instrument sets since some sectors have only one instrument. We are able to learn something, however, about the plausibility of this story from an alternative specification presented below in Section IV*C* that does allow sector-specific RTS parameters. We defer further discussion of parameter heterogeneity until Section IV*C*.

B. Properties of Sectoral Productivity Estimates

In this subsection we describe the comovement properties of the sector-level productivity series implied by our various production function estimates.

As a first step, we examine the volatility of estimated average productivity. Some researchers argue that after one controls for cyclical utilization, the volatility of aggregate productivity is diminished. Our estimate of the standard deviation of sectoral average productivity is stable across all parameterizations. For all three instrument sets and both distance measures, the standard deviation of average productivity growth is 0.007. Our estimate of average productivity growth volatility is close to but less than the value used in many aggregate real business cycle calibration exercises. For example, King, Plosser, and Rebelo (1988) use a standard deviation of 0.01. Although we find less volatile average productivity growth than is consistent with previous real business cycle models, it is also true that more recent models require smaller productivity shocks to drive aggregate fluctuations, such as King and Rebelo (1998).[22]

Volatile aggregate productivity growth is a business cycle fact that survives instrumental variables estimation of production technologies, adjusting for cyclical factor utilization and disaggregation to the two-digit level. Two questions remain. Is sectoral productivity comovement important in generating aggregate productivity volatility? If so, then what can explain the comovement in productivity across sectors?

1. Comovement and Input-Output Relations

This paper's main objective is to report the contribution of productivity comovement in generating aggregate fluctuations and explore the source of this comovement. Rows labeled r_y and r_h in tables 5 and 6 demonstrate the contribution of productivity comovement to the volatility of aggregate productivity. Our construction of r_y and r_h is as follows. Let $\hat{\mathbf{\Sigma}}$ denote the estimated unconditional covariance matrix of sector productivities. For IS2 and IS3, let $\mathbf{H}$ denote a 17×1 vector of ones and let $\boldsymbol{\theta}$ denote the 1992:4 output shares given in table 1. For IS1, only the 11 sectors with custom instruments are used in estimation. In this case, unused sectors are replaced with zeros in $\mathbf{H}$ and $\boldsymbol{\theta}$. We use the following two measures:

$$r_h = \frac{\mathbf{H}'\hat{\mathbf{\Sigma}}\mathbf{H}}{\mathbf{H}'\mathrm{diag}(\hat{\mathbf{\Sigma}})\mathbf{H}}$$

[22] Our estimated average sectoral productivity growth rates also have a low correlation with average output growth, which is a feature of other studies that adjust productivity for cyclical factor utilization such as Burnside et al. (1995).

and

$$r_y = \frac{\theta'\hat{\Sigma}\theta}{\theta'\text{diag}(\hat{\Sigma})\theta},$$

where the function diag selects the main diagonal elements of the covariance matrix. Therefore, r_h and r_y give the ratio of the average and share-weighted variance of sector productivity growth to the variance with off diagonals set to zero. A higher ratio implies a larger role for the covariance terms in generating aggregate productivity volatility. Across the parameterizations, the covariance terms make an important contribution to aggregate productivity volatility. Tables 5 and 6 show that there is a great deal of productivity comovement in our sample. When all 17 sectors are used, between 50 and 60 percent of the variance of average total factor productivity is due to off-diagonal elements. Note that this comovement persists despite our accounting for cyclical capital utilization and allowing for increasing returns.

Our spatial modeling strategy allows us to go beyond documenting comovement and ask whether productivity correlation estimates are systematically linked to observed input-output relations. The function $\hat{\rho}$, defined by (5) in Section III*C*, gives the ratio of the contemporaneous spatial covariance function across sectors to the arithmetic average of sectors' productivity variances. Figures 3 and 4 plot $\hat{\rho}$ for BUY and SELL distances, respectively.[23] Estimated productivities for each metric are calculated using IS2, allowing durables and nondurables to have different coefficients. This choice of instrument set and specifications is representative of all others estimated; $\hat{\rho}$ estimates are strikingly robust to instrument set and specification choice (further documented below).

The solid line in figure 3 plots the point estimate $\hat{\rho}$, the (normalized) estimated covariance as a function of the BUY distance measure. Histograms of distances are reported in Appendix figures B1 and B2, and relative distances between sectors are illustrated in figures 1 and 2. The dotted lines envelop a 95 percent acceptance region for the null hypothesis that productivities are spatially independent.[24] We calculate this acceptance region via a simple bootstrap strategy. Holding distances fixed, we independently draw from the empirical distribution of each sector's productivities with replacement. Then for each bootstrap sample, we calculate a bootstrap estimate of ρ. Finally, for each distance we take an envelope containing the middle 95 percent of the bootstrap

[23] An alternative definition of $\hat{\rho}$ would divide the contemporaneous covariance by the geometric, instead of arithmetic, average of the sector variances. This would imply a substantial upward shift in the normalized covariance functions in figs. 3 and 4.

[24] Serial independence is also imposed rather than just zero serial correlation, as we previously assumed for GMM estimation.

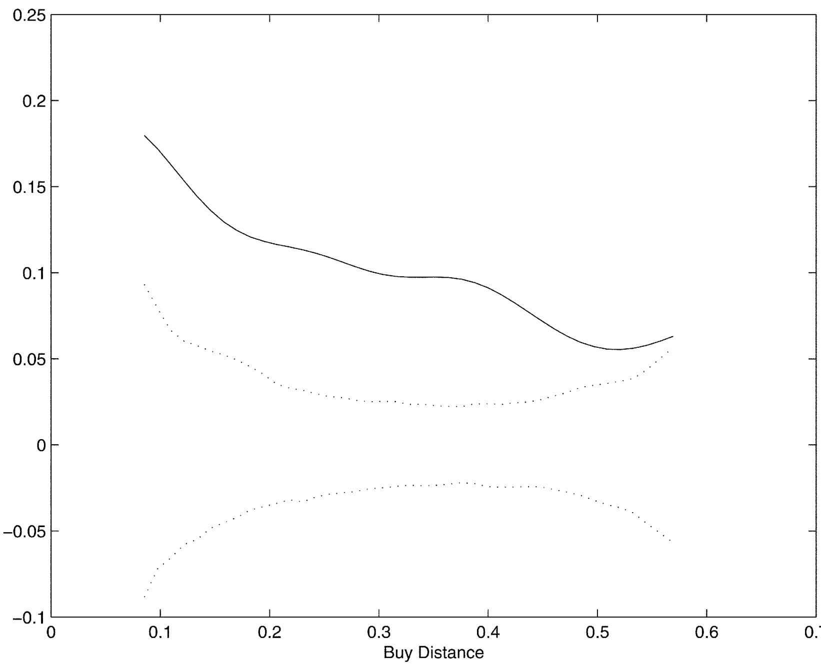

FIG. 3.—ρ estimates for BUY distances and acceptance region for independence. Normalized local average estimate of productivity covariance $\hat{\rho}$ as a function of BUY distance using instrument set 2. Dotted lines are a bootstrap 95 percent acceptance region for the hypothesis of spatial independence (500 draws). A normal kernel with standard deviation 0.05 was used to create these local average estimates.

estimates to generate a pointwise acceptance region for the hypothesis of spatial independence.

Figure 3 shows that productivity covariances are systematically related to BUY distance, and this relationship is statistically significant (we can reject the hypothesis of independence). Covariances as functions of BUY distance are positive and are outside the acceptance region for the null of spatial independence. Covariance generally declines smoothly until 0.5, near the edge of the support of distances. Sectors that are closer to one another tend to have productivities that comove more than those far away. Recall that sectors i and j are "close" to one another at time t in the BUY sense if they have similar input mixes.

Figure 4 plots $\hat{\rho}$ and an acceptance region for the hypothesis of spatial independence for SELL distances. The shape of $\hat{\rho}$ in figure 4 is different from that obtained with BUY distances, declining from 0.3 to 0.6 but then increasing for a substantial portion of the larger distances. The U shape of $\hat{\rho}$ for SELL distances is inconsistent with theoretical models that predict correlation to be increasing in output linkage intensity.

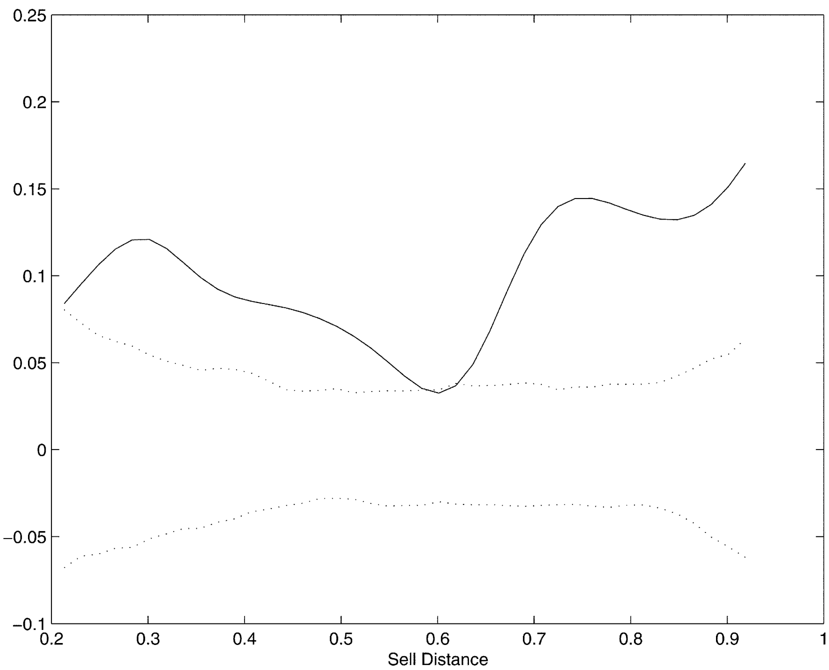

FIG. 4.—ρ estimates for SELL distances and acceptance region for independence. Normalized local average estimate of productivity covariance $\hat{\rho}$ as a function of SELL distance using instrument set 2. Dotted lines are a bootstrap 95 percent acceptance region for the hypothesis of spatial independence (500 draws). A normal kernel with standard deviation 0.05 was used to create these local average estimates.

However, we are reluctant to conclude that the increasing region of $\hat{\rho}$ is an important empirical fact. We demonstrate below that this feature results from a cluster of sector pairs that have small to medium BUY distances; thus it is plausible that the U shape is simply a result of an omitted variable problem.

These results establish a relationship between input-output linkages and productivity covariance. Sectors that are close in BUY distance have covariances that are about 10–17 percent of average sectoral variances. While individually that may not appear to be a large percentage, it is important to remember that there are a large number of sectors. As our estimates of r_h and r_y indicate, these covariance terms collectively generate a large contribution to average productivity fluctuations. Setting the covariance terms to zero, which would be appropriate if ρ were zero, leads to more than a one-half decrease in average productivity volatility in the sample. Therefore, we conclude that covariance as a function of BUY distance is not only statistically present but of considerable importance for aggregate productivity volatility.

We are also interested in testing the hypothesis that all comovement in productivity is due to a common aggregate shock. In this case, ρ would be a nonzero constant for all distances. The evidence we have reported thus far that $\hat{\rho}(r)$ is significantly different from zero is consistent with this hypothesis. Therefore, we use the following bootstrap method to test the hypothesis that productivity shocks comprise an aggregate shock plus sector-specific shocks that are independent of each other. To generate a proxy for the distribution of the aggregate shock, we use the empirical distribution of averages of our sector-specific shocks at each point in time, $(1/17)\sum_{i=1}^{17}\hat{a}_{i,t}$. Our proxy for the distribution of idiosyncratic shocks for sector j is the empirical distribution of deviations of $\hat{a}_{j,t}$ from $(1/17)\sum_{i=1}^{17}\hat{a}_{i,t}$. Each bootstrap sample is obtained by independently drawing aggregate shocks and then adding independent draws of idiosyncratic noise from each sector's proxy distribution.[25] Just as for the acceptance regions above, pointwise 95 percent acceptance regions are constructed by plotting the .025 and .975 quantiles of the bootstrap distributions for each distance. Figure 5 presents this acceptance region for the null hypothesis that there is an aggregate shock and independent, sector-specific shocks. For BUY distances greater than 0.43, point estimates lie outside this acceptance region. This range of distances constitutes approximately 23 percent of the nonzero BUY distances (see the histogram in App. fig. B1). This range of distances is broad enough to reject this hypothesis that these comovements are caused by a common aggregate shock.

The relative importance of our two metrics in explaining productivity comovement can be examined by estimating covariances as a function of both distances simultaneously. We allow covariances to depend on both distances: $\mathrm{Cov}_t(a_{i,t+1}, a_{j,t+1}) = \tilde{c}(D_t^b(i, j), D_t^s(i, j))$. We estimate the function $\tilde{c}$ using a nonparametric regression of $\hat{a}_{i,t+1}\hat{a}_{j,t+1}$ on $D_t^b(i, j)$ and $D_t^s(i, j)$. Figure 6 presents estimates of $\tilde{c}$ normalized by dividing by the average of the estimated sector productivity variances. The productivity estimates used in figure 6 are taken from a specification with durable/nondurable parameters, IS2, and BUY distances. The corresponding surface for the SELL metric is qualitatively identical and is omitted for brevity. A bootstrap 95 percent acceptance region for the null hypothesis of spatial independence was also estimated (using 500 draws), and the

[25] We note that this method will not consistently recover the distributions of aggregate and individual shocks under the null as $T \rightarrow \infty$. Our proxy for each period's aggregate shock, $(1/17)\sum_{i=1}^{17}\hat{a}_{i,t}$, can be written as the true aggregate shock plus an error equal to the average of the 17 sectors' individual shocks. Thus our estimate of the aggregate shock distribution function will converge to the distribution of the aggregate shock plus a small independent error, not the true aggregate shock distribution. However, we feel that this is a still a reasonable approximation since the average of 17 independent individual shocks will contribute a small error.

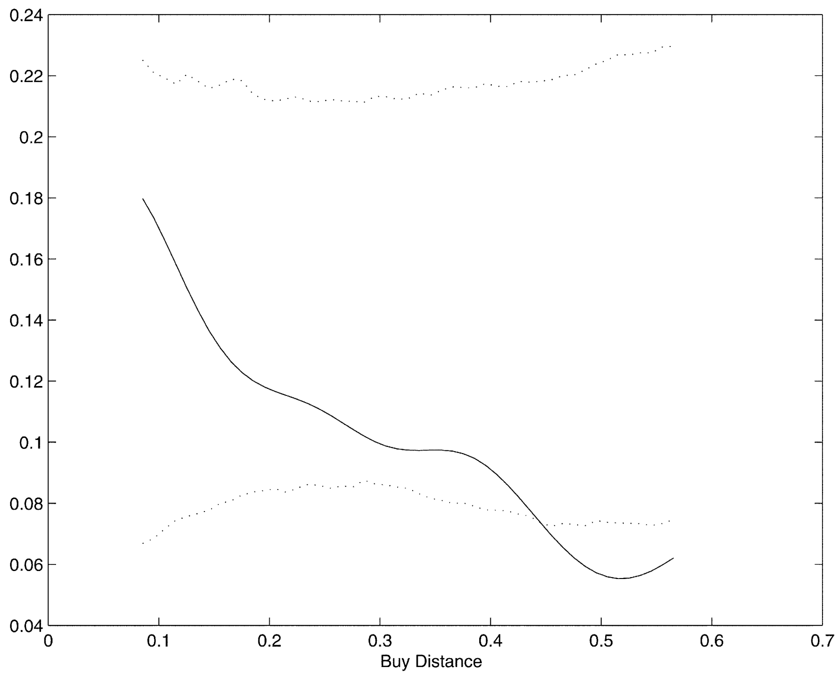

FIG. 5.—Aggregate shock model acceptance region and point estimates for BUY distances. The solid line is the point estimate $\hat{\rho}$ for BUY distances using instrument set 2. Dotted lines are a bootstrap 95 percent acceptance region for the hypothesis that productivity is the sum of an aggregate shock plus independent sector-specific shocks (500 draws). A normal kernel with standard deviation 0.05 was used to create these local average estimates.

shading indicates distances at which the point estimates are outside this acceptance region.

Figure 6 demonstrates covariance patterns that appear dictated by BUY distances. For a given SELL distance, covariance declines as BUY distances grow. For observations of a given BUY distance, there do not seem to be systematic covariance patterns as a function of SELL distance. The apparent trough for SELL distances of about 0.5 and small BUY distances is due to the fact that there no observations with that combination of distances, rather than an anomalous covariance feature of observed data. There happens to be a group of observations with BUY distances around 0.3–0.4 that have large SELL distances. They are the cause for the U-shaped $\hat{\rho}$ estimates for SELL distances. Therefore, we conclude that the main features of covariance patterns are described by $\hat{\rho}$ for BUY distances.

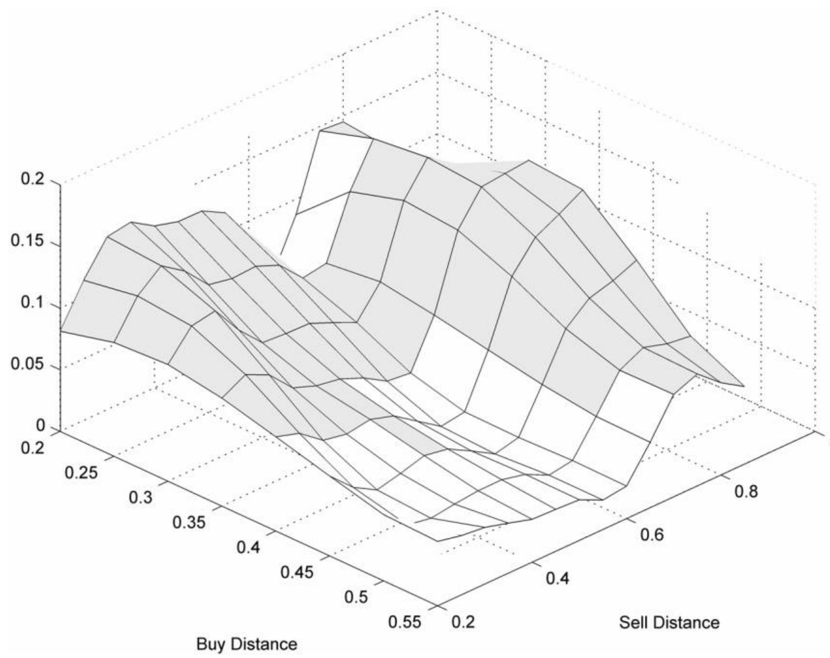

FIG. 6.—Normalized estimate of covariance as a function of both distances. This surface is the normalized point estimate of $\tilde{c}$ depicting productivity covariance as a function of both BUY and SELL distances. Shading indicates that the area is outside a bootstrap acceptance region for the null of spatial independence (500 draws). A product kernel with normal densities with standard deviations of 0.06 was used to create these local average estimates.

2. Robustness to Instrument Choice and Specification

The evidence of covariance as a function of BUY distance is very robust to changes in instrument sets and specifications. The significant, generally decreasing shape of $\hat{\rho}$ is maintained under all instrument sets and regardless of whether durable/nondurable parameter heterogeneity is allowed. This is illustrated in figure 7*a*, which presents $\hat{\rho}$ for all instrument sets when parameters are common across sectors, and figure 7*b*, which presents the corresponding estimates allowing durable/nondurable parameter heterogeneity. In addition, this result still obtains when productivities are estimates under the restriction that there is zero correlation across sectors (reported in App. table B1). We are therefore confident that the relationship between BUY distance and sector productivity covariance is not due to our estimated increasing returns to value-added using IS2. In summary, while RTS estimates are sensitive to instrument selection, the BUY covariance relationship is not.

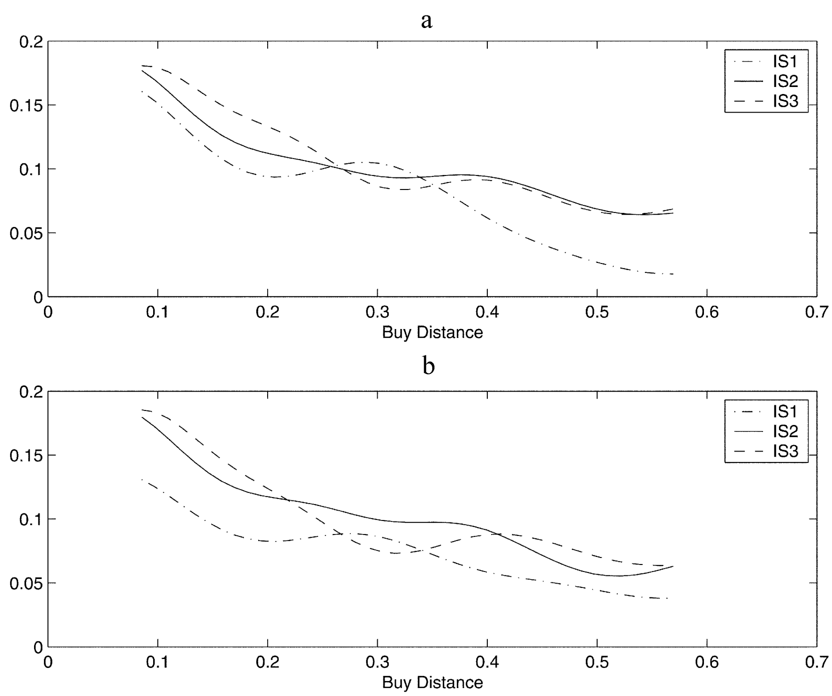

FIG. 7.—ρ estimates for specifications with common parameters and durable/nondurable heterogeneity. *a*, $\hat{\rho}$ estimates for BUY distances when parameters are common across sectors (corresponding to estimates in table 5) with instrument sets IS1 (dot-dash line), IS2 (solid line), and IS3 (dashed line). *b*, $\hat{\rho}$ estimates for BUY distances with separate durable/nondurable parameters (corresponding to estimates in panel A of table 6) with the same instrument sets: IS1 (dot-dash line), IS2 (solid line), and IS3 (dashed line). A normal kernel with standard deviation 0.05 was used to create these local average estimates.

C. *Alternative Specification*

In this subsection we consider an alternative specification that allows RTS to be sector-specific. As mentioned above, limiting heterogeneity to durables/nondurables is a potential source for differences in our estimates of RTS. From Burnside's (1996) work, we know that allowing for sectoral parameter heterogeneity significantly affects parameter estimates. Furthermore, Basu and Fernald (1997*a*, 1997*b*) demonstrate that sectoral heterogeneity in RTS combined with cyclical variation in the intensity of input growth across sectors can generate an upward bias in the "average" economywide RTS.

The lack of sector-specific heterogeneity may partially explain our result of covariance as a function of BUY distance. This is one possible implication of the Basu-Fernald "reallocation" effect. Imagine that (*a*) increasing returns sectors were "close" in terms of our economic distances; and (*b*) not allowing different coefficients across sectors results in our estimating approximately constant returns overall, even though some had increasing returns. In this case, increasing returns sectors might have productivity residuals from estimation that comoved not because there was true productivity comovement but instead because these sectors had unrecognized increasing returns and factor inputs that comoved. In this case, the comovement of estimated productivities is really unmeasured increasing returns together with increased input usage. This would imply that our estimates of ρ are in fact documenting patterns of input reallocation effects as a function of BUY distance.

Allowing for sector-specific parameters is not feasible with our baseline specifications for IS1 and IS2 because of a scarcity of instruments. Our alternative approach uses a generalized value-added production function. A first-order approximation is used in actual estimation:

$$v_{j,t} = a_{j,t} + \gamma_j[c_{Lj,t}l_{j,t} + (1 - c_{Lj,t})k_{j,t}], \qquad (7)$$

which can be derived if (*a*) factor markets are competitive and (*b*) the generalized function is homogeneous of degree γ_j in capital services and labor. Here, $c_{Lj,t}$ represents the time *t*, sector *j* ratio of the wage bill to the total cost of capital and labor. Annual data on cost shares are available from the Jorgenson data set, used in Basu and Fernald (1997*b*). We use the annual data for a particular year in each of the four quarters of that year. Electricity is again used to proxy for capital services. Then, total returns to value added γ_j are allowed to be sector-specific and estimated using spatial GMM with instrument sets IS2 and IS3.[26] Estimates of γ are, of course, comparable to those of $\alpha + \beta$.[27]

The γ_j are imprecisely estimated, making conclusions about individual sectors difficult. Therefore, we focus on averages across sectors of γ_j estimates, as done by Basu and Fernald. In table 7, we report the value-added share-weighted average of γ_j estimates for durables and nondurables sectors, using IS2 and IS3. These weighted averages are most comparable to the RTS estimates of Basu and Fernald, particularly IS3 because of the similarity in instrument sets. For IS3, we find decreasing RTS in share-weighted nondurables, as in Basu and Fernald. Unlike Basu and Fernald, we also find decreasing returns in share-weighted

[26] In results available on request, we also estimate this specification with the same parameter constraints as in tables 5 and 6 to check for differences due to the Jorgensen data/cost shares approach. The resulting estimates of γ are close to the corresponding estimate $\alpha + \beta$ from the baseline model. In particular, when γ is restricted to be identical across sectors, both BUY and SELL estimates find mild increasing returns for IS2 and constant returns for IS3, as in our baseline specification.

[27] Equation (7) is estimated by Burnside (1996) and is closely related to Basu and Fernald (1997*b*). Basu and Fernald also dispense with the assumption that gross output production is Leontief in value-added and materials. Lacking quarterly data on materials by sector, we are unable to drop the Leontief assumption.

TABLE 7
Production Function Estimates: Using Cost Share Data to Estimate Total Returns to Value-Added with BUY and SELL Distances, Durables and Nondurables

	IS2		IS3	
	Durables	Nondurables	Durables	Nondurables
	A. SELL			
γ_{ave}	.919	1.802	.956	.942
	(.761)	(1.163)	(.167)	(.460)
J-test	21.46		24.59	
Degrees of freedom	15		34	
	B. BUY			
γ_{ave}	.884	1.480	.872	.952
	(.187)	(.557)	(.148)	(.478)
J-test	16.92		36.78	
Degrees of freedom	15		34	

Note.—Sample period is 1972:2–1992:4. γ_{ave} is the GDP share-weighted total returns to value-added in the durables/nondurables subgroups, when estimated returns are allowed to vary by sector.

durables.[28] Estimates for IS2 are substantially different with evidence of increasing RTS for both sectors, similarly to our previous results. Disparities due to instrument choice clearly persist under this alternative approach and do not appear to be an artifact of parameter restrictions in our baseline specifications.

Finally, figure 8 examines whether productivity covariance as a function of BUY distance is robust to allowing sector-specific RTS. We plot $\hat{\rho}$ for BUY distances when productivities are obtained using IS3 in specification (7). The estimate of ρ is very similar to those for our baseline specifications. It is downward sloping and outside of the independence acceptance region for a large range of distances. Thus our finding of productivity comovement as a function of BUY distance is robust to this alternative specification and does not appear to be due to the reallocation effect described above.

V. Final Remarks

In this paper, factor demand relations implied by the input-output matrix are used in a spatial model to generate nonparametric estimates of GMM covariance matrices and characterize the covariance structure of sectoral productivities. Our results indicate that there exists strong comovement between total factor productivity growth among two-digit SIC manufacturing industries even after we account for cyclical capital util-

[28] Unlike Basu and Fernald, we control for cyclical capital utilization, which tends to lower RTS estimates (see Burnside et al. 1995).

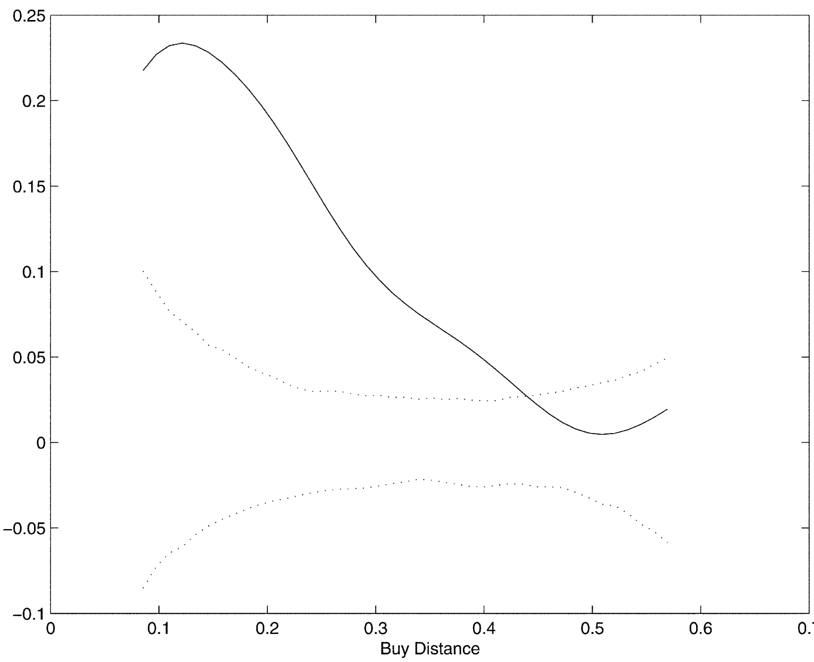

FIG. 8.—Parameter estimates and acceptance region for independence using sector-specific RTS productivities. The solid line is the point estimate $\hat{\rho}$ for BUY distances using productivities from IS3 from the specification with sector-specific RTS. Dotted lines are a bootstrap 95 percent acceptance region for the hypothesis of independence across sectors (500 draws). A normal kernel with standard deviation 0.05 was used to create these local average estimates.

ization and estimate RTS using instrumental variables. While RTS estimates are sensitive to instrument selection, our comovement results are robust. Sectors that share suppliers have more highly correlated productivity growth rates, and the comovement of sector productivities contributes substantially to measured fluctuations in aggregate productivity.

The spatial models we use to characterize productivity are potentially useful for describing patterns in a variety of other sector-level data. In addition, our methods for estimating large-dimension covariance matrices will be useful in any application in which there is a plausible metric describing covariance structure among many time series.

Despite the large body of theoretical research on complementarities and empirical work on aggregate productivity at business cycle frequencies, there is relatively little empirical work on either complementarities or sectoral productivities. Our results lie at the intersection of these two research areas. It is worthwhile to compare our results with previous research.

Costello (1993) provides an early study of the covariance properties of sector productivities. She constructs correlation matrices of sector Solow residuals at approximately the one-digit level of disaggregation for six industrialized countries. She finds significant correlation of productivities between sectors in each of the countries studied—even larger than those reported here. While somewhat diminished quantitatively, our results show that Costello's finding of sector productivity correlation survives disaggregation of data, cyclical capital utilization, nonconstant returns, and instrumental variables.

Shea (2002) tests four alternative models of complementarity: supply and demand factor linkages, aggregate activity spillovers, and geographic spillovers. He estimates the structural parameters from multisector general equilibrium models that display these alternative mechanisms using sector value-added data and the 1977 input-output table. Shea finds that demand-side linkage is an important source of output comovement. While our paper differs from Shea's in that we study the comovement of sector productivities and use a less parametric approach, our results are related. We find the strongest evidence for complementarities using BUY distance, which corresponds roughly to Shea's demand-side linkages.

Bartelsman et al. (1994) study the role of input-output relations and sector productivities. They find that a buy-from weighted aggregate of other industries' output raises productivity in a sector, which they interpret as evidence of external economies of scale. This result has been criticized for two reasons: (*a*) unmeasured factor utilization could generate the appearance of external economies (see Basu and Fernald 1997*b*), and (*b*) the use of aggregate instruments makes it difficult to identify external economies (see Burnside 1996). Our finding that BUY input-output relations may explain productivity comovement survives both adjustments for cyclical capital utilization and the use of industry-specific instruments. It may be possible to interpret our finding as evidence of external economies of scale, although distinguishing between alternative types of complementarity would require stronger identifying assumptions. This is one avenue for future research.

Appendix A

We eliminated two sector-quarter observations because we are confident that there is a data error that affects estimates in some specifications. According to the original data source, the first quarter of 1988 saw a 24 percent increase in the instrument (SIC 38) sector labor force and a 10 percent decline in the electrical machinery (SIC 36) sector workforce. These two growth rates are huge outliers and are implausible. We believe that it is a result of some reclassification of electrical machinery workers into the instruments sector workers (with no corresponding change in sectoral output definitions). In response, we removed these two data points from our panel but have elected to use all subsequent growth rates, in the hope that the misclassified labor data still provide a good approximation once the jump in levels due to the classification change has passed. Data sources are as follows:

1. Input-output data: 1972, 1977, 1982, 1987 benchmark input-output use table (Bureau of Economic Analysis, Interindustry Economics Division).
2. Output of two-digit manufacturing sectors: seasonally adjusted, quarterly average of monthly Federal Reserve Board industrial production index.
3. Total hours of two-digit manufacturing sectors: seasonally adjusted, quarterly average of monthly total employee hours of production workers on nonagricultural payrolls (Citibase acronym LPPXX) and average weekly hours of production workers, Bureau of Labor Statistics estimates (Citibase acronym LPHRXX).
4. Electricity consumption of two-digit manufacturing sectors: seasonally adjusted, quarterly average of monthly kilowatts of electricity used. Industrial Production (Federal Reserve Statistical Release G.12.3).
5. Banking and wholesale trade, health care, rubber: quarterly data constructed from annual chained-dollar output (Yuskavage 1996).
6. Defense: seasonally adjusted, quarterly real federal government defense expenditure (Bureau of Economic Analysis).
7. Construction: seasonally adjusted, quarterly chained-dollars residential fixed investment (Bureau of Economic Analysis).
8. Exports: seasonally adjusted, quarterly average of monthly real exports, net of military aid (Bureau of the Census).

Appendix B

TABLE B1
Production Function Estimates: No Correlation across Sectors Imposed

	IS1	IS2	IS3
β	.56	.59	.77
	(.17)	(.17)	(.09)
α	.70	.56	.31
	(.21)	(.15)	(.11)
$\alpha+\beta$	1.25	1.15	1.08
	(.06)	(.05)	(.07)
J-test	35.32	54.29	52.30
Degrees of freedom	18	30	49
Number of sectors	11	17	17

TABLE B2
ADDITIONAL PRODUCTION FUNCTION ESTIMATES: NO CORRELATION ACROSS SECTORS IMPOSED

	IS1		IS2		IS3	
	Durables	Nondurables	Durables	Nondurables	Durables	Nondurables
β	.61	1.23	.49	.90	.81	.55
	(.19)	(.60)	(.17)	(.27)	(.11)	(.22)
α	.56	.59	.67	.44	.31	.43
	(.23)	(.59)	(.21)	(.28)	(.13)	(.22)
$\alpha+\beta$	1.17	1.82	1.16	1.34	1.13	.98
	(.07)	(.21)	(.07)	(.12)	(.09)	(.14)
J-test	24.97		50.80		47.70	
Degrees of freedom	16		28		49	

NOTE.—Sample period is 1972:2–1992:4. This table presents estimates of eq. (2), as in tables 5 and 6, imposing a restriction of zero productivity correlation between sectors with nonzero distances.

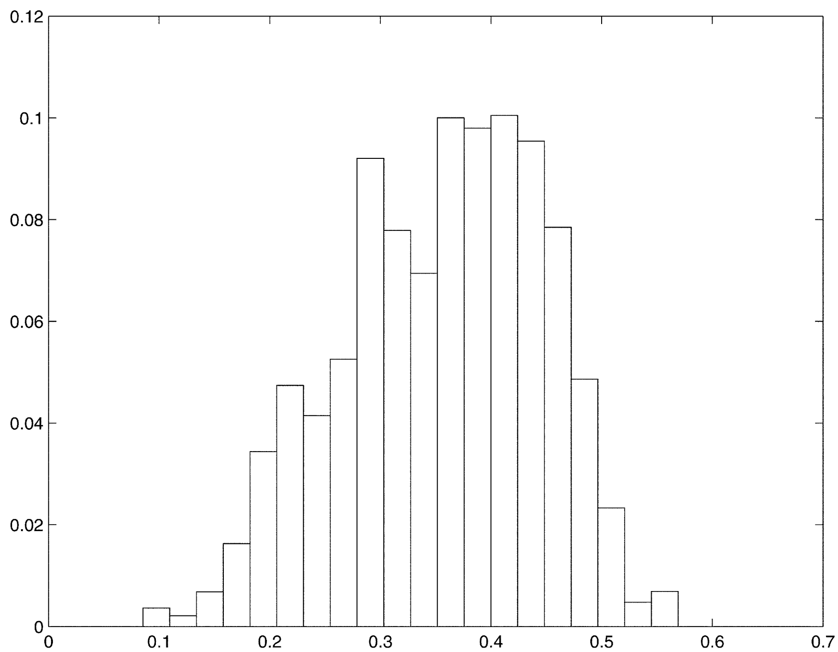

FIG. B1.—Histogram of nonzero BUY distances for the 17 sectors used in estimation

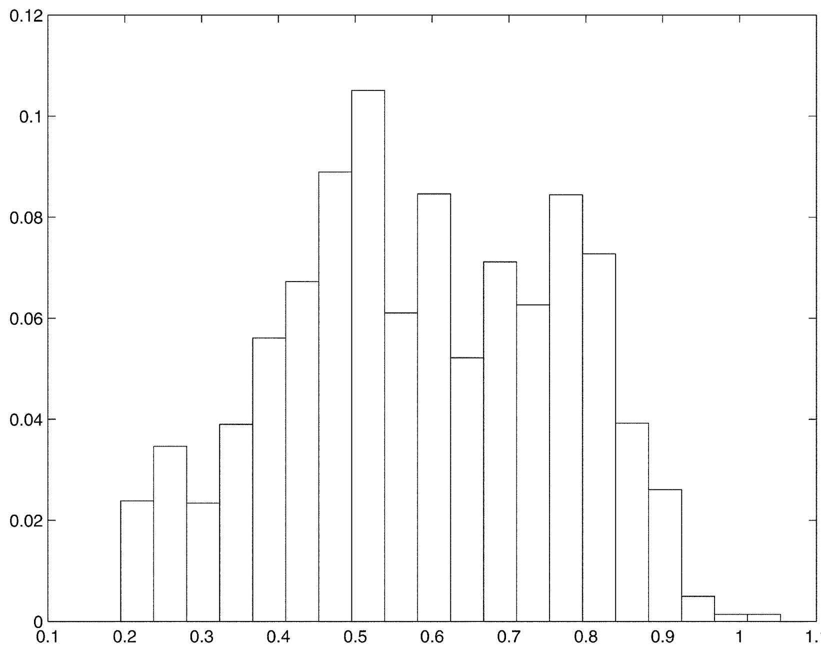

Fig. B2.—Histogram of nonzero SELL distances for the 17 sectors used in estimation

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