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A Dynamic Integration Approach in Regional Input-Output and Econometric Models

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Abstract

The methodology with which regional input-output information is incorporated into an econometric model specification has recently gained attention. Although the interdependency of a region's inter-temporal economic sectors has been emphasized, the dynamic properties of these inter-sectoral relationships have not been fully incorporated. This paper presents an attempt to introduce the dynamic properties of inter-sectoral relationships among the economic sectors of a region. The result is a unique Dynamic Integration Approach (DIA) model that not only accounts for structural change in a region's economy, but also is free from many of the inconsistencies and deficiencies associated with recent embedded-holistic models.

Keywords: Input-Output; Econometric; Holistic embedding; Dynamic integration

JEL classification: R15; C10; C53

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1. INTRODUCTION

The embedding of *a priori* inter-industry information in an input-output econometric model is designed to improve its predictive accuracy. Historically, embedding strategies have mostly been applied to the input-output econometric modeling of metropolitan areas (Coomes, Olson, and Glennon 1991) and of regions consisting of one or more counties (Fawson and Criddle 1994). More recently, Rickman (2002) has applied an integrating strategy to a state-level economy.

In an embedding strategy, the intermediate demand characteristics of an input-output specification are incorporated into a host econometric model. Most of these models collapse the intermediate demand information into a single composite variable. The intermediate demand characteristics serve as *prior* information, representing the inter-industry relationships within a region's economy.

The scope of the model, the level of the industrial detail, and the treatment of the input-output coefficients all help determine an integration methodology within the class of the embedding models. Since employment is both a key policy variable and an important component of the income variable and since regional output data are less widely available than are regional employment data, employment modeling has gained more popularity than output modeling.

Recent literature discloses two classes of embedding strategy: holistic and partitive (Rey 1997; LeSage and Rey 2002). In the holistic embedding approach, intermediate input demand information is implanted into an econometric model as a single composite variable. The composite variable serves as a surrogate for all the inter-industry demand linkages, viewed as a whole, within a sample economy. Holistic models have been developed by Moghadam and Ballard (1988); Coomes, Olson, and Glennon (1991); Stover (1994); and Rey and Jackson (1999). An advantage of holistic models is their simplicity. A disadvantage is their lack of accuracy.

The partitive embedding approach, however, only includes those inter-industry linkages that are determined to be influential, relevant, or otherwise important linkages. In partitive embedding models, intermediate input demand linkages are often introduced in a disaggregated form rather than as a composite variable. White and Hewings (1982); Glennon, Lane, and Johnson (1987); Glennon and Lane (1990); and Magura (1987, 1990) all report results of input-output models with partitive embedding. An advantage of partitive models is their accuracy. A disadvantage is their complexity. For example, it is important to judiciously limit the number of linkages to be included in the model. An inordinately high number of linkages runs the risk of over-parameterization. This is especially true as the level of industrial detail increases.

Recognizing the limitations of recent holistic and partitive studies, the Bayesian approach has now been used to incorporate input-output information (LeSage and Rey 2002, Rickman and Miller 2002). The Bayesian approach incorporates non-sample prior knowledge as the surrogate for the nature of inter-industry relationships. These relationships are incorporated as follows:

> *This information should be combined via Bayes Rule with time series sample data on industry-level regional and national employment to produce parameter estimates that reflect a consistent probabilistic framework for treating non-sample information in econometric estimation problems* (LeSage and Rey 2002, p. 253).

In a Bayesian model, prior distributions of the parameters are assigned. An advantage is the reduction of the risk of over-parameterization. A disadvantage is its reliance on theoretical rather than observed relationships.

Greater theoretical development is required if any of these methods is to prove the best representation of inter-industry input-output relationships. This paper constructs a holistic model of the type developed by Moghadam and Ballard (1988). Its contribution is the development of a strategy to account for the dynamic inter-industrial relationships within a region's economy. Dynamic inter-industrial relationships allow the values of the region's input-output coefficients to change through time. Because this paper follows the holistic embedding format, subsequent use of the word "embedding" refers to holistic embedding.

2. BACKGROUND

A basic embedding model includes an intermediate input demand variable in addition to national, regional, state, or local final demand variables. Moghadam and Ballard (1988) proposed a regional Integrated Small Area Modeling of Industrial Sector (I-SAMIS) model of the following form:

(1) $$E_{it} = \beta_0 + \beta_1 IDV_{it} + \beta_2 Z_{it} + \beta_3 V_{it} + \varepsilon_{it}.$$

I-SAMIS envisions employment in industrial sector i (E_i), at time period t, to be determined mainly by a combination of three independent variables: (1) an Intermediate Demand Variable (IDV_{it}), (2) a national activity variable (Z_{it}), and (3) a local activity variable (V_{it}). IDV_{it} is the link between input-output and econometric specifications. It is defined as:

(2) $$IDV_{it} = \Sigma_j a_{ij} E_{jt},$$

where a_{ij} is the national input-output coefficient expressed in dollar terms and E_j is the employment in sector j. The estimated coefficient of the IDV_{it} in equation (1) accounts for dynamic inter-industry relations as well as structural changes in the region's economy. The argument favoring a dynamic IDV_{it} is regarded as follows:

> *It is absolutely essential that the IDV be used only within a behavioral econometric estimation for several reasons. First, the IDV has become*

> *stochastic. The identities that held together the IO table are no longer valid once we have regionalized the table and added a time element. Second, the behavioral estimation adjusts for the degree of openness of the region. The more the industry relies on non-local demand, the smaller the estimated coefficient on the IDV will be. Third, as the economic composition and trading partners of the region change over time and technology advances further, the inter-industry input-output relationships do not remain unaffected, as implied by a static, fixed-coefficient model…* (Moghadam and Ballard 1988, p. 658).

Several inconsistencies are associated with equation (2). Three are discussed here. First, national input-output coefficients (a_{ij}) are used as proxies for regional input-output coefficients, although the impact of using national coefficients as surrogates for regional coefficients has not been well documented; Moghadam and Ballard (1998) acknowledge that the regional coefficients should be used. Second, the structural change reflected in the inter-industry input-output relationship of a region is treated as constant in the IDV_{it} specification. However, inter-industry input-output relationships are not static. In a dynamic regional economy, changes in technology, demand, relative productivities, and relative wages each cause the values of the input-output coefficients to change. Third, the units of measurement embodied in the IDV_{it} equation are inconsistent. Rey and Jackson (1999) show that the different units of measurement in the components of equation (2) are dimensionally inconsistent. This causes IDV_{it} to be uninterpretable.

Coomes, Olson, and Glennon (1991) extended the work of Moghadam and Ballard (1988). They suggest: (1) using a regional instead of a national input-output table, and (2) replacing the IDV_{it} with productivity-adjusted input-output relationships, which they call the Intermediate Employment Demand Variable ($IEDV_{it}$). That relationship is measured as follows:

$$(3) \qquad IEDV_{it} = \Sigma_j \, (l_j / l_i) \, a_{ij} \, E_{jt},$$

where a_{ij} is the regionalized input-output coefficient and l_i and l_j represent labor productivity ratios in sectors *i* and *j*.

Rey and Jackson (1999) argue that the IEDV approach of Coomes, Olson, and Glennon (1991) has two major contributions. One, IEDV rectifies the dimensional inconsistency problems associated with the Moghadam and Ballard's (1988) IDV_{it} measure. Two, IEDV recognizes labor productivity differentials across all sectors. Rey and Jackson (1999) go on to suggest that Moghadam and Ballard's (1988) equation (2) is a special case of Coomes, Olson, and Glennon's (1991) equation (3). That special case makes equation (2) valid only when labor productivities are identical in sectors *i* and *j*.

In spite of the theoretical improvements made by Coomes, Olson, and Glennon (1991), Rey (1997), and Rey and Jackson (1999) find that no enhancement in predictive accuracy is made by the use of $IEDV_{it}$ rather than IDV_{it}. It is possible that one reason equation (3) provides no predictive benefit over equation (2) is the use of static rather than dynamic embedding in both. The validity of that possibility is an empirical question requiring further consideration, given Stover's (1994) finding that the use of annualized regional input-output coefficients offered no improvement over the use of static benchmark coefficients. Yet, according to Rey and Jackson (1999, p. 1585), "The question of static versus dynamic *labor* coefficients has not been examined to date."

In an attempt to overcome the shortcomings of both the IDV_{it} and the $IEDV_{it}$ approaches, Rey and Jackson (1999) suggest a "Dynamic Intermediate Employment Demand Variable" ($DIEDV_{it}$), where the static labor productivity terms in the $IEDV_{it}$ are updated during the sample period, while the inter-industry relationship (national input-output coefficients) is held constant. Although they show that the $DIEDV_{it}$ displays better performance than does the $IEDV_{it}$ model, the significance of the estimated $DIEDV_{it}$ coefficients and the predictive accuracy of the results are mixed.

The purpose of this paper is to introduce a specification alternative to that offered by Moghadam and Ballard (1988). This alternative is called the Dynamic Integration Approach (DIA) model. The DIA model: (1) replaces the IDV_{it} variable with a non-linear Intermediate Employment Demand Requirement ($IEDR_{it}$) term, and (2) allows the regional labor coefficients to account for structural change (dynamic inter-industry relationship) in the region's economy. The next section contains a discussion of $IEDR_{it}$. To test the efficacy of the DIA model, sample data from Oklahoma are compared with the existing alternative specifications, $IEDV_{it}$ and $DIEDV_{it}$. The tests appraise both within and out-of-sample predictive accuracy.

3. THE DEVELOPMENT OF THE DIA MODEL

Following Coomes, Olson, and Glennon (1991) and Moghadam and Ballard (1988), a standard embedding model of employment is defined as:

$$E_{it} = f\,(IEDR_{it}, FD_{it}, Z_{it}). \tag{4}$$

Employment in each industry within a region at a given time (E_{it}) is a function of: (1) an intermediate employment demand requirements ($IEDR_{it}$) component, (2) a final demand (FD_{it}) component, and (3) a time trend or other related variables (Z_{it}) component.

In order to obtain linear results, equation (4) is written in natural log (ln) form as:

$$\ln E_{it} = f\,(\ln IEDR_{it}, \ln FD_{it}, \ln Z_{it}), \tag{5}$$

where "ln" is a prefix and represents natural log, E_i is employment in sector i at time t, $IEDR_{it}$ is the intermediate employment demand requirement component, FD_{it} is a final regional demand component that consists of local and national final demand activity variables, and Z_{it} represents a time trend or other related variables.

3.1 The Intermediate Employment Demand Requirement Component

The DIA model extends the standard embedding integration model framework by offering a dynamic $IEDR_{it}$ component. The following features distinguish the DIA model from the $IEDV_{it}$ and $DIEDV_{it}$ embedding methodologies.

1. In an effort to account for a dynamic inter-industry relationship, the DIA model formulates a unique methodology that adjusts the values of the regional input-output coefficients through time. The adjustment process is based on the construction of a Cost Adjustment Factor (CAF_{it}) term that is incorporated into the "Intermediate Employment Demand Requirement" ($IEDR_{it}$) component.

2. The $IEDR_{it}$ component for each sector is incorporated within the system rather than being treated as a single exogenous variable.

3. In the DIA model, the productivity ratios are used to transform the regional input-output coefficients to regional labor coefficients.

Additionally, an interesting application of the integrated input-output and econometric models can be found in Israilevich et al. (1997). They used a complex coupling integrated model (Rey 1998, 2000) of the type developed by Conway (1990) to extract the annual regional input-output relationship. The direction of changes in these relationships was used as a proxy for the direction of structural change in the economy of the Chicago metropolitan area.

Once the DIA model is estimated using the estimated coefficients, the regional input-output relationship can readily be extracted for each period. Changes in this relationship in turn point to the direction of the structural change in the region's economy. Forecasting the structural change in the region's economy is, however, left to future research; it is outside the scope of this paper.

In the DIA model offered in this paper, the term $IEDR_{it}$ is determined as shown in equation (6):

$$(6) \qquad IEDR_{it} = \Sigma_j \, r_{ij,t} \, X_{jt}.$$

In equation (6), X_{jt} is total regional output of sector j at time t, and $r_{ij,t}$ is the dollar value of regional input-output coefficient at time t.

3.2 The Cost Adjustment Factor

Regional input-output coefficients are defined as the proportions of input demand that are required to produce one dollar of output by regional producers. Variations in regional input-output coefficients can be explained by structural changes in a region's economy at any given time, relative to a benchmark year in which the values of input-output coefficients are estimated from the national tables. Structural changes can in turn be explained by observing changes in factor costs and factor productivities.

The proportion of local demand that is satisfied by local producers, on the other hand, can be determined by relative profitability. According to Stevens et al. (1983), a profit-maximizing firm would purchase its input needs from local manufacturers as long as it is relatively less costly to purchase locally. Relative costs in turn depend on such factors as: (1) relative wages paid, (2) relative productivity, and (3) transportation costs. Based on Treyz (1983, pp. 314-15), one can make the following argument: "Assuming that one price prevails in all markets, given constant returns to scale for all inputs, and that profit or losses arise when the technology in a particular area differs from the average technology in the nation, we can then show that relative profitability depends on relative factor cost and factor productivity for each industry."

Hence, technological and structural formations in a regional economy can be different from the average national economy in any given time period. These differences are, in part, reflected in wage and productivity differences. Regional input-output coefficients are estimated as deviations from corresponding national input-output coefficients for a benchmark year. Adjustments to these regional estimations are made over time to account for differences in the regional wage to productivity ratios, *vis-à-vis* their national counterpart.

A unique cost adjustment factor (CAF_{it}) is formulated to account for the relative wage and productivity differences between a specific year's regional and the benchmark year's national economy. This measure adjusts the regional input-output coefficients to accommodate the degree to which regional economic and technological structures differ from the national average economy. A CAF can be defined as follows:

$$(7) \qquad CAF_{it} = \frac{\left(\dfrac{LPRO_{i,t}}{LW_{i,t}}\right)}{\left(\dfrac{LPRO_{i,87}}{LW_{i,87}}\right)} \div \frac{\left(\dfrac{NPRO_{i,t}}{NW_{i,t}}\right)}{\left(\dfrac{NPRO_{i,87}}{NW_{i,87}}\right)}.$$

In equation (7), $LPRO_{it}$ is a measure of local productivity for sector i in time t and is defined as per-employee share of value added. $NPRO_{it}$ is a measure of national productivity for sector i in time t and is defined as per-employee share of value added. LW_{it} is average local wage for sector i in time t and is defined as per-employee share of wage and salary disbursement. NW_{it} is average per-worker national wage and salary disbursement in time t. The subscript 87 refers to the year 1987, which is the benchmark year used in this paper.

Equation (7) assumes CAF_{it} to be the ratio of relative local productivity to local average wage to that of its benchmark (1987) counterpart, to the ratio of relative national productivity to average national wage to that of its benchmark (1987) counterpart.

There are benefits associated with this construction. First, the relative difference in "average productivity to wage" in any given time period accounts for differences in technology in a particular area relative to the average technology in the nation. Second, since the regional input-output coefficients are determined for a benchmark year, differences in the relative "average productivity to wage" over time also explain changes in the input-output coefficients over time.

The value of the CAF_{it} can be greater than one, one, or less than one. When $CAF_{it} > 1$, the "productivity to wage" ratio in the region, relative to the benchmark year, is greater than that of the national average. The model's result will be a positive correlation between local intermediate employment demand and CAF_{it}. The practical result will be that regional input-output coefficients will be adjusted upward over time. If $CAF_{it} = 1$, the "productivity to wage" ratio in the region, relative to the benchmark year, equals the national average. No change in input-output coefficients is expected. When $CAF_{it} < 1$, the correlation will be negative and regional coefficients will be adjusted downward over time.

The behavior of regional input-output coefficients can be explained by the following equation:

$$(8) \qquad r_{ij,t} = r_{ij,87} e^{\alpha_i (DCAF_{i,t})} .$$

In equation (8), $r_{ij,87}$ is the regional input-output coefficient for the benchmark year (1987). The italicized factor e is the base of the Napierian logarithm. The exponent α_i determines the degree with which changes in $DCAF_{it}$ cause changes in $r_{ij,t}$. The exponent $DCAF_{it}$ is an endogenous identity, where $DCAF_{it} = CAF_{it} - 1$.

The thrust of equation (8) is that changes in CAF_{it} automatically adjust the regional input-output coefficients through time. Adjustments in regional input-output coefficients in turn reflect: (1) changes in the proportion of national technical coefficients that are satisfied regionally, (2) changes in national technical coefficients, or (3) some combination of the two.

Inserting equation (8) into the equation (6) yields the following:

$$(9) \qquad IEDR_{it} = \Sigma_j \; r_{ij,87} \; e^{\alpha_i (DCAF_{it})} X_{jt} .$$

Following Coomes, Olson, and Glennon (1991), one can convert "the fraction of dollar input required to produce one dollar of output" into the fraction of a job in the input industry required to support a job in the output industry. Thus, the intermediate employment demand requirement ($IEDR_{it}$) of equation (9) can now be expressed as:

$$(10) \qquad IEDR_{it} = \Sigma_j \; r_{ij,87} \; e^{\alpha_i (DCAF_{it})} A_{jt,87} \, E_{jt} .$$

The term $A_{ij,87}$ converts the output values into employment and is the inverse ratio of productivities for sectors *i* and *j* for the 1987 benchmark year:

(11) $A_{ij,87} = (E_{i,87} / Q_{i,87}) \div (E_{j,87} / Q_{j,87})$.

In equation (11), $Q_{i,87}$ is total local gross output of industry *i* for the 1987 benchmark year, and $E_{i,87}$ is local employment in industry *i* for the 1987 benchmark year. $(E_{i,87} / Q_{i,87})$ defines a fraction of a job required to produce one dollar of output in sector *i*. $(E_{j,87} / Q_{j,87})$ defines a fraction of a job required to produce one dollar of output in sector *j*.

The total gross output for the benchmark year for each industry ($Q_{i,87}$) is not readily available at regional levels and needs to be estimated. Using $RGSP_{it}$ (real gross state product) as value added output, $Q_{i,87}$ can be determined, given the standard input-output balance equation. According to Chowdhury (1984, p. 183):

> *If the static Input-Output framework is accepted, this implies a relationship between gross output and value-added (VA) in each sector. This relationship can be expressed as:*
>
> $$VA = B\,Q$$
>
> *where B is a matrix with off diagonal elements equal to zero and diagonal elements equal to one minus the column sums of the direct requirement matrix A. A typical element of B on the main diagonal is then:*
>
> $$b_{ij} = 1 - \Sigma_i a_{ij}, \quad j = 1, 2 \ldots. n$$
>
> *Solving for sectoral gross output in terms of value-added results in:*
>
> $$Q = B^{-1}\,VA.$$

The 1987 values of total gross output for each sector can then be obtained, given the value added data and regional input-output coefficients for that year. That is:

(12) $Q_{i,87} = (1 - \Sigma_i r_{ij})^{-1} RGDP_{i,87} \qquad i = 1, 2 \ldots n,$

where $RGDP_{i,87}$ is real gross state product, serving as a proxy for value added output for sector *i* in 1987.

Equation (12) is used to determine the values of $A_{ij,87}$ in equation (11). Equation (11) is in turn used to determine the $IEDR_{it}$ in equation (10). Equation (10) replaces $IEDR_{it}$ in equation (5). Equation (5) can be written as:

(13) $\ln E_{it} = \beta_0 + \ln\left(\sum_j r_{ij,87}\, e^{a_i(DCAF_{it})} A_{ij,87} E_{jt}\right) + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$

Equation (13) can now be rewritten as:

$$(14) \qquad \ln E_{it} = \beta_0 + \ln \left(e^{\alpha_i (DCAF_{it})} \textstyle\sum_j e_{ij,87} E_{jt}\right) + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$$

The magnitude of $e_{ij,87}$ can be measured as $e_{ij,87} = r_{ij,87} A_{ij,87}$. It is the regional input-output labor coefficient and can be interpreted as a fraction of a job from the input industry required to support a job in the output industry in the benchmark year. Equation (14) represents the generic specification of the DIA model.

Equation (14) can be transformed into the following equation:

$$(15) \qquad \ln E_{it} = \beta_0 + \alpha_i (DCAF_{it}) + \ln(\Sigma_j e_{ij,87} E_{jt}) + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$$

The term $(\Sigma_j e_{ij,87} E_{jt})$ represents the intermediate employment demand for the i^{th} industry (selling industry), originating in all j industries (purchasing industries) and is based on the static input-output coefficients at the benchmark year. Restating $\ln(\Sigma_j e_{ij,87} E_{jt})$ in equation (15) as $\ln IEDOT_{it}$, equation (15) can then be rewritten as:

$$(16) \qquad \ln E_{it} = \beta_0 + \alpha_i (DCAF_{it}) + \ln IEDOT_{it} + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$$

To be estimated, equation (16) is rearranged into the following equation.

$$(17) \qquad \ln EDOT_{it} = \beta_0 + \alpha_i (DCAF_{it}) + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it},$$

where $\ln EDOT_{it} = \ln E_{it} - \ln IEDOT_{it}$.

3.3 The Final Demand Component

The second component of the DIA model specification includes the final local and national demand, or activity variables that explain changes in regional employment. The local and national activity variables used in Coomes, Olson, and Glennon (1991) include the real output of the corresponding national industry, a national productivity variable, an MSA (metropolitan statistical area) payroll variable, and a time trend variable.

Rey and Jackson (1999) use an aggregate national output variable instead of the national industrial output used in Coomes, Olson, and Glennon (1991) and a total personal income variable for the San Diego area. Extensive multicollinearity in the Coomes, Olson, and Glennon (1991) model is one justification for the use of the aggregate national variables by Rey and Jackson (1999). Although they were successful in reducing the impact of the multicollinearity problem, multicollinearity persisted as evidenced by the existence of large condition numbers.

The specifications for the final demand variables in the DIA model differ from Rey and Jackson (1999) in that two interactive variables, $RMGDP_{it}$ and $RMLWT_{it}$, are used in the DIA model. These variables are: (1) the multiple of $RGDP_t$ (Real Gross Domestic Product) and (2) $RLWSDT_t$ (Real Total Wage and Salary Disbursement) with the CAF_{it}.

The justification for the use of these interactive variables is twofold. First, the interactive variables can be interpreted as adjusted final demand variables for the local and national wage and productivity differences, which would serve as additional final demand information in the model. Second, when several different combinations of interactive and non-interactive variables were tried, the use of interactive variables resulted in further reductions of multicollinearity. This was verified by: (1) a reduction in the magnitude of the variance inflationary factors (*VIF*), as defined in Levine and Berenson (2005), and (2) a higher number of significant coefficient estimates.

The existence of multicollinearity, especially in non-linear or forecasting models, is not necessarily unacceptable. However, Rey and Jackson (1999) argue for the reduction of multicollinearity when the focus is on the significance of the intermediate input demand component:

> *As is well known, the presence of multicollinearity can result in large variances in estimated parameters. Thus the interpretation of the significance of the individual parameters becomes more difficult* (Rey and Jackson, 1999. p. 1588).

4. DATA

The model data consist of quarterly, non-seasonally adjusted employment levels in private non-farm sectors of the state of Oklahoma (Sectors 2-8 as they appear in Table 1). The test period extends from the first quarter of 1972 to the fourth quarter of 1994. The data set includes the regional direct requirement coefficient matrix (regional input-output coefficients) that was constructed in the Center for Economic and Management Research at the University of Oklahoma using ADOTMATR (a regional economic modeling system).

5. THE STANDARDS FOR COMPARISON

Several alternative model specifications are constructed, measured, and compared with the DIA model results. These include: (1) an alternative DIA model specification (ADIA); (2) an "IEDV" model, of a type constructed originally by Moghadam and Ballard (1988) and modified by Coomes, Olson, and Glennon (1991); (3) an econometric model (ECO); and (4) a "DIEDV" model specification, of the type constructed by Rey and Jackson (1999).

5.1 Test Model 1

The alternative specification of the DIA model (ADIA) hypothesizes the usefulness of including the national "wage to productivity" ratio in the CAF_{it} specification of equation (7) and is based on the following argument. The regional input-output coefficients are constructed from national coefficients in the benchmark year, given the "local-

TABLE 1

Major Economic Sectors, State of Oklahoma

Sector ID	SIC	Name	Acronym
1	01 – 09	Agriculture	AG
2	10 – 14	Mining	MIN
3	15 – 17	Construction	CONS
4	20 – 39	Manufacturing	MAN
5	40 – 49	Tran, Com, Pub Utility	TCPU
6	50 – 59	Trade	TRA
7	60 – 67	Fin, Ins, and Real Estate	FIRE
8	70 – 89	Services	SER
9	91 – 99	Government	GOV

Note: Based on 1987 Standard Industrial Classification

national wage and productivity" differences in that year. These differences in turn reflect the differences between average national and local technology in the benchmark year. Therefore, variations in the regional input-output coefficients can be explained by deviations of the local "wage and productivity" ratios from their benchmark values. When the productivity to wage ratio in the region's economy, relative to its benchmark year counterpart, exceeds the value of one ($CAF_{it} > 1$), local producers tend to demand more intermediate output from local suppliers and regional input-output coefficients will be adjusted upward. Therefore, the results obtained from ADIA specification should not be significantly different from the results obtained from the DIA specification.

Specification for ADIA can be obtained by modifying equation (7) with the following equation:

$$(18) \qquad CAF_{i,t} = \frac{LPRO_{i,t}}{LW_{i,t}} \div \frac{LPRO_{i,87}}{LW_{i,87}}.$$

In equation (18), $LPRO_{it}$ is a measure of the local productivity of sector *i* in time *t*, LW_{it} is the average local wage for that sector, and the subscript 87 refers to the 1987 benchmark year.

5.2 Test Model 2

The IEDV specification is obtained by removing the dynamic properties of the Intermediate Input Demand Requirement component of the DIA model. In the IEDV model, inter-industry linkages are defined as:

$$(19) \qquad IEDV_{it} = \Sigma_j A_{ij,87}\ r_{ij,87}\ E_{jt}.$$

The Intermediate Employment Demand Variable in Equation (19) is identical to the specification of equation (3) in Coomes, Olson, and Glennon (1991). The DIA model of equation (14) can then be written as:

(20) $\ln E_{it} = \beta_0 + \beta_1 \ln IEDV_{it} + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$

Equation (20) is identical to equation (2) in Coomes, Olson, and Glennon (1991). However, it differs from Coomes, Olson, and Glennon (1991) in that: (1) $RMGDP_{it}$ and $RMLWT_{it}$ are used here as final demand activity variables, and (2) the variables are in natural log form.

5.3 Test Model 3

The econometric model (ECO) is used to examine the effect of introducing inter-industry linkages into an econometric model. The IEDV and DIEDV model specifications are used to compare the DIA methodology with these alternatives. The specification for the econometric model is obtained by dropping the intermediate input demand components from equation (14):

(21) $\ln E_{it} = \beta_0 + \beta_2 \ln FD_{it} + \beta_3 \ln Z_{it} + \varepsilon_{it}.$

5.4 Test Model 4

Specification for the DIEDV model is obtained by modifying the IEDV of equation (20) to adjust to the inverse productivity ratios of sectors *i* and *j* for the sample period:

(22) $DIEDV_{\mathrm{it}} = \Sigma_j A_{ij,t}\ r_{ij,87}\ E_{jt}.$

In equation (22) $A_{ij,t}$ is a measure of the inverse productivity ratios for the sample period. Equation (22) is identical to the REIDV definition of the regional inter-industry variable of Rey and Jackson's (1999) Table 2, with the exception that equation (22) uses regionalized input-output coefficients, and that value added output is used here as a proxy for total output in determining productivity ratios.

All but one of the right-side variables in the alternative specifications are uniformly the same as the variables used in the DIA model specification. Each alternative model differs from DIA only according to its specification for the intermediate demand component. This uniformity is needed to: (1) evaluate the usefulness of the intermediate input demand specification, and (2) consistently compare results across all models. Equations (19) and (22) are used as identities in their respective model specifications.

6. THE COMPUTATIONS

Using the Fair-Park program (Fair 2003), all stochastic equations in the DIA model and each of the four alternative models are estimated by OLS. A total of five models are estimated. All models, with the exception of the econometric model, include seven stochastic equations and eight identities. The identities for each model include seven intermediate demand terms plus one term that serves as a surrogate for total non-farm employment. The models are then solved simultaneously using the Gauss-Seidel solution method. All simulations are dynamic. According to Fair (1984), a dynamic simulation is one in which the predicted values of the endogenous variables from the solutions for the previous periods are used for the values of the lagged endogenous variables for the solution for the current period.

To effectively deal with the problem of serial correlation coefficients, the offending values are treated as structural coefficients, which can be transformed into equations with serially uncorrelated error terms. That protocol eliminates the impact of serial correlation: "It will be useful to consider this transformation first because once it has been done little more needs to be said about serial correlation" (Fair 1984, p. 209).

Each equation is estimated under the assumption of serial correlation. Then the hypothesis that the serial correlation coefficients are zero is tested. If the coefficients are insignificant, they are removed from the system.

Two common measures of predictive accuracy are used in this paper: (1) percent root mean squared error (RMSE), and (2) percent mean absolute error (MAE). The smaller the values of RMSE and MAE, the greater the predictive accuracy of the models tested. A zero value points to perfect predictive accuracy (Fair 1984; Kennedy 1996).

Once the within-sample predictive accuracy of all models is compared, the significance of the differences between RMSEs is verified using a pair-wise Wilcoxon test. To ensure that within-sample predictive accuracies are consistent with out-of-sample predictive accuracies across all model specifications, a deterministic simulation is performed. RMSEs from deterministic simulations can be used to compare predictive accuracy across all models. The mean predicted values of deterministic simulations follow closely to the values of stochastic simulations and can be applied instead of stochastic simulation. Justification for this is stated as follows:

> *…predicted values from deterministic simulations are generally close to expected values from stochastic simulations, so little is likely to be lost by using deterministic simulations* (Fair 1984, p. 290).

Further details explaining these simulation procedures are discussed in Fair (1984, 1994, 2003).

The Fair-Park program is used to generate the RMSE percentages for each "out-of-sample period of 1 to 8." The process can be summarized as follows (Fair 2003). Each of the five models is estimated 49 times. The first estimation period starts in 1972.1 and ends in 1982.4. The second estimation begins in 1972.1 and ends in 1983.1. There are 48 quarters between 1983.1 to 1994.4, and 48 dynamic simulations are run. The first simulation starts 1983.1, the second starts 1983.2, and so on. The length of the first 33 simulations is eight quarters, the length of the 34th simulation is seven quarters, the length of the 35th simulation is six quarters, and so on. Therefore, there are 48 observations for the one-quarter-ahead RMSEs, 47 observations for two-quarter-ahead RMSEs, and so on through 31 observations for the eight-quarter-ahead RMSEs. All of the 48 simulations are outside the sample. The RMSE percentages are given in Table 4 for all models.

7. RESULTS

The econometric results associated with the DIA model and all other alternative specifications are presented in Tables 2 through 5. Table 2 shows the estimated coefficients and their pertinent statistical measures for the DIA model. Table 3 compares the predictive accuracy of all model specifications in terms of RMSE percentage and MAE percentage for the sample period. Table 4 compares the percent RMSEs of up to eight-period-ahead forecast horizons for all five models. An asterisk is used in Tables 3 and 4 to indicate the best performing model.

TABLE 2

Estimated Coefficients (the DIA model), Sectoral Employment (State of Oklahoma)

Equation (Acronym)	Sector	*CNST*	I*EDR*	National Activity	Local Activity	*E*(-1)	DW	R^2
2 (MIN)	Mining	2.13	-0.09	-0.15	0.19	0.15	1.86	0.99
		(*0.04*)	(*-.94*)	(*-1.52*)	(*1.93*)	(*4.73*)		
3 (CONS)	Construction	5.98	1.00	-0.29	-0.77	0.93	1.77	0.93
		(*4.25*)	(*5.14*)	(*-2.50*)	(*-6.40*)	(*13.6*)		
4 (MAN)	Manufacturing	0.31	0.46	0.19	-0.62	0.18	1.67	0.91
		(*0.46*)	(*4.07*)	(*4.32*)	(*-6.41*)	(*1.77*)		
5 (TCPU)	Tran, et al.	1.76	-0.04	0.09	-0.20	-0.03	1.90	0.95
		(*1.40*)	(*-.34*)	(*1.28*)	(*-2.24*)	(*-.54*)		
6 (TRA)	Trade	3.54	0.70	-0.15	-0.38	0.37	1.90	0.96
		(*5.16*)	(*3.49*)	(*-1.99*)	(*-2.82*)	(*4.18*)		
7 (FIRE)	Fin, et al.	2.35	0.27	0.01	0.28	0.12	1.81	0.87
		(*2.02*)	(*2.45*)	(*2.47*)	(*-3.66*)	(*2.01*)		
8 (SER)	Services	1.50	1.13	-0.26	-0.35	0.83	1.90	0.99
		(*5.36*)	(*5.43*)	(*-2.83*)	(*-2.17*)	(*24.6*)		

Notes: *E* is employment and *IEDR* is the Intermediate Employment Demand Requirement Term. National activity is the product of Real GDP and Cost Adjustment Factor (CAF), and Local Activity is the product of Real Local Wage and Salary Disbursement and CAF. All variables are in log form. The t values associated with the estimated equations are given in parentheses below the estimated coefficients.

Table 2 shows that the Intermediate Employment Demand requirement term in the DIA model is a significant explanatory variable in a majority of the Oklahoma economic sectors (five out of the seven sectors) at a level of significance of 0.05. With respect to national and local activity variables, 12 of the 17 estimated coefficients are significant at an alpha value of 0.05.

The predictive accuracy of the dynamic integrated approach model (DIA) is compared with results obtained from alternative model specifications. Alternative model specifications include ADIA, IEDV, DIEDV, and ECON. The structural forms of these specifications are discussed in "The Standards for Comparison" section presented earlier. The within-sample predictive accuracies, which are measured by RMSE Percentage, are given in Table 3.

Compared to DIA, the RMSE percentage values are lower in ADIA in four of the seven industries. However, the differences in the predictive accuracy of the two models are mostly insignificant except for the Services sector and overall non-farm-private employment (EPNF), which is due to error cancellation. This appears to be consistent with the expectation that the results obtained from ADIA specifications do not significantly deviate from those of the DIA model specification.

Table 3 suggests that both DIA and ADIA models significantly outperform the other three models. This is evident by observing the differences in RMSE percentages. The differences in RMSE percentage between the DIA-ADIA and the alternative models are significant at p-values of less than 5 percent measured by the pair-wise Wilcoxon test.

Table 3 also suggests that the performances of the alternative model specifications are mixed. However, no definite conclusions can be derived from RMSE percentage differences until out-of-sample predictive accuracy of these models is compared as well.

TABLE 3

Comparison of Within-Sample Predictive Accuracy, All Model Specifications

	RMSE Percentage					MAE Percentage				
Sector	DIA	ADIA	IEDV	DIEDV	ECON	DIA	ADIA	IEDV	DIEDV	ECON
2. Mining (MIN)	1.06*	1.09	28.86	14.72	12.24	0.8	0.8	22.2	11.0	9.8
3. Construction (CONS)	5.63	5.62*	12.02	12.55	11.80	4.4	4.4	9.7	10.5	10.1
4. Manufacturing (MAN)	1.57*	1.57*	7.35	4.85	5.12	1.3	1.3	5.2	3.5	3.9
5. Tran, et.al. (TCPU)	1.24*	1.24*	7.99	3.63	4.68	1.0	1.0	6.5	2.9	3.7
6. Trade (TRA)	1.57	1.53*	5.51	2.80	2.91	1.3	1.3	4.7	2.3	2.4
7. Fin, et.al. (FIRE)	1.05	0.99*	9.45	2.81	3.54	0.8	0.8	7.9	2.3	2.8
8. Services (SER)	1.84	1.25*	9.44	3.66	3.14	1.5	0.9	10.8	3.1	2.5
(EPNF)	0.09	0.07*	9.57	4.05	3.96	0.7	0.6	8.1	3.0	3.1

Note: EPNF is Private, Non-Farm Employment

Table 4 provides comparative out-of-sample RMSEs for forecasts, extending up to eight periods ahead. The results for out-of-sample estimated RMSEs are inconsistent with the in-sample estimates for two alternatives, the DIA and ADIA models. Although ADIA has a better predictive power over DIA (sectors 3 and 6), the DIA model clearly outperforms the ADIA in most cases and in overall prediction of private non-farm employment. The predictive accuracy of DIA model in sector 4 (Manufacturing), sector 5 (TCPU), and sector 7 (FIRE) increasingly gains over the predictive accuracy of the ADIA as the length of forecast horizons increases. The DIA model also outperforms ADIA in sectors 2 (Mining) and 6 (Trade) in longer forecast horizons (five to eight quarters ahead). The predictive accuracy of the two models is mixed in sector 8 (Services). However, the differences between the two specifications are mainly trivial in that sector.

Table 4 also suggests that the DIA and ADIA model specifications consistently exhibit the lowest forecasting errors for: (1) all sectors and (2) all eight forecasted periods. However, for the three other alternative models the results are mixed. To see whether there are any patterns in terms of predictive accuracy of alternative specifications, the models are ranked according to their predictive accuracy for: (1) all the eight out-of-sample periods and (2) each sector.

Table 5 exhibits the overall rank order of all the model specifications for: (1) each sector and (2) up to eight quarters ahead forecasts. Table 5 suggests that DIA and ADIA model specifications outperform all other model specifications in all sectors. Among the remaining three alternative models, the IEDV model of Coomes, Olson, and Glennon (1991) outperforms others in three sectors: (1) construction, (2) manufacturing, and (3) transportation sectors. An econometric specification, on the other hand, outperforms other specifications in mostly mining and non-manufacturing sectors. These results are, in turn, not inconsistent with the results obtained by Rickman (2002), Rickman and Miller (2002), and LeSage and Rey (2002). They conclude that partitive approaches with Bayesian estimation may outperform the existing holistic models, or a combination of holistic and partitive approaches.

The holistic approach may perform well in the manufacturing sector, but the econometric specification outperforms the former in non-manufacturing, and thus inclusion of a few, most relevant employment variables in the model is expected to improve the model accuracy over the existing holistic models.

Moreover, the DIEDV model of the Rey and Jackson (1999) type more consistently performs in fourth place in both the manufacturing and the non-manufacturing sectors. Note that DIEDV adjusts the intermediate demand variable for differences in productivity through time. Hence, in terms of consistency of performance, DIEDV outperforms the: (1) IEDV and (2) ECON specifications. This in turn suggests that adjusting the productivity ratios in the integrated models may improve the model applicability across more economic sectors.

TABLE 4

RMSE Percentage of Outside Sample Forecast Test Period: 1983.1 – 1994.4

Sector	Model	Number of Forecasting Periods-Ahead							
		1	2	3	4	5	6	7	8
2. Mining (MIN)	DIA	1.12*	1.17*	1.26	1.28*	1.37	1.35*	1.47*	1.53*
	ADIA	1.15	1.19	1.23*	1.28*	1.35*	1.36	1.51	1.56
	IEDV	3.54	5.54	7.40	9.05	10.78	13.56	16.87	22.44
	DIEDV	5.14	10.41	16.04	20.79	24.96	28.69	31.85	34.97
	ECON	2.98	4.92	6.61	8.34	9.79	10.61	11.41	11.86
3. Construction (CONS)	DIA	7.78	9.03	10.93	12.66	15.48	17.62	20.63	23.45
	ADIA	7.72	8.86*	10.82*	12.33*	15.10*	17.06*	19.88*	22.66*
	IEDV	5.97*	9.36	11.08	12.95	17.03	20.42	22.97	34.40
	DIEDV	6.23	10.59	12.72	15.21	20.53	25.96	29.91	25.78
	ECON	6.10	10.18	12.18	14.45	19.40	24.32	27.98	31.94
4. Manufacturing (MAN)	DIA	1.46*	1.51*	1.54*	1.64*	1.69*	1.81*	1.82*	1.81*
	ADIA	1.85	2.05	2.80	3.08	3.65	4.06	4.66	5.02
	IEDV	1.72	2.63	3.34	3.95	4.70	5.57	6.63	8.01
	DIEDV	1.76	2.87	3.79	4.71	5.52	6.34	7.15	7.71
	ECON	1.83	3.16	4.84	6.71	8.92	11.35	14.27	17.42
5. Transportation, Communication, Public Utilities (TCPU)	DIA	0.93*	1.08*	1.07*	1.01*	1.05*	1.11*	1.18*	1.26*
	ADIA	0.96	1.09	1.07*	1.08	1.08	1.19	1.22	1.31
	IEDV	1.47	2.25	2.54	2.94	3.66	4.60	5.48	6.71
	DIEDV	1.75	2.59	3.08	3.54	3.92	4.24	4.53	4.80
	ECON	1.68	2.48	3.31	3.96	4.82	5.63	6.46	7.27
6. Trade (TRA)	DIA	1.78	1.72*	1.82	1.86	2.06	2.13*	2.25*	2.43*
	ADIA	1.77*	.72*	1.80*	1.84*	2.04*	2.20	2.37	2.56
	IEDV	2.39	3.30	4.29	5.29	6.76	8.19	9.68	11.35
	DIEDV	2.31	3.00	3.52	4.06	5.21	6.25	7.18	8.22
	ECON	2.35	2.82	3.03	3.48	4.30	4.50	5.56	6.08
7. Finance, Insurance, Real Estate (FIRE)	DIA	1.25*	1.29*	1.27*	1.33*	1.43*	1.42*	1.44*	1.49*
	ADIA	1.77	1.72	1.80	1.84	2.04	2.20	2.37	2.56
	IEDV	2.39	3.36	4.29	5.30	6.76	8.19	9.68	11.35
	DIEDV	2.31	3.00	3.52	4.06	5.21	6.25	7.18	8.22
	ECON	2.35	2.82	3.03	3.48	4.30	4.50	5.56	6.08
8. Services (SER)	DIA	2.06	2.36	2.40*	2.70	3.10*	3.77	4.04*	4.58
	ADIA	2.04	.22*	2.62	2.63*	3.39	3.59*	4.06	4.39*
	IEDV	1.99	3.81	4.52	7.51	10.54	14.14	18.60	24.20
	DIEDV	2.00	3.75	5.33	7.06	9.73	12.90	16.84	21.79
	ECON	.54*	2.47	3.06	3.65	4.73	5.71	6.54	7.35
Employment, Private non-farm (EPNF)	DIA	0.92*	0.91	0.90*	0.97*	1.12*	1.37*	1.39*	1.46*
	ADIA	0.94	.88*	1.09	1.03	1.36	1.40	1.55	1.57
	IEDV	1.61	2.73	3.70	4.77	6.35	8.16	10.28	12.90
	DIEDV	1.59	2.57	3.49	4.46	5.94	7.57	9.33	11.42
	ECON	1.42	2.04	2.48	2.97	3.89	4.77	5.56	6.32

TABLE 5

Test Models: Ranked by Predictive Accuracy, Across All Sectors
Out-of-Sample Forecasts

Ranked Order	Mining	Constr.	Man.	TCPU	Trade	FIRE	Service	EPNF
1st	DIA	ADIA	DIA	DIA	ADIA	DIA	ADIA	DIA
2nd	ADIA	DIA	ADIA	ADIA	DIA	ADIA	DIA	ADIA
3rd	ECON	IEDV	IEDV	IEDV	ECON	ECON	ECON	ECON
4th	IEDV	ECON	DIEDV	DIEDV	DIEDV	DIEDV	DIEDV	DIEDV
5th	DIEDV	DIEDV	ECON	ECON	IEDV	IEDV	IEDV	IEDV

8. SUMMARY AND CONCLUSIONS

Of the most recent embedding approaches, the work of Moghadam and Ballard (1988) and its modifications by Coomes, Olson, and Glennon (1991) have attracted the greatest attention (LeSage and Rey 2002; Rickman and Miller 2002; Rickman 2001; Rey and Jackson 1999; Motii 1998; Rey 1997; Stover 1994). Research has focused on the methodology with which the input-output characteristics are incorporated into the econometric specification. The methodological concerns have centered on several issues. These include: (1) the dynamic properties of inter-industrial relationships, (2) the use of regionalized input-output coefficients, and (3) problems resulting from strong multicollinearity.

Although the dynamic inter-industrial relationship has been addressed, the dynamic properties of the input-output coefficients, which are the core of inter-industrial relationship, have been ignored. Instead, updating productivity ratios in a model of the type introduced by Coomes, Olson, and Glennon (1991) has been suggested. Additionally, the problems of strong multicollinearity remain unresolved. Even though the embedding strategies have been applied mostly to small regions usually extending no further than a few counties, they can be extended to a region of one or more states as well. Recently, Rickman (2002) applied such an embedding strategy to a state-level economy.

This paper is an extension of the holistic embedding work of Moghadam and Ballard (1988); Coomes, Olson, and Glennon (1991); and Rey and Jackson (1999). The Dynamic Integration Approach (DIA): (1) uses regionalized input-output coefficients, (2) accounts for dynamic regional inter-industry relationships among the economic sectors, and (3) follows Rickman (2002) by expanding the scope to include an entire state. Further, by using interactive right-side variables, the DIA strategy reduces multicollinearity to acceptable levels as measured by the Variance Inflationary Factor (VIF). Moreover, in the embedding process, the productivity ratios are used to transform the regional input-output coefficients into regional labor coefficients.

The analysis reveals that the DIA strategy dominates ADIA and other embedding strategies, in terms of the predictive accuracy of the models. However, both DIA and

ADIA models consistently outperform all the other models for all economic sectors, as well as out-of-sample forecasts for all forecasted periods.

At best, the predictive accuracy of the alternative specifications (IEDV, DIEDV, and ECO) is mixed. It appears that the alternative embedding models outperform an econometric specification for manufacturing and construction sectors, but the econometric approach outperforms other alternative specifications in most other sectors.

In terms of consistency in performance, the DIEDV model of the type developed by Rey and Jackson (1999) outperforms both the econometric and the IEDV model specifications. This suggests that adjusting for labor productivities in the integrated models may result in applicability across a wider range of sectors in a region's economy.

While this study shows overwhelming superior performance of the DIA model *vis-à-vis* earlier holistic embedding models, further empirical investigation is needed. Application of the DIA model to: (1) other time periods, (2) different regions, and (3) other states is needed to verify or refute its forecasting performance. Since there is controversy surrounding the reliability of regionalized national coefficient matrices (Israilevich et al. 1996), the use of national input-output *vis-à-vis* regionalized coefficients deserves further consideration.

According to Rey (2000), applications of integrated models have been extended to include structural analysis. Using the DIA model specification, annualized input-output relationships can readily be extracted from the model. One application of this, similar to Israilevich et al. (1997), is structural regional economic analysis. Finally, the ADIA model specification may have promising implications for adjusting national input-output coefficients through time. However, more research is needed to examine the adequacy and implications of the ADIA specification.

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