Modern Macroeconomics and Regional Economic Modeling

by

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1. Introduction

Regional forecasting and policy models historically have been patterned after models originally developed for country-level analysis. The national input-output framework of Wassily Leontief quickly became adopted in regional economic impact analysis (Richardson, 1985). As a neoclassical extension of the fixed-price input-output model, the Walrasian applied general equilibrium model gradually became used for regional policy analysis (Partridge and Rickman, 1998a; forthcoming). The macroeconometric equation system modeling approach developed at the Cowles Commission for analysis of the post-World War II U.S. economy (Valadkhani, 2004) likewise was adapted for application at the regional level (Bolton, 1985). Regional versions of the national models were modified somewhat though to reflect differences in economic structure and data realities.

These models continue to be used both at the regional and national levels, including widespread use by practitioners and policy makers. However, numerous criticisms of the Cowles Commission macroeconometric equation system approach led to the development of competing macroeconomic modeling paradigms. Macroeconometric equation models were criticized for their lack of microeconomic underpinnings, ad hoc equation specification, and for suffering from the Lucas critique (Lucas, 1976). Their emphasis on the demand side of the economy also led to forecast failures during the stagflation period of the 1970s. The emergent macroeconomic paradigms which attempt to overcome these critiques are the vector autoregression (VAR) and the dynamic stochastic general equilibrium (DSGE) approaches.

By their formulation as reduced-form models, VARs avoid ad hoc equation specification (Sims, 1980). But their lack of theoretical structure makes them unsuitable for policy analysis and the absence of exclusion restrictions often leads to over parameterization and poor forecasting performance. Pseudo-Bayesian approaches to VAR modeling (BVAR) (Doan, Litterman and Sims, 1984) were developed to overcome the over parameterization problem, subsequently leading to their widespread in macroeconomic forecasting (Litterman, 1986; Ciccarelli and Rebucci, 2003). Attempts also were made to use VARs for examining causal dynamic relationships among macroeconomic variables. Yet, early attempts were more mechanical than theoretically-based (Cooley and LeRoy, 1985). This led to the structural vector autoregression (SVAR) approach in which structural restrictions derived from macroeconomic theory are used to transform the reduced-form equations into structural form (e.g., Bernanke, 1986; Sims, 1986).

Dynamic stochastic general equilibrium (DSGE) modeling began with work in real business cycle (RBC) analysis (Kydland and Prescott, 1982; Long and Plosser, 1983). The use of first principles in deriving DSGE model relationships is an attempt to make them independent of policy regime, addressing the Lucas critique. The models assume fully-specified optimizing behavior by forward-looking agents, possess well-defined stochastic structure of exogenous forces, and impose explicit general equilibrium structure. In providing the microeconomic underpinnings which were largely absent in macroeconomic models, DSGE models provide a theoretically consistent framework for testing macroeconomic theories and for quantitative policy assessment (Kydland and Prescott, 1982).

Despite the explosion of interest in macroeconomic analysis, the new generation of macroeconomic models has yet to be fully embraced by regional economists. This author has yet to find a published account of a regional DSGE model. Likewise, regional economists have not fully explored the potential of VAR models for policy analysis and forecasting to the extent seen in macroeconomics, including their integration with DSGE models. Regional input-output models continue be widely used as are simultaneous econometric equation frameworks, while regional CGE models are primarily used only for qualitative policy assessment (Partridge and Rickman, forthcoming). Therefore, this paper discusses the potential for greater use of this new generation of macroeconomic models in regional forecasting and quantitative policy analysis.

The paper begins below by summarizing and discussing the development of macroeconomic VAR and DSGE models. This is followed by discussion of their current and potential uses in regional economic modeling. I argue that although DSGE models have primarily been used for higher frequency macroeconomic data, DSGE methodology as it has evolved provides useful insights for how to make CGE models more useful for quantitative policy assessment. This includes the possibility of using VAR analysis in the evaluation and specification of CGE models. I also suggest instances where DSGE models might become substitutes for existing regional modeling paradigms, such as the widely used simultaneous econometric equation approach to policy analysis. The paper ends with concluding thoughts.

2. DSGE and VAR Macroeconomic Modeling

Forecast failures of macroeconometric models in the 1970s and dissatisfaction with their structure not only led to extensions and refinements of these models (Wallis, 1989), but also to the emergence of two popular competing paradigms of macroeconomic inquiry. One alternative approach is to formulate structural models with deep parameters (Lucas and Sargent, 1978) rather than with econometrically estimated relationships between endogenous and predetermined or exogenous variables. This line of inquiry includes the widely used method of dynamic stochastic general equilibrium (DSGE) modeling. The second approach is the atheoretical vector autoregression (VAR) framework of Sims and his followers (Sims, 1980), in which all variables are endogenous.[1]

DSGE models replace the behavioral equations of Cowles Commission models with equations reflecting optimization with deep parameter functions such as for utility and production and explicit treatment of expectations and stochasticness. Yet, mixed success has been reported in terms of these models being able to replicate dynamic macroeconomic properties, particularly in early applications (Watson, 1993). In contrast, reduced-form VARs (and their extensions) have been used extensively for forecasting, but are less suitable for investigating dynamic macroeconomic structure; hence, the development of the structural VAR approach. Comparative deficiencies in the two approaches have led to studies which integrate them.

2.1 VAR Modeling

The vector autoregression (VAR) approach began as an atheoretical alternative to structural econometric equation modeling. In reduced-form VARs, all variables are endogenous:

(1) $x_t = \mathbf{A(L)}x_{t-1} + e_t$,

[1]Nonstructural forecasting has intellectual roots pre-dating Keynes and subsequent Cowles Commission macroeconometric models (see Diebold, 1998 for related discussion).

where x represents the vector of endogenous variables, L denotes lag operator, **A(L)** is a matrix of reduced-form coefficients relating past variable values to current values, and e is a vector of reduced-form errors with covariance matrix $\mathbf{\Sigma_e}$. The only prior restrictions relate to the choice of included variables and their lag length. Reduced-form VARs have the advantage of avoiding the imposition of exclusion restrictions which often were criticized as being ad hoc and untested (Sims, 1980). Because of the lack of exclusion restrictions, a disadvantage is the large number of parameters requiring estimation in large systems easily leads to over parameterization and poor out-of-sample forecasting performance. In addition, estimated reduced-form VARs reveal little about the underlying economic structure, allowing for a number of different inferences to be drawn from the same data. Consequently, in response to these deficiencies two important extensions of the reduced-form VAR have been pursued: (1) Bayesian vector autoregression (BVAR); and (2) structural vector autoregression (SVAR).

The BVAR approach was originally developed by Litterman (1980), Doan, Litterman and Sims (1984) and Litterman (1986) as an alternative to traditional macroeconometric forecasting. In what has become known as the Minnesota prior, the original BVAR models imposed Theil-Goldberger inexact restrictions on the VAR coefficients through the use of hyperparameters. The Minnesota prior reflected the belief that economic systems generally follow a multivariate random walk. The Minnesota prior is easy to implement in which the equations can be estimated separately and early on enjoyed some forecasting success when compared to more traditional approaches (Ashley, 1988; Artis and Zhang, 1990). The BVAR improved forecast performance over the unrestricted VAR both by reducing the inefficiency associated with over parameterization and in correcting coefficient bias resulting from series nonstationarity (Bewley, 2002).[2]

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[2] Kadiyala and Karlsson (1993) found other families of priors producing more accurate forecasts than the Minnesota Prior by allowing for dependence between equations, though at the cost of increased complexity in application. Robertson and Tallman (1999) find improved forecast performance of U.S. aggregates from using fairly tight priors regarding long-run VAR properties developed by Sims and Zha (1998). Ciccarelli and Rebucci (2003) review the BVAR literature and examine extensions to the basic model.

Estimated reduced-form VARs also were then used to examine macroeconomic structure. Early attempts typically examined time-series Granger-causality between variables and orthogonalized the innovations to compute impulse response functions and variance decompositions. As noted by Cooley and LeRoy (1985), Granger-causality does not closely relate to the concept of exogeneity used in Cowles Commission models, while the orthogonalization was mechanical and difficult to justify with established economic theory. This led to explicit use of economic theory in deriving restrictions for the orthogonalization of the innovations in what has become known as the structural vector autoregression (SVAR) approach (e.g., Bernanke, 1986; Sims, 1986).

The SVAR corresponding to the reduced-form VAR in Equation (1) can be written as

(2) $\mathbf{B}x_t = \mathbf{C(L)}x_{t-1} + \mathbf{D}\varepsilon_t$,

where **B** is the matrix of structural parameters for the contemporaneous variables, **C(L)** is a matrix of polynomials relating contemporaneous to lagged variables, and **D** measures the contemporaneous responses of endogenous variables to exogenous shocks. Assuming **B** is invertible, pre-multiplying by $\mathbf{B}^{-1}$ produces the reduced-form VAR in Equation (1), in which $\mathbf{A(L)}=\mathbf{B}^{-1}\mathbf{C(L)}$, and $e_t=\mathbf{B}^{-1}\varepsilon_t$. If **B** and **D** were known, **C(L)** and ε could be calculated and the structural dynamic properties would be revealed. But because they are unknown, theoretical restrictions are imposed to identify the structural parameters and innovations.

Hence, in contrast to the BVAR approach where restrictions are imposed directly on **A(L)** in estimation of Equation (1), in the SVAR approach restrictions derived from theory are imposed on **B**.[3] Two common forms of restrictions used in the SVAR literature are contemporaneous exogeneity (delay) and long-run neutrality restrictions (Keating, 1992). Contemporaneous exogeneity restrictions generally are considered to be more restrictive than long-run restrictions (Stock and Watson, 2001). However, very often too few long-run restrictions can be found in a model relative to the number of shocks (Canova, 2007), and in the absence of additional strong restrictions the estimated long-run influences of shocks are

[3] **D** is typically normalized as a diagonal matrix which associates each structural shock with an endogenous variable (Keating, 1992). Also see Keating (1992) for an early review of the SVAR literature.

not reliable for infinite dimensional VARs which are estimated with finite sample data (Faust and Leeper, 1997).

The SVAR approach contrasts with Cowles Commission style models which imposed structure (e.g., on Equation 1) by assuming exogeneity of the policy variables and by imposing exclusion (zero coefficient) restrictions for model identification. Although over-identifying restrictions were routinely tested, the over-identification test is couched within the identifying structure of the model and does not test the statistical adequacy of the model itself. Thus, although debate continues regarding their ability to accurately distinguish between alternative macroeconomic theories, (Christiano, Eichenbaum, and Vigfusson, 2006; Fernández-Villaverde et al., 2007; Chari, Kehoe, and McGrattan, 2008), SVARs continue to be used for imposing structure in a more theoretically explicit and statistically satisfying manner.

2.2 DSGE Modeling

The earliest DSGE models were formulated in an attempt to provide an internally-consistent framework to investigate real business cycle (RBC) theory. RBC models are underpinned by neoclassical general equilibrium economic theory (Kydland and Prescott, 1991b). In these models, rational, infinite-lived, identical households maximize intra- and inter-temporal utility over consumption and leisure, use of capital and labor in production of an aggregate good is governed by constant-returns-to-scale technology, and markets clear each period. Net investment in each period determines the change in capital stock.

In contrast to computable general equilibrium models, agent maximization takes place within a stochastic environment. Technological progress is assumed to follow an AR(1) process; the level of technology in each period depends on the previous period level plus a random component. Production is typically represented by a Cobb-Douglas function in RBC models, while utility is represented by constant relative risk aversion (Dejong and Dave, 2007, pp. 90-91). Because of their focus on the role of supply shocks and the absence of frictions, there is no role for macroeconomic policies.

The early models primarily relied on the method of calibration for parameterization. The Cobb-Douglas function could be calibrated using the long-run average labor share of output while a Cobb-Douglas utility function in terms of consumption versus leisure could be calibrated using the average fraction of time spent in non-leisure activity (Kydland and Prescott, 1991a). Explicit decision rules are derived which relate the choice variables to the predetermined and exogenous variables. These usually cannot be derived in closed form because of nonlinearities and stochastic features; thus, dynamic programming is used to obtain nonlinear stochastic difference equations. Solution of the model equations is typically obtained by log-linearization or second-order approximation around the steady state of the economy. Computational experiments can then be performed by perturbing the economy and observing the adjustment back to the steady-state path.

A problem with the early RBC models was predictions of macroeconomic dynamics which were in conflict with actual data.[4] This easily can arise because of the calibration of parameters using long-run averages, which ignores other information about actual macroeconomic dynamics. In addition, Ingram, Kocherlakota, and Savin (1994) showed that for DSGE models to be nonsingular there must be as many shocks as there are endogenous observable variables. To the extent the number of driving forces (shocks) is less than the number of endogenous variables, the solution to the DSGE will not represent the true data generating process (DGP). The designing of DSGE models to overcome the Lucas critique also led to some criticism that they are only capable of answering policy questions which are completely unprecedented, which may make them of little use for commonly examined policies (Leeper, Sims, and Zha, 1996).

Subsequently, DSGE models have become more complex as the number of structural shocks considered has increased and frictions have been added on both the real and monetary sides of the economy for added realism and improved empirical fit to the data (Canova, 2007). For example, New

[4] For example, RBC models predicted a correlation of one between hours worked and average labor productivity, while the correlation in the data for the post-WWII U.S. economy equaled zero (McCallum, 1989).

Keynesian DSGE models incorporate monopolistic competition and nominal wage and price rigidity. Alternative procedures also have been developed to more formally parameterize DSGE models (Canova, 2007): full-information maximum likelihood estimation, generalized method of moments (GMM) estimation, Bayesian estimation, and matching VAR and DSGE dynamic responses to structural shocks. Work also continues on evaluating the validity of policy experiments in macroeconomic models, such as overcoming the Lucas critique for likely policies of interest (Kremer et al., 2006).

Empirical evaluation of the DSGE is facilitated by recognition that it can be reasonably approximated with a VAR with sufficiently long lags. The DSGE can be thought to impose restrictions on the VAR in Equation (2) (Diebold, 1998; Canova and Pina, 2005).[5,6] Yet, rather than using theory solely to impose limited restrictions on **B** in Equation (2) as in the SVAR approach, or on **A** in Equation (1) as in the BVAR approach, the DSGE implies a richer set of cross-equation restrictions on **B**, **C** and **D** (Canova, 2007).

Advances in DSGE modeling have led central banks to increasingly become interested in using DSGE models for quantitative macroeconomic analysis (e.g., Pagan, 2003). Nevertheless, the current workhorse models, such as that used by the U.S. Federal Reserve Board model, are in the Cowles Commission tradition (Del Negro and Schorfheide, 2003). Thus, research continues on improving DSGE models in hopes they can eventually replace early generation macroeconomic models as the primary tool for quantitative macroeconomic forecasting and policy making.

2.3 Integrated DSGE and VAR Modeling

Limitations of each approach and interest in empirical evaluation of DSGE models have led to their integration with VAR models. Because of misspecification, data simulated from DSGE models may not be reflective of the DGP (Schorfheide, 2000), invalidating classical maximum likelihood estimation. In fact, misspecification is what led Kydland and Prescott (1982) to originally eschew

[5] Imposition of cross-equation restrictions on reduced-form macroeconomic representations dates as far back as Sims (1972) and Hansen and Sargent (1980).

[6] The approximation also improves to the extent the dynamics are linear (Del Negro and Schorfheide, 2003).

estimation in favor of calibration. While VARs with sufficiently long lags can be made to generally reflect the DGP they typically lack sufficient structure for policy analysis.

Recognition of the restrictions imposed by the DSGE model on the VAR representation naturally leads to a Bayesian approach in which the restrictions of the DSGE are used to construct priors for the VAR. Advantages of Bayesian estimation are it does not rely on asymptotic properties that require the DSGE model to be correctly specified, it can be used with sparse data, and the parameter space can be restricted to regions where the DSGE model is well-behaved. This DSGE-VAR approach has been used both to construct improved VAR forecasting models and to evaluate and refine DSGE models.

The DSGE-VAR studies are commonly implemented using the mixed estimation or pseudo-Bayesian framework routinely applied in BVAR forecasting. In a pioneering DSGE-VAR study, Ingram and Whiteman (1994) find that a BVAR based on a prior derived from a real business cycle model produced slightly more accurate out-of-sample forecasts for U.S. macroeconomic aggregates than a BVAR using the Minnesota Prior. Del Negro and Schorfheide (2003, 2004) similarly find that out-of-sample forecasts based on a prior derived from a simple New-Keynesian DSGE model outperform BVAR forecasts based on the Minnesota prior. Compared to the Minnesota prior, DSGE priors also produce models more useable for policy analysis. Subsequently, Del Negro and Schorfheide (2006) used the DSGE-VAR framework to examine the extent of misspecification in DSGE models by finding out how much the DSGE restrictions had to be relaxed to fit U.S. macroeconomic data. They further investigate the extent to which New Keynesian frictions help the DSGE fit the data.

There also are reports of DSGE models comparing favorably to VARs in terms of empirical fit. Smets and Wouters (2003) find that the posterior odds and root mean squared forecast errors of a Bayesian-estimated New Keynesian DSGE model are close to those from the most accurate unrestricted VARs and Minnesota BVARs (based on lag length), in which the DSGE performs better than the least accurate VARs and BVARs. Using real-time data for the U.S. economy, Rubaszek and Skrzypczyński (2008) implement a small-scale DSGE model which produced more accurate out-of-sample forecasts for

GDP growth than those produced by a (Minnesota prior) BVAR model or by the Survey of Professional Forecasters, though the DSGE forecasts were less accurate for short-term interest rates and inflation.

3. Implications for Regional Economic Modeling

Although the empirical success of the new generation of macroeconomic models has been mixed and they continue to evolve (Canova, 2007), there would likely be significant benefits both from implementing them at the regional level and from incorporating some of their features within existing regional modeling approaches. For one, the emphasis in DSGE modeling on explaining time series behavior of macroeconomic aggregates in their evaluation and parameterization could be adopted in regional CGE modeling. In addition, for policies where aggregate analysis is sufficient, DSGE or SVAR models may be used in place of traditional semi-structural regional econometric equation approaches. As an example, they could be used in place of the simultaneous econometric equation approach for policy analysis such as the partial adjustment model of Carlino and Mills (1987) which has been widely used and extended, but generally falls within the Cowles Commission tradition. Discussion of the relative weaknesses of current regional modeling approaches and how insights from the new generation of macroeconomic models could be used to improve or replace them follows below.

3.1 Regional Computable General Equilibrium Modeling

Computable general equilibrium (CGE) modeling pre-dates the development of DSGE models.[7] In fact, the DSGE approach borrowed heavily from CGE modeling both in terms of specification and computation. Both approaches are grounded in microeconomic assumptions about tastes, technology, constrained optimization, and equilibrium. Also, early RBC models used the method of calibration ubiquitously used to parameterize CGE models (Partridge and Rickman, 1998a).

While CGE models often are comparative static, they can be made dynamic through incorporating intertemporal optimization and expectations. A primary difference though is that CGE models are deterministic rather than stochastic. Stochasticity makes DSGE models more difficult to

[7] For a presentation of equations and structure of a typical regional CGE model see Partridge and Rickman (1998a).

solve, typically leading to greater aggregation and fewer variables; this is particularly true for higher-order approximations which are required for welfare analysis (Winschel and Kratzig, 2008). Besides its theoretical purity, an advantage of the stochastic specification is it naturally leads to estimation and the fitting to time series data. In contrast, even dynamic CGE models are routinely calibrated to cross-sectional data with the dynamic properties given by steady-state growth extrapolation of the initial static equilibrium or solution of a reasonable path based on initial conditions (Partridge and Rickman, 1998a). DSGE models are hence naturally better suited for studying dynamics of the aggregate economy and cyclical fiscal and monetary policy effects, while CGE models are used more for long-run microeconomic policy analysis (e.g., international trade or tax policies).

Despite these differences, there are lessons to be learned for regional CGE modeling from the estimation or dynamic fitting of DSGE models. Partridge and Rickman (1998a; forthcoming) argue the reason CGE models have not replaced more traditional regional economic policy tools in quantitative assessments is that CGE models have yet to be demonstrated to more accurately reflect the workings of regional economies or provide empirically-based time dimensions to policy responses. For example, like the early prediction failures of RBC models, failures of some CGE models to accurately predict the magnitude of trade effects arising from the North American Free Trade Agreement led to questioning of their validity (Kehoe, 2003).[8]

Although econometric estimation of CGE models has been advocated (e.g., McKitrick, 1998), insufficient data typically exist for estimation of large complex equation systems with deep parameters, leading to the routine use of calibration. Yet, the typical methods of calibrating and making regional CGE models dynamic have not been verified empirically for regions (Partridge and Rickman, forthcoming). Utility and production function elasticities are drawn from other studies, of which many are out-dated or at the country level. In the short run, regional dynamic CGEs typically reflect a short-run capacity-constrained neoclassical model, while long-run properties typically are observationally

[8] Other studies suggest some CGE models performed well in comparison to predictions by macroeconomic models and traditional trade theory (e.g., Burfisher, Robinson, and Thierfelder. 2001).

consistent with a regional input-output system (McGregor, Swales and Yin, 1996). Short-run demand responses such as labor migration, or capital adjustment, also are routinely based on outside empirical studies. There have been only limited attempts to incorporate information on the region of study in the specification of deep parameters for regional CGE models (e.g., Adkins, Rickman and Hameed, 2003; Haddad and Hewings, 2005). As DSGE modeling has moved from calibration in early RBC models to exploring estimation and dynamic fitting so should regional CGE modeling.

Along these lines, a few CGE studies use time series data to evaluate or parameterize a CGE model. In ex post evaluation, Kehoe, Polo and Sancho (1995) compare comparative static CGE predictions regarding fiscal reform in Spain against reality, while also incorporating two exogenous shocks unrelated to fiscal reform. Arndt, Robinson and Tarp (2002) use a maximum entropy approach to CGE parameterization based on prediction of several target variables over several points in time for Mozambique. Using time series data for an extensive array of variables, but taking structure and elasticities as given, Giesecke (2002) calibrates a recursive dynamic regional CGE model of Tasmania, Australia to derive structural, policy, and external shocks. Once calibrated, the model is historically simulated to assess the contribution of the derived structural and policy shocks to economic outcomes.[9]

While the above described efforts are notable and bear some resemblance to the DSGE philosophy of dynamic fitting and evaluation, they are not fully reflective of DSGE methodology. An effort reported to be more in line with the DSGE approach is Liu, Arndt and Hertel (2004). They explicitly introduce a stochastic error into a CGE model for maximum likelihood estimation of key parameters and evaluation of model goodness-of-fit. Consistent with conventional recursive dynamic CGE modeling and dynamic fitting efforts, the model replicates some base year data set and attempts to minimize prediction errors for endogenous variables in other years for which data are available while using actual values for exogenous variables. However, the estimates are conditional on the model structure and other pre-specified parameters.

[9] Abrego and Whalley (2005) describe this approach as ex post decompositional analysis and discuss and present an example in the international trade area.

Further efforts to parameterize and evaluate large-scale CGE models using time series data likely would prove to be fruitful. Consistent with DSGE-VAR methodology (Del Negro and Schorfheide, 2006), recursive dynamic CGE models could be used to simulate time paths of key regional variables for use in the imposition of restrictions on a VAR representation of the same variables.[10] This would both provide alternative priors to the Minnesota prior in BVAR forecasting while also serving as a means for checking how consistent the restrictions are with the data. If the restrictions are found to be inconsistent with the data, restrictions from alternative CGE models for the same region could be compared for their accuracy; e.g., akin to the comparison of two competing DSGE models by Schorfheide (2000). As a simple example, Rickman, Miller and McKenzie (2009) compared the accuracy of two-sector (basic and nonbasic) BVARs, in which the alternative priors consisted of a Keynesian economic base prior, and a fixed factor neoclassical general equilibrium prior, finding evidence in favor of the former.[11]

Small-scale regional DSGE models with aggregate household and production sectors could be used to test features of particular interest in CGE models. Yet, rather than emphasizing intertemporal optimization of consumption and savings and growth in capital stock as in national DSGE and CGE models, assumed excess savings in dynamic regional models (Partridge and Rickman, forthcoming) make forward looking behavior on the part of regionally mobile firms and households paramount.[12] DSGE models with alternative labor market specifications could be formulated and compared in terms of their ability to replicate aggregate regional labor market dynamics. Competing views of labor mobility, unemployment, labor force participation responsiveness and wage flexibility could be incorporated and evaluated. Specifications evaluated as best reflecting regional labor market dynamics could then be used

[10] With the number of variables examined in the VAR likely being a subset of the CGE model variables, care would need to be taken to avoid the problem of observational equivalence, which also is an issue in DSGE modeling (Canova, 2007). Observation equivalence also can arise if the data contain little information, such that alternative priors fairly equally fit the data.

[11] Successful regional BVAR forecasting models have been produced by the imposition of input-output restrictions (LeSage and Magura, 1991; Partridge and Rickman, 1998b) and spatially-based restrictions (LeSage and Krivelyova, 1999; Rickman, Miller and McKenzie., 2009).

[12] For example, Gallin (2004) empirically finds potential labor migrants responding more to permanent changes in wages than to temporary changes.

in large-scale CGE models containing greater institutional detail. A model based on such an exercise would provide decision makers needed institutional detail of policy responses, greater confidence in predicted total quantitative responses and information on the time path of responses.

3.2 Regional Simultaneous Econometric Equation Modeling

In contrast to the experience in macroeconomic policy analysis, DSGE models have yet to become competitors with the simultaneous econometric equation framework for regional policy analysis. And as discussed above, because of an absence of an empirically-based time dimension, regional CGE models have yet to become the dominant quantitative regional policy tool, allowing for continued widespread use of traditional regional models such as regional simultaneous econometric equation models. Yet, the criticisms leveled at national econometric models also apply to regional simultaneous econometric equation models; they suffer from the Lucas critique, equation parameters may be unstable over time, and their lack of deep structure confounds interpretation of estimated parameters.

A workhorse model for regional policy analysis has been the partial adjustment simultaneous equation model of regional employment and population by Carlino and Mills (1987). As first introduced by Steinnes and Fisher (1974) in an urban location model, static optimization theory of households and firms underlies the empirical employment and population equations. Yet, the two equations are a subset of the structural model equations (e.g., prices are solved out of the model), making them a "semi-structural" representation of the full model (Steinnes and Fisher, 1974, p. 70). As acknowledged by Steinnes and Fisher this semi-structural formulation makes identification and interpretation of the equation coefficients problematic. For example, employment and population are labor market outcome variables, not independent structural measures of labor demand and supply.

Despite the acknowledged limitations by Steinnes and Fisher and the critiques leveled at macroeconometric models, the extension of this model by Carlino and Mills (1987) continues to be widely used for regional policy analysis. Carlino and Mills introduced disequilibrium into the Steinnes-Fisher two-equation empirical model by incorporating partial adjustment mechanisms from the macroeconomics literature. Among the determinants of growth examined by Carlino and Mills were fiscal policies and natural amenities. Beginning-of-period values were assumed to make the fiscal policy variables exogenous or pre-determined. Per capita taxes were specified as identifying the employment equation, while unionization and industrial revenue development bonds were specified as identifying the population equation. Clark and Murphy (1996) follow this approach while expanding the list of fiscal and amenity variables considered. Measures of business conditions such as accessibility, industry concentration, and labor market strength were specified as identifying the population equation while demographic and neighborhood characteristics were specified as identifying the employment equation. As was common then, weak instruments and over-identification tests were not performed in these studies, leaving open to question whether the two equations in these studies were indeed identified, even in semi-structural form.[13]

Mulligan, Vias, Glavac (1999) argue that the estimated adjustment process in the Carlino and Mills approach can be derived from alternative theoretically-based assumptions on economic adjustment, making them observationally equivalent in practice. In their implementation of the approach, they found inconsistent coefficient signs over time, verifying the critique regarding parameter instability in less structural models. Deller et al. (2001) add an adjustment equation for per capita income, though because of difficulty in finding acceptable instruments for identification of (semi) structural relationships between employment, population and income, they estimate reduced-form equations for each, leading to alternative observationally-equivalent interpretations of their results. Developable land is added as a third variable by Carruthers and Mulligan (2007), while following Boarnet (1994) they add a spatial dimension for application to intraurban location analysis.

Carruthers and Mulligan (2007, p. 81) best describe the Carlino-Mills model as one in which "the central premise is that the distribution of population and employment is constantly adjusting toward an unknown spatial equilibrium and, along the way, the two are jointly determined."[14] Estimated parameters

[13] Examples of instrument testing within this approach can be found in Boarnet (1994) and McGranahan (2008).
[14] Carruthers and Mulligan (2007) also provide an extensive list of studies using the Carlino and Mills approach.

of the model capture the co-movement of the two series, though policy responses lack structural interpretation and may lack empirical validity generally. Only the factors correlated with employment and population adjustment can be determined, not the structural sources of their adjustment. The limitations of the approach outlined above are some the very ones which led to the development of alternative approaches to Cowles Commission style macroeconometric models.

While DSGE models of regional economies have yet to be developed as alternatives, SVAR models with theoretically-based restrictions have been. In a widely cited study, Blanchard and Katz (1992) use an SVAR model containing variables for employment, wages, the unemployment rate and wages to examine the functioning of U.S. state labor markets. Although not examined directly, they conclude migration was the sole labor supply response to state-level demand shocks, in which its responsiveness provided a high degree of labor market flexibility. Despite finding statistical evidence to the contrary they assume long-run stationarity of employment rates and wages, which drives the conclusion regarding the role of migration.[15] In addition, consistent with the Carlino-Mills approach, Blanchard and Katz assume employment represented labor demand in identifying the model.

Partridge and Rickman (2003; 2006) formulate theoretically-based long-run restrictions SVAR models to analyze regional labor markets recognizing: 1) that employment and population were both labor market outcome variables and not independent measures of labor demand and supply; and 2) the difficulty of finding instruments for identifying both population and employment in a simultaneous equation approach. Two long-run restrictions are derived from theory; only productivity shocks are assumed to have long-run effects on state wages, implying that migration and internal labor supply shocks have no long-run impacts on wages. As mentioned above as a common problem with the long-run restrictions SVAR approach (Canova, 2007), a lack of additional theory-based restrictions led the imposition of an ad hoc restriction. The studies report U.S. labor market flexibility and the role of labor

[15] Blanchard and Katz (1992) ignored Augmented Dickey Fuller unit root tests because of their low power in small samples. Using more reliable data and several methods of testing for unit roots, Rowthorn and Glynn (2006) generally failed to reject the null hypothesis of a unit root for U.S. state-level employment rates. Partridge and Rickman (2006) likewise fail to reject a unit root in relative state wage rates based on a variety of tests.

demand in explaining regional economic fluctuations as overstated by Blanchard and Katz. Further they note that the simultaneous econometric equation framework cannot adequately address this issue, in which only elasticities of co-movement of population and employment to each other can be estimated, being unable to estimate the magnitude of labor demand and supply shocks.

In estimating the sources of metropolitan area fluctuations, Coulson (1993) constructs metropolitan area SVAR models with contemporaneous exogeneity restrictions inspired by the regional shift-share model. Similarly, Carlino, Defina and Sill (2001) construct metropolitan area SVAR models with contemporaneous restrictions among local industries based on input-output linkages. As an alternative to the spatial econometric equation approach, Chang and Coulson (2001) utilize contemporaneous restrictions in an SVAR to examine spatial spillovers between central cities and suburban areas of selected U.S. metropolitan areas.

Borrowing from empirical CGE and DSGE modeling, Rappaport (2008a, 2008b) formulates and calibrates a static general equilibrium model of a representative U.S. metropolitan area economy. He simulates the model to examine the likely variations in quality of life and productivity that underlie differences in metropolitan area population density and in other economic outcomes such as housing prices and wages. Following DSGE methodology, Rappaport relies on empirical regularities in the data and those established econometrically in the parameterization and simulation of the model.

As Rappaport (2008a) suggests, the model alternatively could be formulated in a dynamic context in which regional fluctuations would be driven by productivity and quality-of-life shocks. A DSGE model formulated along these lines could become a serious competitor to regional SVAR models and simultaneous econometric equation models in quantitative regional policy analysis. Such a model would provide a theoretically consistent laboratory for regional policy assessment much the same way DSGE models have for testing macroeconomic theories.

4. Conclusion

This paper has argued that although regional scientists have in some instances incorporated elements of modern macroeconomic methodology in their empirical investigations, significant potential exists for greater use. DSGE methodology, particularly when integrated with VAR methodology, likely would provide insights into how regional CGE models might be formulated to become much more widely used for regional quantitative policy assessment. DSGE models also could be used as substitutes to regional simultaneous econometric approaches for forecasting and policy analysis.

This is not to suggest that the new generation of macroeconomic models have been perfected and should be used in place of all other approaches. Numerous challenges remain in terms of empirical identification, parameterization and verification (Canova and Sala, 2006; Canova, 2007). Yet, these issues also could be explored within the context of regional economic applications and much would be learned about regional economies along the way. Practical solutions may be found which make the models sufficiently more useful for regional forecasting and policy analysis. As noted by Summers (1991), approaches which are technically the most virtuous may not be those making the greatest contribution to knowledge. But we do not know what would be gained until we try.

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