Enhancing Our Understanding of a Regional Economy: The Complementarity of CGE and EIO Models

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The Complementarity of CGE and EIO Models

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Enhancing Our Understanding of a Regional Economy: 
The Complementarity of CGE and EIO Models

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September 24, 2020

Abstract
Economic impact models are powerful tools for the assessment of policy changes in regional economies. Computable General Equilibrium (CGE) models have grown in popularity, becoming the dominant choice of practitioners and academics in this field. This popularity has been at the expense of an older class of model, the Econometric Input Output (EIO). The present paper demonstrates how both models, using the same input data, may yield different outcomes. However, the paper suggests that EIO has been underutilized even though it provides a strong complementary tool accompany that enhance analyses using a CGE approach. This paper urges regional economists to rediscover the EIO model, especially two variants that are described in the paper, and bring them to the forefront of their research agenda.

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1 Introduction

Regional economic impact analysis has a long and established history from the seminal work of Haig (1926) to the latest interregional dynamic econometric models of Kratena et al. (2013). Researchers have sought to construct analytical frameworks through which economic actions could be forecasted and impacts estimated. One of the main tools of the field is still the Input Output (IO) model and its continued use for over 75 years is in no small part due to its importance as a building block for most regional economic models. In the last 40 years, the ability to design and estimate ever more complex empirical models has grown exponentially aided by improved statistical methods, increased frequency of data and computing power (Tesfatsion and Judd, 2006; see also Brooke et al., 1992). This led to the development of more sophisticated models namely the Econometric Input Output (EIO) that had the ability to generate dynamic forecasting and impact analysis. Developed first by Isard (1951) the model combined the sectoral detail of IO models with time series information, providing researchers with a powerful tool to understand long-run phenomenon beyond the scope of the traditional static model. Its development was further enhanced by Stone (1961) and Almon (2017) at the national level and Conway (1990) at the regional level. However, today, the EIO remains a rarely used model in most parts of the world and it is certainly not widely used in regional analysis. Part of this lack of recognition is caused by the success and growth of another class of model that occurred during the same timeframe, the regional Computable General Equilibrium (CGE) model. CGE models began to appear in the 1970’s but it was not till the 1990’s that it became the dominant tool in regional economic modeling (Partridge and Rickman, 1998). The model offered a reliable, sophisticated technique to incorporate supply side relationships into the demand side dominated IO. Coupled with easily accessible software, this fueled its rise to prominence across the globe particularly, in recent years, in developing nations. However, the model often lacks some of the original benefits of the EIO such as forecasting and detailed sectoral information, although some recent developments suggest that these limitations can be accommodated (see, for example, the TERM models, Wittwer, 2017). The goal of the present paper is to assess the practical and theoretical differences between EIO and the CGE and to assess paths along which integration of the two approaches might be realized. It should be noted that a recent contribution by Heim (2017) has presented a challenge to the current tendency at the national level to eschew standard econometric models for Dynamic Stochastic General Equilibrium (DSGE) formulations and Vector AutoRegressive (VAR) models. Heim (2017) has developed a 56 equation model of the US economy and tested its forecasting ability against the DSGE and VAR models with considerable success.

It is in this spirit, namely the need to provide more comparative analyses of competing and complementary models, that the present paper is offered. The outline of this paper is as follows; first, the background and history of both the EIO and the CGE are discussed. Next, the strengths and weaknesses of both models are considered as well as the underlying theoretical bases of each. This section also comprises a comparison of multipliers from an EIO and CGE model both of which used the same IO table for their construction. The paper then proceeds to discuss why the outputs from both models are different by focusing on the operationalization of each one. Finally, conclusions are drawn on complementarity of both models and suggestions for future development are made.

2 Econometric Input Output Modeling

The standard IO model has been the workhorse for regional economists for decades and has become an invaluable tool for economic impact analysis (Miller and Blair, 2009). The model has seen many modifications to update individual components or to allow the integration within more complex analytical frameworks. To detail all these modifications is beyond the scope of the present paper but for important contributions see the work of Isard (1951), Stone (1961) and Conway (1990). For a while, spurred by Klein’s (1969) proposal for regional econometric models and Glickman’s (1977) monograph, regional econometric models were popular

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1 The authors note the continued use of the Chicago and Illinois EIO models built and maintained by REAL at the University of Illinois Urbana Champaign.

2 The CGE spoken about in this paper is the standard model used in most regional studies. The authors are aware of the recursive dynamic strand of the CGE literature but this model remains elusive in regional work thus is not directly compared to the EIO.
(see Bolton, 1985 for a review) but few survived or were maintained into the 1990s and beyond.

One of the first regional econometric input-output models was the INFORUM system initially developed by Almon (this history is reviewed in Almon, 2017). The philosophy underlying the development of this model was effectively summarized as follows:

Simply put, an economic model is a set of equations which describe how the economy or some part of it functions. Its equations should make sense. And it should be possible to test how adequate our understanding is by running it over the past and seeing how well it can reproduce history. By changing some of its assumptions and rerunning history with the changed assumptions, it is possible to analyze the effects of policies. Finally, it should be useful not only for policy analysis but also for forecasting. By studying the errors of the forecast, the builder of the model may hope to improve his or her understanding of the economy. (Almon, 2017, p. 11)

However, the EIO model has garnered less attention in the recent literature particularly at the regional level. Although there has been a recent decline in the construction of EIO models compared to their CGE counterparts, they have existed for over four decades. The attraction of combining intersectoral information as well as a closed dynamic approach drew a number of followers to the method (see, for example, L’Esperance et al. 1977; Isard & Anselin 1982; Moghadam & Ballard 1988; Anselin & Madden 1990; Bertuglia et al., 1990; Conway 1990; West 1991; West & Jackson 1998; Rey 1998, 2000; Motii 2005). Embedding the IO in an econometric estimation framework allows the IO to accomplish more complicated tasks such as forecasting, something that is more difficult with a CGE model. By incorporating econometric estimation, traditional restrictions imposed on the IO model such as static coefficients can be relaxed, allowing for a more flexible “realistic” dynamic to be achieved. One of the great advantages of the EIO is the ability to self-test the consistency through the extraction of the IO tables for each year. This characteristic allows for endogenous structural change but it also provides a way to test that the modified IO coefficients satisfy the Hawkins-Simon conditions and generate a consistent set of time series IO tables (see Israilevich et al., 1997).

These advantages aside, what created much debate in the literature around EIO was the way in which the integration actually takes place, that is, the way in which econometrics are incorporated into the static structure of the benchmark values. The EIO is often wrongly portrayed as a single model; however, it is actually a class of models rather than a specific one. To appreciate the diverse nature of this class is difficult and can lead to unfounded criticism as an alternative to CGE. Some of the very early approaches of incorporating econometrics into IO can be found in the work of L’Esperance et al. (1977), Stevens et al. (1981), Kort & Cartwright (1981) Kort et al., (1986), Liensch et al. (1992). The original approaches focused on econometric estimation as a means of closing the otherwise open framework. The mechanisms for achieving this link were classified into a typology by Rey (1998) namely, as embedding, linking, and coupling. Briefly these classifications can be summarized as follows:

**Embedding** involves the IO model being completely encompassed within an econometric model; thus, the focus of the analytics from this tool is the formulation of the econometric model. This dominance means that the coefficients from the IO model can have less influence on the overall outcome than if there were two separate frameworks.

**Linking** approach is a much less integrated framework that similarly takes the form of using the output from one module as the input into the other in a recursive manner.

**Coupling** requires the construction of a full set of final demand accounts that permits a high degree of model closure and interaction between the Econometric and the IO modules. This approach is similar to that of a CGE in the sense that in order for the model to work there needs to be a high degree of calibration of the IO to fit the underlying econometric framework.

An assessment of these approaches was conducted in the studies of West and Jackson (1998), Rey (1998) and later by Masouman and Harvie (2012). The work of West and Jackson compared the use of two of these techniques using IO data from the US and from Australia. They found that different approaches can yield very different results; in particular, embedding is superior for employment forecasting. The coupled approach, when attempting to forecast employment, can introduce error propagation through the more widely developed inter-industry structures. These approaches are of particular importance in small open economies where
exogenous shocks are the primary catalyst for employment change. The work of Masouman and Harvie (2012) adds weight to this argument by finding significant differences in output by employing coupling and embedding using the same regional data. The same authors found forecasting using embedding performs better than coupling. There were also substantial differences for impact analysis; the primary reason for these differing results can be explained by the formulation of the employment demand equations. Each of the approaches treats sectorial employment slightly differently, whether seeing it as a function of output and labor productivity, or just one or the other (see Rey, 1998). Using holistic embedding, employment is specified by a traditional econometric approach (Masouman and Harvie, 2013), whilst the variance in the coupled strategy is in accordance with the detailed sectorial disaggregation of the IO analysis while retaining the dynamics of the econometric model to a greater extent than the coupled strategy.

Whichever of the approaches is adopted, the EIO focuses on the inclusion of important structural dynamics into the analytics. The EIO introduces a dynamic time path for the economy; this means that the model does not have to return to equilibrium, allowing the underlying dynamics to better replicate reality. This continual state of disequilibrium, although bringing a realistic nonlinearity, means the process of estimating the model can be complex and often relies on model specific approaches making its construction rather laborious. It is important to note that the Washington EIO (Conway, 1990) did adopt an equilibrium at a point in time; this was done by setting excess demands to zero through the adjustment of the IO coefficients. However, this approach differs from the CGE in which excess demands are set to zero through price adjustment. Dewhurst and West (1991) note that although time consuming, the EIO approach of endogenizing linkages between factor inputs and final demand delivers a more complete model.

The mechanism used to close the EIO model is traditionally implemented by integrating a series of endogenous econometric relationships. This closure allows a feedback mechanism between primary factors and final demand making the impact analysis more accurate and akin to the real world (Conway, 1990). The EIO model is dynamic due to the econometric specification, but not dynamic in the sense of optimization. This means only one component of the EIO, e.g., the exogenous factors such as wages, is dynamic. Models such as COMPASS (Uno, 2002) and GINFORS (Lutz et al., 2005) have pioneered this closing mechanism but remain as tools for high level policy analysis rather than being used for widespread regional research. One factor that has possibly resulted in a lack of extensive use has been the fixed supply side dynamics. As in a simple IO, it remains a demand driven model although with some supply-side constraints, the many advantages detailed above show how it still can be a powerful tool for policy analysis for practitioners.

However, starting with Almon (2017), but the work predates the publication by several decades, many EIO modelers have explicitly addressed the role of households through greater attention to migration and the income-consumption interactions. As Kim et al. (2015) noted, household consumption accounts for approximately 70% of expenditure on the expenditure side of GDP in the US yet many models ignore household heterogeneity by adopting a representative household formulation. Drawing on the Stone-Geary consumption estimation, and the contemporaneous AIDS approach (Deaton and Muellbauer, 1980), Almon (1979) suggested what has subsequently been referred to as PADS (Perhaps Adequate Demand System). Kim et al. (2015, 2016) disaggregated households by age and income and showed the significant differences in forecasts using an EIO with a representative household and one with disaggregated households. CGE modelers seem to have addressed the workings of the labor market more effectively than EIO models. The demand side approach in EIOs usually permits labor market augmentation through migration but this is not modeled formally (i.e., if local labor supply is not sufficient, it is assumed that there will be net in-migration. The reverse would be true if there was excess labor supply). Further, Kim and Hewings (2018) offer a Bayesian approach to the estimation of labor income by a comparable set of disaggregated households as those adopted on the consumption side. With this addition, EIO models are now better able to handle issues such as income distribution impacts over time.

One advantage of exploring consumption behavior in EIO models is the ability to capture life cycle effects. In this regard, Kratena and Streicher (2017) have explored adaptation of buffer-stock ideas within the context of a multi-regional macroeconomic input-output model. The buffer stock concept was offered as an alternative to the life cycle or permanent income ideas (see Carroll, 1997 and Attanasio and Weber, 1995); Luengo-Prado (2006) and Luengo-Prado and Sorensen (2004) have explored this with reference to consumption of durables, nondurables and housing down payments and applied it using a panel dataset for US states.
Foellmi (2005) has provided a further perspective, advancing the notions of an hierarchy of wants in contrast to the notion of a basket of goods whose composition remains unchanged across individuals or households. In contrast, Foellmi (2005) claims that this consumption structure will change with income (and or age) and will be characterized by an hierarchy in which certain goods will be considered first (such as food, basic clothing and housing) and then if funds permit, other goods and services will be considered. In a strict hierarchy, the competition for funds will be between goods considered at each level and not across levels.

Finally, the work of Jorgenson et al. (2013) should be noted since the approach here is for an econometric approach to modeling within the CGE framework; within this framework, they propose a new model of aggregate consumer behavior that captures both temporal (wealth) effects and within period allocations among consumer goods and services.

All of these papers noted in this section together with the work of Keung (2018) on consumption sensitivity of high income consumers and Mian and Sufi (2011) and Mian et al. (2013) have been exploring the impacts of disaggregated households consumption profiles over time. Aladangady (2017) has been examining consumption and savings behavior for different income categories. All of this work has made use of available microdata that has enabled analysts to explore heterogeneity across households of different types and in different geographical locations. However, only a modest set of these new developments has been incorporated into either EIO or CGE models.

3 Computational General Equilibrium Models

Regional versions of Computable General Equilibrium (CGE) began to emerge during the 1970’s; Partridge and Rickman (1998) noted that “CGE models represent a significant advancement in regional economic analysis.” The true value of regional CGE models, and what has driven their popularity amongst academics, is their ability to link both supply and demand effects into a single framework (Torma and Rutherford, 2002).

The regional CGE is effectively an economy-wide model as it describes the motivations and behaviors of all producers and consumers in an economy. The cornerstone of the model is its theoretical consistency, whereby the model adheres to the strong underlying economic principles governing the behavior of agents. In addition, it allows the analysis of the linkages between those agents. This is achieved by using optimization techniques to detail the behavior of agents as a series of equations that describe all aspects of their interactions in the economy. Both exogenous and endogenous variables are combined with a market clearing constraint. All of the equations are solved simultaneously allowing equilibrium in which prices are determined and quantities of supply and demand are equal in every market. The CGE model has become very popular in developing nations where limited time series data are available precluding detailed econometric investigations and the tool represents a significant leap forward in sophistication (Sanchez, 2004).

CGE differs from the EIO model as it is primarily an optimization technique (West, 1995). By constructing equations, an optimal solution is computed based on the endogenous variables response to exogenous shocks such as tax or tariff changes (Gunning and Keyzer, 1995). The CGE introduces supply constraints that reflect its foundations in accordance with neoclassical theory. The model takes the standard transaction values of a sectorial account, traditionally a Social Accounting matrix (SAM), and splits them into two components, quantity and price. These, in turn, take two forms: intermediate inputs (locally produced and imported goods) and primary inputs (labor); within the model, prices are determined endogenously. Taking the SAM and using multi-level nested production functions, one then optimizes based on the theoretically consistent set of equations described above. This approach makes it possible to find a solution to the model in terms of quantities and prices rather than simply an equilibrium value of supply and demand (Burfisher, 2011).

The true value of the CGE is in its use as an experimental tool; by altering and changing exogenous variables it is possible to examine the effect of shocks to the economy (Wing, 2004). Once shocked, the new market equilibrium allows conclusions to be drawn as to the effect of these changes.

In fact, there has been a great deal of soul-searching about the efficacy of macroeconomic models (see Vines and Wills, 2018 and implications for regional modeling are addressed by Donaghy, 2020). While issues of agent heterogeneity are discussed, few macro analysts consider the role of spatial heterogeneity.
The regional construction of CGE models has seen a significant growth over the last 25 years building on the early work of Whalley and Trela (1986) and Kimbell and Harrison (1984); a complete historical synthesis is beyond the scope of this present work but an excellent account can be found in Partridge and Rickman (1998). The general construction of the CGE as described in the previous paragraphs has at its core two fundamental data components that directly influence the operation of the model, the sectorial transaction information and the elasticities (Burfisher, 2011). Tables of sectorial transactions are simply a database of values, usually a social accounting matrix (SAM). The elasticities allow the dynamics of the model to be operationalized and, consequently, they have the largest impact on the output results (Dominquies and Haddad, 2005).

Elasticities, as in traditional economics, are dimensionless parameters that capture behavioral responses (Horridge et al., 2012). Core elasticities in a CGE model for example, export demand and expenditure, are some of the integral features for solving the model (Burfisher, 2011). Unlike the transaction information that is readily available at the regional level in most developed nations, the information required to estimate elasticities is rarely available. As a result, there has become a culture of “borrowing,” in the sense that modeler’s consult the literature to find appropriate values for the elasticities (Sanchez, 2004). This has led to significant criticism (see for example Nganou, 2005; Jorgensen, 1984; Lau, 1984; Jorgensen et al., 1992 and Diewert and Lawrence, 1994). One of the primary concerns from using borrowed values is the lack of regional specific information conveyed in them, inherently important within a regional model.

There have been some attempts to address this concern by employing sensitivity analysis, which has become commonplace in CGE modeling. However, given the calibration required for the CGE model, data are often modified to accommodate the equilibrium benchmark year (Shoven and Whalley, 1984). Over time, the use of some of these techniques has created another controversy, particular over the “black box” nature of the modeling approaches, referring to the lack of clarity of operations (Wing, 2004). Panagariya and Duttagupta (2001) note “Unearthing the features of CGE models that drive [their results] is often a time consuming exercise.” A recent paper by Rokicki et al. (2020) explores the role of different sources of multiregional input-output information on the results of analysis with a CGE model.\(^4\)

This problem arises often because their sheer size, facilitated by recent advances in computer technology, making it difficult to pinpoint the precise source of a particular result. A similar criticism was made in Partridge and Rickman (1998) following their extensive survey of the regional CGE literature; they noted “In many of the articles surveyed, it was difficult determining what the authors did, making interpretation of their results problematic.” These criticisms arise from the complex and often very large number of equations and assumptions needed to capture economic theory and in order for the model to converge. However, these criticisms have come about in part as a result of one of the underlying successes of the CGE model and that is its strong theoretical structure. Authors have attempted to incorporate more flexible functional forms (see for example, Arndt et al., 2001, Tourinho et al., 2003) but it often results in very complex models to solve, and having to make compromises on detail such as the numbers of sectors or types of agents being studied.

An excellent piece of work by (McKitrick, 1998) demonstrates that functional forms impose influential restrictions on the model’s structure. However, what has been the subject of less criticism in the literature has been the actual process of calibration. This is the adjustment of data to replicate a benchmark year. Whether using dynamic or static calibration, modelers face the same issue of having to adjust values or even data to replicate an equilibrium value (Shoven and Whalley, 1984, Sánchez, 2004). To put it another way, calibrated models already have a “solution” and thus parameterization supports this pre-derived and constrained view of the world through deductive means. This is at odds with an econometrically estimated model, which is inductive, and that seeks to establish the statistical probability for the interaction of variables within a model, constructed to test a theory.

4 What are the main difference between the EIO and CGE?

To date, there have been few attempts in the literature to draw distinctions in terms of operation, implementation, and contrasting benefits of the EIO and CGE with the notable exception of West (1995). The present

\(^{4}\)A similar exercise was conducted using alternative sources of input-output data for the Chicago Region Econometric Input-output Model (see Israilevich et al., 1996)
paper now discusses the differences between the models in terms of four areas:

- The Strengths and Weaknesses of both Models
- Assumptions and Properties of both models
- Model Output
- Simulations

In order to avoid bias in this exercise, the simplest most commonly used forms of both models are assessed. This was established by using Google scholar to collate research papers as well as government and consultancy sources. It is acknowledged that other formulations of both the CGE and EIO exist but have not become commonplace primarily as a result of either theoretical restrictions or data requirements. First, some recent examples of CGE and EIO models and their uses are detailed in table 1. The number of regional CGE models is large and, hence, precludes a detailed account (for a more detailed list see Partridge and Rickman, 1998). EIO has been much less popular amongst researchers and policy makers and, as such, few models outside of the US have flourished. One reason that might contribute to this lack of popularity is the more extensive data requirements, including long time series as well as detailed forecast information. On the other hand, CGE has been the model of choice for developing nations since, with much less data required, its popularity has grown exponentially. Using Google scholar, since 2009 alone CGE models were the subject of nearly 9,800 academic papers with the majority using data from developing countries. It was possible to identify less than 9 distinctive EIO models from the literature.

### Table 1

<table>
<thead>
<tr>
<th>Author</th>
<th>Model</th>
<th>Primary Purpose</th>
<th>Regional Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kim et al (2014)</td>
<td>CREIM + Con</td>
<td>Forecasting and Simulation</td>
<td>Interregional</td>
</tr>
<tr>
<td>Kratena et al (2013)</td>
<td>FIDELIO</td>
<td>Dynamic EIO</td>
<td>Interregional</td>
</tr>
<tr>
<td>Masouman (2013)</td>
<td>Illawarra EIO</td>
<td>Forecasting and Simulation</td>
<td>Single Region</td>
</tr>
<tr>
<td>Cambridge Econometrics (2003)</td>
<td>E3ME</td>
<td>Forecasting and Simulation</td>
<td>Interregional</td>
</tr>
<tr>
<td>Jackson (1996)</td>
<td>OPSM</td>
<td>Forecasting and Simulation</td>
<td>Single Region</td>
</tr>
<tr>
<td>Israilevich et al (1994)</td>
<td>CREIM</td>
<td>Forecasting and Simulation</td>
<td>Interregional</td>
</tr>
<tr>
<td>Treyz et al (1993)</td>
<td>REMI</td>
<td>Forecasting and Simulation</td>
<td>Interregional</td>
</tr>
<tr>
<td>West (1991)</td>
<td>QUIP</td>
<td>Impact Assessment</td>
<td>Single Region</td>
</tr>
<tr>
<td>Conway (1978)</td>
<td>WPSM</td>
<td>Impact Assessment</td>
<td>Single Region</td>
</tr>
</tbody>
</table>

### Regional CGE

<table>
<thead>
<tr>
<th>Author</th>
<th>Model</th>
<th>Primary Purpose</th>
<th>Regional Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horridge and Roos (2013)</td>
<td>IndoTERM</td>
<td>Policy Simulation</td>
<td>Interregional</td>
</tr>
<tr>
<td>Dixon et al (2012)</td>
<td>USAGE-R51</td>
<td>Policy Simulation of Trade</td>
<td>Interregional</td>
</tr>
<tr>
<td>Wittwer and Griffith (2011)</td>
<td>TERM-H2O</td>
<td>Policy Simulation of Water</td>
<td>Interregional</td>
</tr>
<tr>
<td>Hanson (1998)</td>
<td>AMIGA</td>
<td>Policy Simulation</td>
<td>Single Region</td>
</tr>
<tr>
<td>Harrigan (1991)</td>
<td>AMOS</td>
<td>Policy Simulation</td>
<td>Single Region</td>
</tr>
</tbody>
</table>

### 4.1 Strengths and Weaknesses

Table 2 summarizes the strengths and weaknesses of both model. Taking the EIO first, the level of sectoral detail as well as the forecasting ability of the model are clear strengths. The CGE’s ability to model supply and demand in a consistent manner as well as the ability to allow substitution with flexible prices also provides significant strengths. The complexity of solving the EIO creates a significant disadvantage. On the contrary, the ability to quickly and efficiently build and solve a CGE model with commercially available software makes it one of the most compelling strengths.\(^5\)

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\(^5\)REAL did contract with a commercial software provider to place regional econometric input-output models in a more general framework but this has yet to be released.
Table 2

<table>
<thead>
<tr>
<th></th>
<th>EIO</th>
<th></th>
<th>CGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strengths</td>
<td>Weaknesses</td>
<td>Strengths</td>
<td>Weaknesses</td>
</tr>
<tr>
<td>Case Specific models</td>
<td>No preparatory software currently available</td>
<td>Readily Available software packages</td>
<td>Model Can be general and a spatial of the geographical area under study</td>
</tr>
<tr>
<td>tailored to a region or group of regions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Significant model detail and specification</td>
<td>Data requirements are significant</td>
<td>Data requirements are relatively small</td>
<td>Use of &quot;borrowed&quot; coefficients</td>
</tr>
<tr>
<td>Forecasting and Impact Analysis</td>
<td>Relies on national forecasts for some equations</td>
<td>Simulation and Impact Analysis</td>
<td>Does not generate a true forecast</td>
</tr>
<tr>
<td>Allows a time path for policy analysis</td>
<td>Complex to Solve</td>
<td>Relatively straightforward to solve</td>
<td>Some elements have been accused of being a &quot;black box&quot;</td>
</tr>
<tr>
<td>Sartorially Detailed</td>
<td>Does not incorporate supply side</td>
<td>Supply and Demand Driven</td>
<td>Significantly fewer sectors</td>
</tr>
</tbody>
</table>

One possible conclusion to draw from collating this table is the inverse symmetry in strengths and weaknesses between EIO and CGE: that is the comparative success of one is a relative weakness of the other. This would imply a complementarity if one chose to develop both classes of model for a given region, the two tools might provide a detailed, more comprehensive understanding of an economy.

4.2 Assumptions and Properties

Table 3 builds on the descriptions of West (1995) and summarizes the primary assumptions and properties of both an EIO and CGE model. From initial observation, both have a considerable number of similarities from non-linearity to initial Leontief functions. However, it becomes more noticeable where both models diverge when the behavior of agents is explored. The maximization behavior of households assumed in the CGE provides the backbone of the “deep parameters” or the functioning of the model (micro-foundations). Deep parameters characterize the tastes and technology of an economy and are concrete in the context of a given model (Hansen and Heckman, 1996). Alternatively, in an EIO, the influence of deep parameters can be questioned; in fact, the estimation of behavioral parameters will change throughout the temporal horizon of the model (Altissimo, et al. 1999).

This restriction also means that the CGE model must keep a large number of the variables exogenous. The EIO is more flexible and is potentially capable of endogenizing more components. Finally, and probably one of the largest differences, is the temporal dimension. EIO models operate within a particular period and solutions at different points in time may be extrapolated. Traditional CGE models, still widely used, adopt instantaneous adjustment or highly regulated adjustment. This approach means that analyzing specific year shocks is more difficult and models often set a time horizon (i.e. 20 years) rather than a specific year. Some dynamic CGE models such as the TERM developed by the Victoria (formerly Monash) group have introduced partial adjustment processes (see for example Horridge and Wittwer, 2010). However, this in turn can introduce consistency problems because the variables that change from one equilibrium solution to the next are not necessarily consistent with each other during the period of change (see the criticism of this problem in Kydland and Prescott, 1977).
Table 3

<table>
<thead>
<tr>
<th>EIO</th>
<th>CGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dynamic allowing temporal effects</td>
<td>Static (dynamic only within multiple iterations of Benchmark data)</td>
</tr>
<tr>
<td>Non Linear Functions</td>
<td>Non Linear Functions</td>
</tr>
<tr>
<td>Demand Driven through the use of Econometric Estimation allowing</td>
<td>Demand and Supply Driven. Often Labor Supply is fixed to</td>
</tr>
<tr>
<td>Heterogeneity to be captured</td>
<td>correspond to the representative household and optimization</td>
</tr>
<tr>
<td>Some Price Effects, limited by data</td>
<td>Full Response to price, although lack of elasticity data means they</td>
</tr>
<tr>
<td></td>
<td>are largely dependent on the function form chosen e.g. CD, GL, TL</td>
</tr>
<tr>
<td>Long term Equilibrium, short term disequilibrium demonstrates</td>
<td>General Equilibrium, some limited partial equilibrium work but</td>
</tr>
<tr>
<td>transitional pathways</td>
<td>primary result of CGE is captured from change in equilibrium</td>
</tr>
<tr>
<td>Although some data cleaning, model describes the world as it exists</td>
<td>Optimization model, reflects the economy working at full</td>
</tr>
<tr>
<td></td>
<td>capacity-without slack therefore unrealistic</td>
</tr>
<tr>
<td>Impact and Forecasting both are analyzed in terms of estimated</td>
<td>Impact, some attempts at forecasting have been made (Dixon</td>
</tr>
<tr>
<td>dynamics of model components</td>
<td>and Rimmer 2009) but results do not support CGE as a tool for</td>
</tr>
<tr>
<td></td>
<td>this form of analysis.</td>
</tr>
<tr>
<td>Total Income, can incorporate changes across time</td>
<td>Total Income, model ignores the process of income growth, and</td>
</tr>
<tr>
<td></td>
<td>real adjustment to price changes. Rarely will payments from</td>
</tr>
<tr>
<td></td>
<td>labor from firms equal household income</td>
</tr>
<tr>
<td>Household Expenditure Determined by dynamic consumption Function-</td>
<td>Household Expenditure Determined by Utility Maximization, often</td>
</tr>
<tr>
<td>constrained by data</td>
<td>adjusted to reflect equilibrium conditions by Calibration</td>
</tr>
<tr>
<td>Intermediate Demands Determined by Leontief Function</td>
<td>Intermediate Demands Determined by Leontief Function</td>
</tr>
<tr>
<td>Primary Factor Demands Determined by Econometric Estimation of</td>
<td>Primary Factor Demands determined by CES- Cost Minimization.</td>
</tr>
<tr>
<td>behavior</td>
<td>Elasticities used within models come from literature rather than</td>
</tr>
<tr>
<td></td>
<td>region specific information</td>
</tr>
<tr>
<td>Technology shock examined through capital labor ratio change across</td>
<td>Technology exogenous as it will push model into disequilibrium</td>
</tr>
<tr>
<td>time and can be endogenized</td>
<td></td>
</tr>
<tr>
<td>Production can model diminishing returns to scale</td>
<td>Production constant returns to scale assumption</td>
</tr>
<tr>
<td>Time frame is acknowledged based upon impacts in each forecast year,</td>
<td>Time frame dues to instantaneous adjustment impacts cannot</td>
</tr>
<tr>
<td>solutions can be short and long run</td>
<td>be given at a specific year. Model is a-temporal, solutions are</td>
</tr>
<tr>
<td></td>
<td>all long run</td>
</tr>
</tbody>
</table>

4.3 Model Output Comparison

To truly compare both models, an empirical exercise has been undertaken. Using a new regional IO table explicitly built for this work, two model derivations, an EIO and a CGE, have been constructed: the Welsh Output Long-run Forecast (WOLF) and the Welsh Computable General Equilibrium (WCGE) model. Both are 14-sector models relying on the same underlying base IO table for the year 2015 for Wales. The IO table was built by updating the existing IO table published in 2007 by the Welsh Economy Research Unit (Jones et al., 2011) using the RAS methodology. The original WOLF model was built for project INTERIM, an EU Marie Curie grant. The CGE was built and solved using GAMS, the structure of the model is reflective of most generic CGE using standard solvers. The code was downloaded from the IFPRI website and was calibrated with the Welsh SAM model produced by Long et al. (forthcoming). To allow ease of comparison, sectors were aggregated up from the original IO table and no complex or uniquely model-specific changes.

6http://cordis.europa.eu/project/rcn/107346_en.html
7http://www.ifpri.org/publication/standard-computable-general-equilibrium-cge-model-gams-0
were made. This might lead one to question the individual values yielded by both models but that is not the purpose of this paper. This strategy was adopted to provide a more representative comparison between the outputs of both models. It must also be noted that in this exercise it is not the magnitude of the multipliers that are of interest, but it is the difference between output values.

Although the full description of the WOLF model is beyond the scope of the present work, the basic premise assumes that exports are exogenous and the rest of final demand is endogenous which lead to changes in output. The output \( z \) is expressed in constant-prices; here, output is a function of the summation of all the individual sector outputs.\(^8\) \( A \) is a matrix of technical coefficients; \( B \) is a coefficient matrix normalized to 1 and \( F \) is a matrix of final demand.

\[
z = Ao + BF
\]

To understand the EIO we can further express this as:

\[
\log \frac{\alpha_i}{z_i} = f_i(\cdot) + \varepsilon_i
\]

The function \( f_i \) contains the lagged dependent variables and time dummy variables. The difference between \( \alpha_i \) and \( z_i \) represents the overall change in technical coefficients over time (see Israilevich et al., 1997 for details).

### 4.3.1 Comparison of models

There are numerous, different ways in which the models could be contrasted directly. However, to avoid bias by specifically looking at different analysis where the strengths of each model could come in to play such as detailed sectorial breakdown or supply shocks, a basic multiplier analysis was run. Value added and employment multipliers are established and presented in tables 4 and 5. Using UK monetary units (pound), the value-added multipliers represent the pound change in value-added per unit pound increase in final demand. The employment multipliers represent a million-pound increase in final demand. The multipliers reported are deliberately short run, that is assuming capital supply is fixed thus again maintaining consistency between both models.

First, looking at table 4, there are significant variations in the size of multipliers estimated from both models. The EIO consistently over-estimates the multipliers compared to the CGE, this is in part because of the additional induced demographic effects the EIO uses within its calculative process. The EIO model used in this work uses UK data for a number of its equations that, as a result, can inflate the multiplier value for a given region.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Value-Added Multiplier EIO</th>
<th>Value-Added Multiplier CGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, forestry and fishing</td>
<td>0.90</td>
<td>0.63</td>
</tr>
<tr>
<td>Food and Drink and Tobacco</td>
<td>0.85</td>
<td>0.71</td>
</tr>
<tr>
<td>Wood products, paper and publishing</td>
<td>0.63</td>
<td>0.64</td>
</tr>
<tr>
<td>Metal and Metal Products</td>
<td>0.78</td>
<td>0.53</td>
</tr>
<tr>
<td>Machinery</td>
<td>0.79</td>
<td>0.58</td>
</tr>
<tr>
<td>Consumer Electronics</td>
<td>0.73</td>
<td>0.48</td>
</tr>
<tr>
<td>Vehicles</td>
<td>0.84</td>
<td>0.71</td>
</tr>
<tr>
<td>Furniture and other manufacturing</td>
<td>0.78</td>
<td>0.62</td>
</tr>
<tr>
<td>Construction</td>
<td>0.88</td>
<td>0.57</td>
</tr>
<tr>
<td>Wholesale and retail</td>
<td>0.79</td>
<td>0.67</td>
</tr>
<tr>
<td>Other professional services</td>
<td>0.89</td>
<td>0.71</td>
</tr>
<tr>
<td>Public administration</td>
<td>0.89</td>
<td>0.93</td>
</tr>
<tr>
<td>Education and Health</td>
<td>0.78</td>
<td>0.81</td>
</tr>
<tr>
<td>Other public and private services</td>
<td>0.58</td>
<td>0.34</td>
</tr>
</tbody>
</table>

\(^8\sum \alpha_i = 1\)
It must also be noted that in the long run, after constraints on capital are relaxed in a CGE model, the multipliers would likely move closer to their EIO counterparts (as can be seen in some of the long-run CGE multipliers estimated in McGregor et al., 1996). One interesting finding from this exercise that although variation exists in the ordering of sectors, largest to smallest, both models are in agreement that “Other public and private services” yields the smallest value-added multiplier. Turning to the employment multipliers in table 5, the CGE produces much larger results than the EIO model. This is likely to be caused by the Keynesian-type closure mechanism that was not altered in the code. This is particularly noteworthy in “public administration.” The employment multipliers across the board do yield variation. This simple exercise was undertaken to show that, even with the same input data, both models yield significantly different results. This also gives weight to the expectation that the choice of one of these models for regional analysis has inherent bias in the results. This is not to suggest that one model is better than the other; the main concern is that the models generate different outcomes from the same set of inputs.

### Table 5

<table>
<thead>
<tr>
<th>Sector</th>
<th>Employment Multiplier EIO</th>
<th>Employment Multiplier CGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agriculture, forestry and fishing</td>
<td>22</td>
<td>26</td>
</tr>
<tr>
<td>Food and Drink and Tobacco</td>
<td>23</td>
<td>27</td>
</tr>
<tr>
<td>Wood products, paper and publishing</td>
<td>16</td>
<td>21</td>
</tr>
<tr>
<td>Metal and Metal Products</td>
<td>21</td>
<td>16</td>
</tr>
<tr>
<td>Machinery</td>
<td>15</td>
<td>12</td>
</tr>
<tr>
<td>Consumer Electronics</td>
<td>17</td>
<td>14</td>
</tr>
<tr>
<td>Vehicles</td>
<td>19</td>
<td>25</td>
</tr>
<tr>
<td>Furniture and other manufacturing</td>
<td>14</td>
<td>10</td>
</tr>
<tr>
<td>Construction</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td>Wholesale and retail</td>
<td>13</td>
<td>18</td>
</tr>
<tr>
<td>Other professional services</td>
<td>14</td>
<td>11</td>
</tr>
<tr>
<td>Public administration</td>
<td>15</td>
<td>40</td>
</tr>
<tr>
<td>Education and Health</td>
<td>16</td>
<td>23</td>
</tr>
<tr>
<td>Other public and private services</td>
<td>15</td>
<td>27</td>
</tr>
</tbody>
</table>

#### 4.4 Simulation Comparisons

A final simulation exercise is set up to explore how impact and forecasting results vary by using both models. To allow the most meaningful comparison, we model each of the scenarios in the short-run as detailed previously since the long-run would allow a less meaningful comparison (McGregor et al., 1996). We compare the effect on output (GDP) from the following two scenario:

a. New car production facility coming online in Wales (95% increases in sector revenue)

b. A large expansion of the agricultural sector (200% increase)

Figures 1 and 2 shows the impacts using both the EIO and CGE model for each simulation over 6 periods. Note that we have specified large values of shocks in order to maximize possible differences in simulation results. All results are reported in percentage change and we only show the aggregate effects (rather than individual sectors).

The results note a divergence between both models, with the EIO estimating higher output increases to begin with in scenario A, but then smoothing over time and the CGE catching up. In scenario B the CGE consistently under-estimates the shock to output compared to the EIO. Some caveats should be noted; we are aware the models are designed for different purposes, the EIO is a forecast tool, the CGE does not forecast but allows us to assess the impact of changes. However, by comparing how the models handle these scenarios in the short-run there is a fundamentally larger impact found from using the EIO. This is largely driven by the demographic/population generated demand increases present in the EIO model. The CGE would also

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9The term period is used intentionally as only the EIO explicitly specifies dates.
perform very differently if this was a long-run analysis and other capital restrictions were lifted. The key take-away from this exercise is that using the same data and the same scenarios yields different results in a short run assessment. Both have merits but must be couched against the assumptions of each model.

**Figure 1**

Scenario A

![Graph showing Scenario A with percentage change from base year on the y-axis and period on the x-axis.]

**Figure 2**

Scenario B

![Graph showing Scenario B with percentage change from base year on the y-axis and period on the x-axis.]

Legend:
- **GDP EIO**
- **GDP CGE**
5 Why are the outputs different using the same inputs?

EIO and CGE have become reliable analytical tools for their respective modelers and have enjoyed much success within regional economic analysis. However, as the previous section of this paper demonstrates, both models can yield different outputs meaning model choice or justification becomes imperative in research and policy work. To understand why these models are so different, this paper now explores three underlying differences.

5.1 Functional Form

One of the primary differences in the operationalization of a CGE and an EIO is in the choice of functional forms for the actions of both consumer and producer. The functional form determines to a great extent how the model will run and how the data will influence the final outcome. CGE models are characterized by having less restrictive structures than the EIO model. Although the functional forms are driven by theoretical consistency, the adopted functional forms may vary depending on the goals of the modeler. This is in contrast to the EIO which has at its heart a balanced IO structure homogeneous of degree zero and results in a system of demand in conformity with Walras Law (Shoven and Whalley, 1984). This being said restrictions over consistency in the CGE do impede the free choice of functional forms and as a result they have been dominated by Cobb Douglas and CES functional forms (Perroni and Rutherford, 1998).

This is not to say other functional forms are not in use (see for example the calibration work of Burniaux and Van der Mensbrugghe, 1991). CET, as well as trans-log have been used but their popularity is much less given the greater challenges of incorporating the form and results into the CGE environment. The EIO may be restrictive in terms of the IO table advanced but some flexibility exists by allowing disequilibrium; the model has given researchers the ability to incorporate and use many different functions and estimators in the same model. The greater restriction comes from data requirements particularly limiting when regionalized models are being constructed. To use the identical functional forms in both models would be challenging; indeed, integrating simply the output of an EIO into a CGE without losing any of the detail through calibration becomes complex. Instead, it would seem logical to take the findings of each model as complementary pieces of data providing a different interpretation of the outcome from an economic scenario. Some advances in this direction have been explored by Jorgenson et al. (2012) and Kratena and Streicher (2009, 2017).

5.2 Closure Mechanism

Price is one of the greatest differences between the CGE and the EIO approach. A CGE model operates by prices adjusting to clear markets in such a way as to maximize welfare. However, individual market clearing for goods is distinctly not possible in a CGE model. Rather, changes in prices of factors (wages and profit rates) permit the full employment of labor and capital. This allows CGE models to delink price and quantity relationships essential to close the system. This economy is Keynesian in nature but integral to its solution is the optimization choices of agents. The EIO closure mechanism relies on the use of commodity information rather than price to close the model. The price adjustment mechanism exists though unobserved in most EIO models although Almon (2017) offers an approach to handle such adjustments. Instead, the focus of the closure is on quantity adjustment mechanisms hence the system shares more Marshallian characteristics (see Israilevich et al., 1997 for further discussion). These two distinct mechanisms are difficult to integrate operationally as the model will never produce the same closure results without extensive data manipulation.

5.3 Calibration

One of the primary differences identified from the literature and synthesis in this paper is the lack of consistency and meaning surrounding the term calibration. To make the problem more complex, calibration is a different process in EIO and CGE. From the review of work to date, it is evident that a conflation of terms in the literature has often exaggerated the debate between the two different schools of modelers (Balistreri and Hillberry, 2006).

The term calibration has come to have multiple meanings for different researchers and can be partly explained
by the lack of a clear methodological approach employed particularly within CGE (for examples, see Partridge and Rickman, 1998). These authors note the lack of clarity from researchers determining what was precisely done in terms of model solution. Dawkins et al. (2001) describe calibration as an imprecise term despite its extensive use within economic analysis and there has been no fixed set of rules for its use within modeling. For example, one might offer two examples of the distinction in the use of the term in both sets if models:

Calibration of CGE models is used to determine the required parameters in order to establish a baseline equilibrium on which the model is based, allowing a closing mechanism to be drawn.

Calibration in EIO is done to evaluate the difference between an estimated parameter and its counterpart at a different point in time.

Following on from the work of Kratena et al. (2012), there has been an increased attempt to bridge the gap between the perceived differences in the methodological approaches and the focus has been changing to view econometric estimation in EIO as a form of dynamic calibration. EIO is based on the principle of estimating historic data to establish parameters for the model; once these are established from data and statistically tested thorough econometrics, the full model can be solved Conway (1998). Calibration within CGE establishes parameters often from the literature using data from other regions or countries; this can result in the augmentation of dynamics in favor of having a theoretically rigorous model.

6 Discussion

By comparing the structural and operational differences in the EIO and CGE, it is possible to see that both models can present different perspectives on the same problem. Rather than viewing the models being as competing agents, one would suggest that they should take their respective places as complementary tools for regional analysis. The goal of this paper has been to highlight and contrast the distinctive features of both models in order to show where both have distinctive differences.

By comparing the output of both models using the same IO data, the paper suggests there are three areas that really differentiate the models in terms of very different operations namely, Calibration, Functional Form, and Closure mechanisms.

There is a more fundamental difference between both models and that is the respective starting points of EIO and CGE modelers. EIO modelers seeks to often forecast or assess long-run or short run impact bound around a statistical framework established through econometric means. CGE modelers use calibration as an adaptive strategy seeking a parsimonious solution to preserve the fundamentals of the model, that is of a theoretically consistent nature. The output of an EIO reflects the reality of a situation, but may be seen to lack a perfectly defined economic theory (i.e., is it consistent with microeconomic foundations?). In contrast, the CGE by its very nature means it can preserve the theoretical underpinnings or deep parameters yielding more consistent, replicable results. It becomes evident that both models warrant use in a regional economic setting sitting along-side each other bringing the benefits of each. It would be impossible to envisage a situation where theory and reality in economics holds perfectly for any large impact model. It may be concluded that the popularity of CGE must now be accompanied by additional development of EIO models, something that, to date, has been lacking. It is clear to see why CGE models have become so popular driven by readily available software, significant online data resources as well as recognition in policy-making circles.

It is equally clear to see why EIO models have, to date, not become as widespread, since the complexity of estimation and data requirements remain significant hurdles to overcome.

7 Conclusion

The future direction of economic impact models has been thought to lie in an either-or strategy with researchers choosing either to develop EIO or CGE models. However, this paper suggests a dual approach, developing both models in tandem to give policy makers and research a richer set of tools to tackle complex problems. An important area this paper has not addressed is the development of integrated models. There is some nascent evidence of the development of hybrid models such as Jorgenson’s (2012) econometric approach
to CGE modeling and Kratena and Streicher’s (2017) fiscal policy model that introduces the notion of price spillovers. In addition, there is a need to explore the sensitivity of outcomes from both models to the choice of an input-output table (see Israilevich et al., 1996) and most certainly the choice of parameters, especially in the CGE models. For multiregional versions of both models, the specification of the labor market becomes of critical importance (handling issues such as labor force participation rate variations, migration and daily/weekly commuting, skills mismatches and so forth). In this regard, one attractive approach might be to build modules for the labor market or consumption that could be appropriately modified for inclusion in any type of model. Each module could be formally embedded in either model type or integrated through some micro-macro mechanism as proposed in Atuesta and Hewings (2013).

However, any integration of both models would need to avoid compromising the strengths of each without delivering significant benefits. Integration may not fill the needs of modelers to balance the weakness in one model with the strengths in another. The development of EIO and CGE provide researchers with the opportunity to explore sensitivity of outcomes to model choice and thus provide an alternative to more traditional robustness checks. One of the biggest issues for CGE modelers is its ability to replicate reality. This has led to it having a “blackbox” reputation where those studying the model may not fully understand the precise workings. Added to this is the ad hoc nature with which key parameters are borrowed from the literature. The EIO has frailties such as not taking account of the supply side directly as well as data requirements. Therefore, it is recommended that modelers should pursue the development of each, and that EIO often neglected should once again be developed as a tool for regional impact analysis along-side CGE.
References


Horridge, M, Wittwer, J (2010) Bringing regional detail to a CGE model using census data. Spatial Economic Analysis, 5, 229-255.


Long, Z (Forthcoming) Developing a CGE model of Wales an Assessment of Fiscal Devolution PhD Thesis Cardiff University UK.


Stone, R (1961), Input-Output and National Accounts Paris, OEEC.


