ESSAYS ON PRODUCTION CHAINS AND DISRUPTIONS: NEW INPUT-OUTPUT PERSPECTIVES ON TIME, SCALE AND SPACE

BY

ANDRE FERNANDES TOMON AVELINO

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Agricultural and Applied Economics
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2018

Urbana, Illinois

Doctoral Committee:

Professor Emeritus Geoffrey J. D. Hewings, Chair
Associate Professor Sandy Dall'erba
Professor Hayri Onal
Professor Yasuhide Okuyama, University of Kitakyushu

ABSTRACT

Modern production chains have captured the gains from economies of scale and industrial specialization by creating local and global networks of intermediate and final goods. Nonetheless, enhanced industrial interdependency has also magnified regional exposure to external shocks transmitted through both demand and supply channels. Natural and man-made disasters have a major role in creating these local disruptions, which regional reverberations depend on the magnitude of physical damages, location, timing and resilience of up and downstream industries. Although stock damages are well understood and measured in the literature, higher-order flow effects taking place in the post-disaster period tend to be overlooked. As a result, current mitigation and preparedness strategies are myopically applied to the affected region as if they had no spatial and temporal linkages. In this dissertation, I advance the theoretical background and broaden the policy implications of the input-output (IO) framework to disruptive events by revising the topics of time, scale and space. In Chapter 1, I explore the issue of *intra-year* seasonality in production chains and its implications for the IO framework. Due to the limited amount of multi-sectoral data at sub-annual level, I propose a novel methodology to disaggregate IO tables in time that relies solely on quarterly GDP information to estimate intra-year tables. I estimate the quarterly IO tables for Brazil in 2004 and show that the multipliers for agriculture in Brazil deviate more than 6% within year from the annual model. Because of the fine geographical scale of disruptive events, it is essential to be able to consider such seasonal variations at a regional level. In Chapter 2, I provide a roadmap of publicly available data to estimate quarterly IO tables in the US for any state and county. Since data is even scarcer at these scales, I devise a maximum cross-entropy solution that allows the inclusion of specific temporal information for the region. As an example, I highlight the seasonal economic characteristics of the State of Illinois and two of its counties (Cook and Iroquois). Chapter 3 introduces a dynamic demo-economic model that synthetizes existing contributions in the disaster literature and includes production scheduling, demographics and seasonality in assessing unexpected events. In Chapter 4, I apply this new dynamic model in a real disaster event, the 2007 Chehalis Flood in Washington State, and compare its results with current models in the literature. I highlight the importance of accounting for labor markets' dynamics and fluctuations in the sectoral structure intra-year when assessing the costs of

disruptive events. I also show how significant the timing of the disruption is in assessing economic losses of disasters. The advancements accomplished in this dissertation should provide the basis for more detailed analysis of production chains vulnerabilities and resilience, further reflections on seasonality patterns and their effect on industrial linkages, and the role of industrial linkages in regional dynamics.

ACKNOWLEDGEMENTS

Throughout this entire journey my lovely wife has always been by my side, unconditionally loving, supporting and caring for me. True love is giving up everything and coming to a place in the middle of the cornfields to an unknown future. Thank you for being my soul mate, for always being there listening to my complaints, for being always willing and ready to have your brain picked, even after long hours of work, for calming me down when I was stressed out, and for contributing with all aspects of my life. Thank you for all your advice, comments, discussions, edits and encouragement during my PhD. We are a team, and I couldn't have made it without you.

This arduous and exciting journey would also not have happened without the unconditional love and support from my parents, who fostered in me this eager curiosity and desire to continuously learn and understand the world. Thank you for providing me the foundations to achieve my goals and for all the opportunities you gave me.

To my advisor, Professor Geoffrey Hewings: I am still humbled that you accepted me at REAL when we first met back in 2010. Ever since then you have been more than an advisor, but a true friend. I know I would not be here if it were not for you. Thank you for guiding me, advocating for me, supporting all my research ideas, and for all the time, money (and coffees) you spent on me. You are incredibly inspiring as a researcher and a human being, and I am so honored (and lucky) to have you as a mentor. I will never be able to repay you for everything you gave me, but I promise to do my best to make you proud and reflect the teacher, researcher and person you showed to me how to be.

Professor Sandy Dall'Erba, I was so lucky to have crossed paths with you. These past years working together in so many projects have taught me so much. Words cannot express my gratitude for your presence in my academic career, and for all your constant efforts supporting me, advocating for me in so many different instances, nominating me to awards, and relentlessly recommending me. Thank you.

Professor Hayri Onal, thank you for your classes, discussions and for always proposing new exciting ideas when we meet. I deeply appreciate all your comments and suggestions for this dissertation, and I was thrilled to have you in my committee.

A special thank you also goes to Professor Yasuhide Okuyama, for accepting to be in my dissertation committee and for all the discussions we had throughout the years, since we met back in 2011 at the International Input-Output conference in Alexandria. It was such an invaluable experience having someone with your level of expertise commenting on and guiding my dissertation.

Professor Kathy Baylis, thank you for being a great teacher and co-author, and for always being welcoming and excited about new research ideas. Thank you for supporting and incentivizing my interdisciplinary side and for advocating for me during all these years.

Since the path towards obtaining my PhD actually started at the University of São Paulo, with Professor Joaquim J. M. Guilhoto, I thank him for introducing me to the field of input-output analysis, for mentoring and incentivizing my research, and for his friendship and constant support. Another fundamental contributor in my undergraduate years in Brazil was Professor Edgar Cornacchione, who gave the opportunity to spend a semester at the University of Illinois back in my senior year, whom I thank for this life changing experience.

Oh, those good old initial years of the PhD… long hours of studying, stress and little sleep… I couldn't have endured it without the friendship and support of my cohort. I would like to specially thank Andrés Ham Gonzales, Leonardo Bonilla Mejia, David Quigley, Kashi Kafle and Chiyu Niu for all the discussions, group studies and non-economic conversations we had. Hey, we all made it!

I have learned so much from the professors at the Department of ACE and Economics, and I appreciate all the time, effort and care they all have given to their classes. A special thanks for the late Professor Weiner Baer for all his support in the first years of the PhD. You were a great teacher, researcher and friend, and your legacy will live forever with all of us.

Also significant in this journey were all the scholars at the Regional Economics Applications Laboratory that I had the pleasure to meet during my PhD. This community was invaluable in shaping my research in Regional Science. I thank all of you for the coffees at Espresso Royale, conversations at the office and research discussions. Among all of those, I would like to specially thank my Spanish friends and co-authors of so many papers André Carrascal Incera, Alberto Franco Solís, Diana Gutiérrez Posada and Fernando Bermejo Patón for all the talks, brainstorming and discussions we had, and for agreeing to work on so many of my crazy ideas; and Yizhou Zhang, Xian Fang-Bak, Kijin Kim, Fernando Rubiera Morollón, Alfredo

Cartone and Vinícius de Almeida Vale for all the countless hours of discussion (mostly research related) we had.

Finally, last but by no means least, I would like to thank Dr. Wen-Huei Chang and the financial support of the U.S. Army Corps of Engineers during my last years of the PhD. I also thank everyone at the Smart Energy Design Assessment Center for all the time I spent with you. Special thanks to Professor Brian Deal for mentoring me during this period and for introducing me to a system thinking approach which has permeated my view of new research questions ever since; and for Aaron Petri for your friendship, research discussions and countless lunch meetings when we came up with so many research ideas.

TABLE OF CONTENTS

CHAPTER 1: DISAGGREGATING INPUT-OUTPUT TABLES IN TIME: THE TEMPORAL INPUT-OUTPUT FRAMEWORK[1]

1.1. Introduction

Traditional input-output (IO) tables are aggregated in three dimensions: industry, space and time. Data are usually presented for aggregated sectors by combining individual firm level information for different NAICS (North American Industry Classification System) into a single production structure. Due to the complexity and costs of producing the necessary data to assemble the tables, their construction has been coupled with the routine gathering of national economic statistics, providing, thus, tables for a particular country and year.

However, the level of aggregation in any dimension conflicts with two main hypotheses supporting the IO framework: stability and homogeneity. In terms of homogeneity, the less aggregated the matrix, the less heterogeneous the production mix will be among the aggregated industries and, thus, the production structure portrayed in each sector better approaches a microeconomic firm aggregation. Conversely, the more aggregated the matrix, the more stable the calculated technical coefficients are, since the lower cross-elasticities derived generate lower substitution effects, supporting the constant input/output ratios assumption. The same reasoning applies to space and time. Moreover, the aggregation bias in each dimension is dependent on the aggregation level in the other dimensions.[2]

Although several techniques have been developed to disaggregate industries and regionalize tables (e.g. Wolsky, 1984; Sargento, 2009), the time dimension has had a more distinct focus. In much of the IO literature, time has been a concern regarding the *inter-year* stability of technical coefficients (Temurshoev, Webb, & Yamano, 2011).[3] Since changes in market shares, technology and prices affect the production structure of an industry, and given the Leontief-type production function assumed in the model (complementary inputs), not adjusting

[1] Part of this chapter is reprinted with permission from Avelino, A. (2017). Disaggregating Input-Output Tables in Time: the Temporal Input-Output Framework, *Economic Systems Research*, 29(3), 313-334. Copyright 2017 by Taylor and Francis.
[2] For instance, in more aggregated industries it is more likely to observe the production structure varying within the year, especially if seasonality affects the aggregated sectors distinctly. In such case, the *intra-year* oscillation in interindustrial flows and total production may not follow the same proportion derived from the annual IO table.
[3] Due to the sole availability of annual IO tables, the literature on coefficient change has focused on the *inter-year* stability of technical coefficients and its determinants.

for such changes may significantly bias long run estimates.[4] In terms of *intra-year* stability, some of the dynamic IO models built on Leontief's (1970) approach couple econometric techniques to estimate adjusted total production vectors or to update technical coefficients for intervals of time less than a year (Romanoff & Levine, 1981; ten Raa, 1986; Aulin-Ahmavaara, 1990; Israilevich, Hewings, Sonis, & Schindler, 1997; Ryaboshlyk, 2006; Donaghy, Balta-Ozkan, & Hewings, 2007, Kratena *et al*., 2013). Nonetheless, the major drawback in this literature is the use of annual technical coefficient matrices as benchmarks to study *intra-year* shocks. The loss of information that the temporal aggregation imposes on the annual technical coefficients by suppressing the distinct economic structure in each period and only considering the aggregated flows at the end of the year, biases the technical coefficient matrix.[5] This Chapter addresses such problem by developing the Temporal EURO method (T-EURO) – a major adaptation of the EURO method (Beutel, 2002; Eurostat, 2008) –, which disaggregates the annual table into *intra-year* tables with specific technical structures using commonly available quarterly GDP data. These tables can then be used for impact analysis or embedded in a dynamic model (see Chapters 3 and 4). In this way, it will be possible to more accurately account for seasonality, production variations and within-year events.

The intertemporal heterogeneity of the production structure arises from seasonal dynamics and industrial aggregation. Heterogeneous final demand and fluctuating industrial production through the year affect scale economies and input substitution, leading to different economic structures. In addition, since industrial aggregation determines how the production structure of the aggregated industry differs from its individual sectors, it also influences the irregularity of the intertemporal dynamics. As industrial output is usually composed of different products with distinct input compositions (e.g., consider the aggregated Agriculture sector reflecting the production of several crops), their heterogeneous dynamics within the year will also affect the economic structure at any point in time.

---

[4] Following Carter's (1970) seminal work, there is a general understanding on the short-term stability of the economic structure, driven by the gradual adoption and spread of technology/production changes in the economy (there is a general inertia of capital in the economy, i.e., old capital takes time to be replaced by newer technology depending on depreciation, investment cycles, etc. (Vaccara, 1970)). Hence, the annual structure portrayed in the table is reasonably valid for a few years (Miller & Blair, 2009).

[5] The temporal aggregation of annual tables produces a misleading structure since it smooths any seasonality in the production structure within the year. In fact, the variance of annual coefficients is a weighted sum of the variance of *intra-year* coefficients and their temporal shares, what filters most of the within year heterogeneity, as shown by Sevaldson (1970) for the case of industrial aggregation. This issue will also be demonstrated in the T-EURO application in Section 1.4.

A major temporal issue in using annual IO models is the evaluation of transient phenomena: short-term events with unevenly distributed economic shocks through time. By evaluating their impacts in a temporally aggregated model, homogeneity of the economic structure throughout the year is implicitly assumed, and time becomes irrelevant. Nevertheless, if we expect that different periods within a year exhibit distinct economic structures, timing is significant to more accurately estimate overall effects. For instance, the duration and period of disruptive events for transportation will entail different economic outcomes given the shipping pattern in each season. Also, the immediate loss in capital and production caused by natural disasters followed by localized recovery stimuli (1995 Kobe Earthquake in Japan, 2008 Cyclone Nargis in Myanmar, 2012 Hurricane Sandy in the US, 2011 radioactive leak in Fukushima, Japan) would have distinct total impacts if their timing was different (Hewings, Changnon, & Dridi, 2000; Okuyama & Santos, 2014). Likewise, the direct, indirect and induced effects of large construction projects (highways, power plants, etc.) will vary throughout the year since input purchases depend on their stage of implementation (Romanoff & Levine, 1977). Therefore, by assuming a constant production structure, these nuances in impacts and their idiosyncratic dynamics are ignored.

In terms of methodological contributions, this Chapter proposes a novel technique for the temporal disaggregation of the IO table, which has not previously been addressed in the literature. Besides the advantage of matching the temporal dimension of the model with those of events, having a complete set of *intra-year* IO tables will provide a more accurate benchmark for current dynamic models to build upon. In terms of application, the tables can now be analyzed to identify key sectors, value chains, industrial linkages, output and income multipliers for each individual time period. This is especially important in order to assess the impact of unexpected climatic events in the economic structure, as well as other disruptive phenomena within a year. For planners and policy makers, it provides a model to more accurately estimate overall outcomes and the evolution of an intervention (infrastructure projects, tax hikes, etc.) throughout the year, so that the optimal timing for implementation can be determined. Finally, IO models with environmental extensions can more adequately link time-varying variables, such as pollution patterns, to the economic structure dynamics to evaluate environmental processes that operate in a time interval shorter than a year.

The next Section provides a literature review on current updating/disaggregating techniques that will serve as a starting point for the proposed temporal disaggregation method. Section 1.3 describes the latter, which is denoted the Temporal EURO method (T-EURO), due to its roots in the EURO method, and also provides a performance analysis of the T-EURO in relation to the traditional RAS method. Section 1.4 presents an application for Brazil to demonstrate the advantages of the methodology in relation to the traditional IO model. Conclusions follow.

1.2. Literature Review

Due to the required time and cost of surveys to construct IO tables, in most countries official national tables are released with a 3-5 years delay. Such time lag, coupled with the fact that official regional tables are not usually compiled, led to the development of non-survey and hybrid methods to update and regionalize national tables. This literature gained momentum in the 1950s with the proposition of the interregional model by Isard (1951) and the seminal work of Stone and Brown (1962) on the bi-proportional updating technique (RAS), and it remains an active area of research (Töben & Kronenberg, 2015).

Non-survey methods are mainly used for regional disaggregation and are considered top-down approaches, since the national table is taken as a base to be adjusted using regional indicators (Sargento, 2009). These methods revolve around modifications of location quotients, which measure the capacity of a particular sector to supply its own regional demand by assessing its concentration in the region in relation to the nation.[6] The disaggregation of regional tables is performed by assuming the same technology as the nation and rescaling its coefficients according to the quotients.

Due to their simplicity, significant assumptions are required: productivity of factors and consumption shares between the nation and region are equal; regional and national industrial aggregation comprises the same mix of products; any export industry i fully supplies local markets and the nation neither imports or exports i's production in net terms (Richardson, 1985).

[6] In its basic formulation, using industry output data x_i^{r} for a particular industry i in region r, $LQ_i^{\mathrm{r}} = \left(\left(\frac{x_i^{\mathrm{r}}}{x^{\mathrm{r}}}\right)/\left(\frac{x_i^{\mathrm{nation}}}{x^{\mathrm{nation}}}\right)\right)$.

Notice that cross-hauling effects[7] thus become a major source of issues for location quotients.[8] Crosson (1960) also highlights that product heterogeneity significantly affects the performance of these techniques, since one may be comparing different sets of activities under the same sectoral categorization. Moreover, the use of quotient approaches implies that national technology is uniform across regions and the observed variation in input coefficients is a function of idiosyncratic regional capacity to supply own-regional demand (Miller & Blair, 2009). Although for a few sectors this assumption is adequate, for the most part it poses an inconsistency. In sum, by reviewing several non-survey methods, Tohmo (2004) argues that such restrictive assumptions tend to generate systematic biases and relatively inaccurate table estimates.

Hybrid approaches, conversely, combine non-survey techniques and superior data (information from surveys, official sources, experts, etc.), to improve upon non-survey estimates by imposing more consistency in the constraints. These techniques have been used in updating, regionalizing and reconciling IO matrices. Several methods have been developed, especially in terms of proportional correction, with a variety of data requirements. Acknowledging the limited information available for updating and regionalizing IO matrices, the approaches face a trade-off between accuracy and the minimum amount of information required. This is particularly important for temporal disaggregation since information is scarcer *intra-year* than *inter-year*.

Initial methods in the area were of proportional univariate correction type, in which a base IO matrix (from previous years or for the nation) is adjusted by applying a correction factor uniformly over rows or columns. Examples can be found in Matuszewski, Pitts and Sawyer (1964) and Tilanus (1968). Their major drawback is the possible inconsistency of the non-adjusted dimension. Since both rows and columns are meaningful in the IO framework, they both need to be considered when adjusting the base matrix, otherwise the resulting input structure may be economically unreasonable.

To overcome the previous limitation, bi-proportional methods were developed by adding constraints to both dimensions, which increased their robustness in relation to univariate approaches (Temurshoev *et al*., 2011). Among those, the RAS technique initially proposed by

---

[7] When a region exports and imports the same good (which invalidates the third assumption).

[8] Although some early solutions proposed by Isserman (1977) and Norcliffe (1983) mitigated the issue, a more effective approach is the CHARM method by Kronenberg (2009).

Stone and Brown (1962) has been the most common approach used in the IO field due to its low information requirements, tractability, preservation of signs and conservative adjustment process.

The RAS adjusts rows and columns of a base year matrix ($\mathbf{Z}^0$) simultaneously (bi-proportional scaling) to estimate $\mathbf{Z}^t$ for a target year t.[9] The only required information for the traditional method is the row and columns sums of $\mathbf{Z}^t$:[10] $\mathbf{u}^t = \mathbf{Z}^t\boldsymbol{\iota}$ and $\mathbf{v}^t = \boldsymbol{\iota}'\mathbf{Z}^t$ respectively (assuming a $n \times n$ $\mathbf{Z}^t$ matrix). The base matrix is taken as the initial estimate ($k = 0$) of $\mathbf{Z}^t$ (call it $\tilde{\mathbf{Z}}^{t,0} = \mathbf{Z}^0$) and its row totals computed in $\tilde{\mathbf{u}}^{t,0}$. The row adjustment factor is then calculated as the ratio between the latter and the true row totals $\mathbf{r}^{t,1} = \mathbf{u}^t \oslash \tilde{\mathbf{u}}^{t,0}$ and proportionally applied to the rows of the initial estimate, yielding new estimates $\tilde{\mathbf{Z}}^{t,1} = \hat{\mathbf{r}}^{t,1}\tilde{\mathbf{Z}}^{t,0}$. In the next step, row totals for $\tilde{\mathbf{Z}}^{t,1}$ are computed ($\tilde{\mathbf{v}}^{t,1}$), column adjustment factors are calculated $\mathbf{s}^{t,1} = \mathbf{v}^t \oslash \tilde{\mathbf{v}}^{t,1}$ and applied proportionally to $\tilde{\mathbf{Z}}^{t,1}$, yielding $\tilde{\mathbf{Z}}^{t,2} = \tilde{\mathbf{Z}}^{t,1}\hat{\mathbf{s}}^{t,1} = \hat{\mathbf{r}}^{t,1}\tilde{\mathbf{Z}}^{t,0}\hat{\mathbf{s}}^{t,1}$. This process iterates until $\mathbf{r}$ and $\mathbf{s}$ converge to unity or are below a set threshold.

The uniform change that $\mathbf{r}$ and $\mathbf{s}$ impose on rows and columns can be interpreted as substitution and fabrication effects respectively (Snower, 1990).[11] Thus, the RAS procedure follows a consistent economic basis for updating the tables. Also, it tends to converge relatively quickly and the use of additional exogenous information as constraints tends to improve its accuracy (Miller & Blair, 2009).

Following Jackson and Murray (2004) the RAS can be conveniently expressed in terms of a mathematical programming problem (where $t = 0$ indicates the base year):

---

[9] The standard IO notation is used in this Chapter. Moreover, matrices are named in bold capital letters, vectors in bold lower-case letters and scalars in italic lower-case letters. The Greek letter $\boldsymbol{\iota}$ (*iota*) denotes a unitary row vector of appropriate dimension. Finally, a hat sign over a vector indicates diagonalization, a prime sign indicates transposition and $\otimes$, $\oslash$ indicate element-wise multiplication and division respectively. In this Chapter, the indices for time (t) and iteration (k) are superscripted in this order.

[10] In case of the technical coefficient matrix $\mathbf{A}^t$, one also needs the total output vector for the target year ($\mathbf{x}^t$) to recover the interindustrial matrix $\mathbf{Z}^t = \mathbf{A}^t\hat{\mathbf{x}}^t$, since forecasted data is usually available for $\mathbf{Z}^t$ row/column sums only. As shown in Dietzenbacher and Miller (2009), however, using a transaction matrix ($\mathbf{Z}^t$) or a technical coefficient matrix ($\mathbf{A}^t$) yields identical results (this does not hold in other commonly used RAS extensions such as GRAS and CRAS).

[11] The pre-multiplication of the matrix by $\mathbf{r}$ implies changing the flow of products of a particular industry to all other industries uniformly while maintaining the sale structure constant. As each column of the interindustrial matrix reflects the input structure of an industry, such operation reduces/increases the use of a particular input in all the economy, which can be interpreted as an input substitution effect. Conversely, the post-multiplication of $\mathbf{s}$ changes the ratio between value added and total purchases of the industry while its input structure remains constant. This is denoted fabrication effects and reflects technology changes that affect the proportion of industrial and non-industrial (labor, land) requirements.

$$\min_{\mathbf{A}^t} I(\mathbf{A}^t \mid\mid \mathbf{A}^0) = \sum_i \sum_j \mathbf{A}_{ij}^t \ln \frac{\mathbf{A}_{ij}^t}{\mathbf{A}_{ij}^0} \tag{1.1}$$

subject to

$$\sum_i \mathbf{A}_{ij}^t \mathbf{x}_j^t = \mathbf{v}_j^t \quad \forall j \tag{1.2}$$

$$\sum_j \mathbf{A}_{ij}^t \mathbf{x}_j^t = \mathbf{u}_i^t \quad \forall i \tag{1.3}$$

$$\mathbf{A}_{ij}^t \geq 0 \qquad \forall i, j \tag{1.4}$$

The conservative adjustment property of RAS comes from the fact that in its equivalent mathematical programming formulation it minimizes information gains (Bacharach, 1970). This implies that the estimated matrix is as close as possible to its prior, thus implicitly assuming a structural relationship of flows between periods. Obviously, if structural changes between the base year and the projected period are substantial, the RAS method will not yield satisfactory results. To mitigate these effects, other alternative formulations for the objective function were proposed, such as penalizing changes in small coefficients (Matuszewski *et al.*, 1964), square differences, etc. However, as Jalili (2000) and Dietzenbacher and Miller (2009) show, the formulation in Equations 1.1-1.4 still outperforms them in terms of estimation accuracy.

In order to mitigate some of the original RAS limitations, several extensions to the method were proposed. Gilchrist and St. Louis (1999) developed a tri-proportional algorithm (TRAS) to accommodate aggregation constraints in the traditional procedure through an additional adjustment step at the end of each iteration. In order to eliminate the RAS assumption of a non-negative matrix, Junius and Oosterhaven (2003) propose the Generalized RAS (GRAS) to allow for both positive and negative entries in the matrix. The method modifies the original formulation by partitioning the matrix between negative and positive transactions (no new information is required). The KRAS method proposed by Lenzen, Gallego and Wood (2009) deals with inconsistent constraints and conflicting external information when applying RAS. In order to mitigate the low flexibility in structural change, Mínguez, Oosterhaven and Escobedo (2009) propose an adapted RAS procedure in which time-series information for the table is used to make coefficient adjustments more flexible. This so-called Cell-Corrected RAS (CRAS) uses past matrices to obtain coefficient variation distributions and minimizes how coefficients deviate from their historical mean weighted by the inverse of the standard deviation. Its main drawback is the requirement of a long series of past IO tables. Finally, to relax the sign preserving property of RAS that creates issues for the estimation of the change of inventory and taxes less subsidies part of the IO table, Lenzen, Moran, Geschke and Kanemoto (2014) propose a non-sign preserving RAS. By adjusting initial estimates in sign changing coefficients, the rescaled constraint becomes RAS-feasible, allowing solutions with sign reversal.

Despite all RAS extensions, the method still requires information on row and column totals for the target year. These data are usually not officially available, and estimations become necessary. Given how highly sensitive the procedure is to these constraints (Bacharach, 1970; Hewings, 1977; Beyers, 1978), even small estimation errors may have a significant impact on results. In order to avoid this estimation step, an alternative method denoted EURO was proposed by Beutel (2002).

The EURO method was conceived to require only official macroeconomic statistics released by most countries and has been recently used by Eurostat in table adjustments (López & Cantuche, 2013). In contrast to the RAS method, it is designed to estimate the full IO table so that the entire economic structure is considered and affected by substitution, fabrication and price effects, imposing consistency between demand and supply. The only set of exogenous variables is official forecasts for the GDP (value added by industry, total exports, total imports and final demand), while output and demand vectors are endogenously determined. The latter feature creates flexibility to the adjustment process, ultimately allowing for thriving sectors to gain and declining sectors to lose importance in the structure (Eurostat, 2008).

The iterative procedure is depicted in the left portion of Figure A.1 in the Appendix. In the first step, the actual growth rates of value added are taken as a first approximation of the growth rates of each sector’s input and output structure, and the rates for aggregated imports, exports and final demand are used as the initial approximation for the respective vectors. In the next step, these growth rates are then applied to both rows and columns and each element is averaged, creating an inconsistent IO table. Since there is more information on the input structure side of the table, a Leontief model is solved with the adjusted technology and a quantity model is applied to reconstruct an internally consistent IO table. In the third step, growth rates in the adjusted table are compared to the true growth rates and, in case of deviation, marginal corrections in the rates are made in the next iteration. The method proceeds until a pre-determined deviation threshold is met.

The main advantages of EURO are its low information requirements, avoidance of arbitrary changes in coefficients (that may occur in RAS), consistency between supply and demand, and reliance on only official macroeconomic statistics as exogenous variables. Nonetheless, an important drawback is that such method does not guarantee convergence, as noted by Temurshoev *et al*. (2011).

In sum, although widely used, the traditional RAS method is not suited for the purpose of this Chapter. Since the intratemporal matrices are structurally different from its annual counterpart, and the goal of the temporal disaggregation is to unveil such heterogeneity, the method is too rigid in terms of the structural variation it allows to arise in the estimated tables. Besides, no time-series of *intra-year* tables is available to apply a CRAS variation instead. Conversely, the EURO method is more adequate to deal with our limited information environment and it allows more flexibility for heterogeneity to arise. Adaptations, however, are necessary. These are explored in the following Section.

1.3. Methodology

1.3.1. Estimating Intratemporal Tables: the T-EURO Method

Given the limited available data to generate a survey-based intratemporal IO table, as well as significant structural variations some sectors may experience throughout the year, the traditional RAS method is not appropriate for our purposes.[12] Because a more flexible methodology is necessary, this Chapter proposes a modified version of the EURO method. A major advantage of this method is the sole requirement of the limited official data released in

[12] The main challenge and distinction from the usual regionalization procedure is that national comprehensive surveys for industrial production, services and expenditures are not available within a year.

conjunction with GDP statistics, thereby reducing the uncertainty of using estimated data as a base for the target matrix.[13]

A fundamental concern in the EURO method is the non-guarantee of convergence, since at the end of each iteration, new correction factors are determined independently of previous corrections, and are applied to the base table (Temurshoev *et al*., 2011). The first modification of the method, thus, ensures its convergence by adjusting the previous correction factors in each iteration. The second major modification is the conversion from an updating procedure to a disaggregating procedure by solving all intratemporal tables in parallel and imposing a temporal aggregation constraint in each iteration. A general view of the T-EURO method is shown in Figure 1.1 and can be compared to Figure A.1 in the Appendix. In addition, a 3-sector, 2 periods example is presented in Appendix B, following the derivation ahead.

Denoting by n the number of sectors in the economy and by f the number of components in the final demand, except exports, the following matrices are defined:[14]

$\mathbf{Z}$: matrix of interindustrial flows $(n \times n)$

$\mathbf{m}$: row vector of imports $(1 \times n)$

$\mathbf{t}$: row vector of taxes $(1 \times n)$

$\mathbf{v}$: row vector of value added $(1 \times n)$

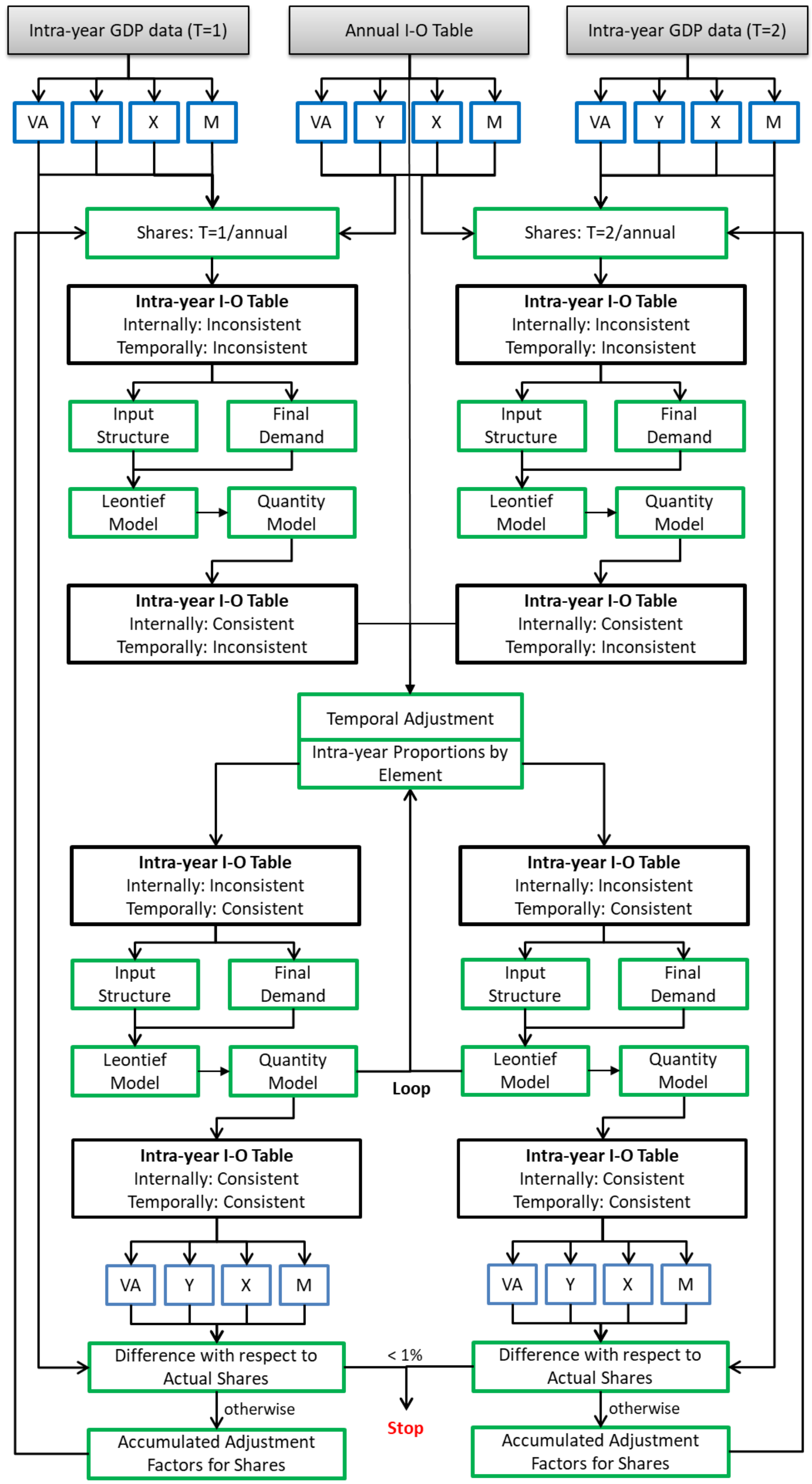
$\mathbf{Y}$: matrix of final demand except exports $(n \times f)$

$\mathbf{e}$: column vector of exports $(n \times 1)$

$\boldsymbol{\iota}$: summation vector of appropriate dimensions

The derivation will follow the notation ${}^{\mathrm{S}}\mathbf{Z}_{ij}^{t,k}$. The post-superscripts t, k indicate the time dimension ($t = 0$ denotes the annual table while $t = 1, 2, \ldots$ denotes *intra-year* tables), and the iteration number ($k = 1,2, \ldots$). The post-subscripts ij indicate row/column and an asterisk sign $(*)$ denotes the sum in the respective dimension. Finally, the pre-superscript indicates if the variable is a share (S), corrected share (S^{C}), external data (E), or an endogenous variable (no letters).

[13] Which are usually released quarterly in most countries.
[14] For expositional purposes (to simplify the derivation), it is assumed that final demand does not import, and that exports and final demand do not collect taxes, otherwise matrices partitions would need to be performed in several steps. Nonetheless, this assumption can be easily dropped during implementation.



Notes: VA: value added by sector; Y: total final demand; X: total exports; M: total imports.

Figure 1.1. Temporal EURO method

The required data for each time period t are ${}^{\mathrm{E}}\mathbf{v}_j^t \mid j = 1, \dots, n$, ${}^{\mathrm{E}}\mathbf{Y}_{*j}^t \mid j = 1, \dots, f$ and the aggregates ${}^{\mathrm{E}}m^t = {}^{\mathrm{E}}\mathbf{m}_{1*}^t$, ${}^{\mathrm{E}}t^t = {}^{\mathrm{E}}\mathbf{t}_{1*}^t$ and ${}^{\mathrm{E}}e^t = {}^{\mathrm{E}}\mathbf{e}_{*1}^t$, besides the full annual table (${}^{\mathrm{E}}\mathbf{IOT}^0$). Hence, in this example, the annual IO table is defined as:

$$ {}^{\mathrm{E}}\mathbf{IOT}^0 = \begin{bmatrix} {}^{\mathrm{E}}\mathbf{Z}^0 & {}^{\mathrm{E}}\mathbf{Y}^0 & {}^{\mathrm{E}}\mathbf{e}^0 \\ {}^{\mathrm{E}}\mathbf{m}^0 & 0 & 0 \\ {}^{\mathrm{E}}\mathbf{t}^0 & 0 & 0 \\ {}^{\mathrm{E}}\mathbf{v}^0 & 0 & 0 \end{bmatrix} \tag{1.5} $$

Finally, define ${}^{\mathrm{S}}\mathbf{v}_j^{t,k}$, ${}^{\mathrm{S}}\mathbf{y}_j^{t,k}$ ${}^{\mathrm{S}}m^{t,k}$, ${}^{\mathrm{S}}t^{t,k}$ and ${}^{\mathrm{S}}e^{t,k}$ as the temporal shares of sectoral value added (by sector), final demand (by component), total imports, total taxes and total exports respectively, calculated at iteration k for time period t in relation to the annual data. For simplicity, assume two time periods only. Initially ($k = 1$), the "true" shares are calculated:

$$ {}^{\mathrm{S}}\mathbf{V}^{t,1} = {}^{\mathrm{E}}\hat{\mathbf{v}}^t \times \left({}^{\mathrm{E}}\hat{\mathbf{v}}^0 \right)^{-1} \tag{1.6} $$

$$ {}^{\mathrm{S}}m^{t,1} = {}^{\mathrm{E}}m^t \times \left({}^{\mathrm{E}}\mathbf{m}_{1*}^0 \right)^{-1} \tag{1.7} $$

$$ {}^{\mathrm{S}}t^{t,1} = {}^{\mathrm{E}}t^t \times \left({}^{\mathrm{E}}\mathbf{t}_{1*}^0 \right)^{-1} \tag{1.8} $$

$$ {}^{\mathrm{S}}e^{t,1} = {}^{\mathrm{E}}e^t \times \left({}^{\mathrm{E}}\mathbf{e}_{*1}^0 \right)^{-1} \tag{1.9} $$

$$ {}^{\mathrm{S}}\mathbf{Y}^{t,1} = {}^{\mathrm{E}}\hat{\mathbf{Y}}_{*j}^t \times \left({}^{\mathrm{E}}\hat{\mathbf{Y}}_{*j}^0 \right)^{-1} \tag{1.10} $$

Both ${}^{\mathrm{S}}\mathbf{V}^{t,k} = {}^{\mathrm{S}}\hat{\mathbf{v}}^{t,k}$ and ${}^{\mathrm{S}}\mathbf{Y}^{t,k} = {}^{\mathrm{S}}\hat{\mathbf{y}}^{t,k}$ are diagonal matrices of dimensions $n \times n$ and $f \times f$ respectively, and all other rates are scalars. In the first step, these shares adjust the annual matrices in both columns and rows. Because value added is the only exogenous data disaggregated by sectors, we proxy any sectorial adjustment using the value added information:

$$ \mathbf{Z}^{t,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\mathbf{V}^{t,1} \times {}^{\mathrm{E}}\mathbf{Z}^0 \right) + \left({}^{\mathrm{E}}\mathbf{Z}^0 \times {}^{\mathrm{S}}\mathbf{V}^{t,1} \right) \right] \tag{1.11} $$

$$ \mathbf{m}^{t,1} = 0.5 \times \left[\left({}^{\mathrm{S}}m^{t,1} \times {}^{\mathrm{E}}\mathbf{m}^0 \right) + \left({}^{\mathrm{E}}\mathbf{m}^0 \times {}^{\mathrm{S}}\mathbf{V}^{t,1} \right) \right] \tag{1.12} $$

$$ \mathbf{t}^{t,1} = 0.5 \times \left[\left({}^{\mathrm{S}}t^{t,1} \times {}^{\mathrm{E}}\mathbf{t}^0 \right) + \left({}^{\mathrm{E}}\mathbf{t}^0 \times {}^{\mathrm{S}}\mathbf{V}^{t,1} \right) \right] \tag{1.13} $$

$$ \mathbf{Y}^{t,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\mathbf{V}^{t,1} \times {}^{\mathrm{E}}\mathbf{Y}^0 \right) + \left({}^{\mathrm{E}}\mathbf{Y}^0 \times {}^{\mathrm{S}}\mathbf{Y}^{t,1} \right) \right] \tag{1.14} $$

$$\mathbf{e}^{t,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\mathbf{V}^{t,1} \times {}^{\mathrm{E}}\mathbf{e}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{e}^{0} \times {}^{\mathrm{S}}e^{t,1} \right) \right] \tag{1.15}$$

$$\mathbf{v}^{t,1} = {}^{\mathrm{E}}\mathbf{v}^{0} \times {}^{\mathrm{S}}\mathbf{V}^{t,1} \tag{1.16}$$

Notice that the pre-multiplication of the matrices by the temporal shares maintains the sales structure of the table, while the post-multiplication maintains the input structure. This allows for input substitution and fabrication effects respectively. However, the resulting total outputs are not necessarily consistent, i.e.:

$$\left(\mathbf{Z}_{i*}^{t,1} + \mathbf{Y}_{i*}^{t,1} + \mathbf{e}_{i}^{t,1} \right) \neq \left(\mathbf{Z}_{*j}^{t,1} + \mathbf{m}_{1j}^{t,1} + \mathbf{t}_{1j}^{t,1} + \mathbf{v}_{1j}^{t,1} \right) \;\; \forall i = j \tag{1.17}$$

In the second step, the *internally inconsistent* table is converted to an *internally consistent* one via the Leontief model. Assume the new technology is represented by the input structure of this inconsistent matrix and define $\mathbf{q}_{j}^{t,1} = \left(\mathbf{Z}_{*j}^{t,1} + \mathbf{m}_{1j}^{t,1} + \mathbf{t}_{1j}^{t,1} + \mathbf{v}_{1j}^{t,1} \right), \forall j = 1, \dots, n$. Hence, $\mathbf{q}^{t,1}$ is a $(1 \times n)$ vector with a first approximation of the total output. Such approximation is then updated to become the base of the internally consistent table using the Leontief's demand-driven model:

$$\mathbf{x}^{t,1} = \left(\mathbf{I} - \left(\mathbf{Z}^{t,1} \times (\hat{\mathbf{q}}^{t,1})^{-1} \right) \right)^{-1} \times \left(\left(\mathbf{Y}^{t,1} \times \boldsymbol{\iota} \right) + \mathbf{e}^{t,1} \right) \tag{1.18}$$

Therefore, the *internally consistent* table is obtained by applying the quantity model:

$$\mathbf{Z}^{t,1} = \mathbf{Z}^{t,1} \times (\hat{\mathbf{q}}^{t,1})^{-1} \times \hat{\mathbf{x}}^{t,1} \tag{1.19}$$

$$\mathbf{m}^{t,1} = \mathbf{m}^{t,1} \times (\hat{\mathbf{q}}^{t,1})^{-1} \times \hat{\mathbf{x}}^{t,1} \tag{1.20}$$

$$\mathbf{t}^{t,1} = \mathbf{t}^{t,1} \times (\hat{\mathbf{q}}^{t,1})^{-1} \times \hat{\mathbf{x}}^{t,1} \tag{1.21}$$

$$\mathbf{v}^{t,1} = \mathbf{v}^{t,1} \times (\hat{\mathbf{q}}^{t,1})^{-1} \times \hat{\mathbf{x}}^{t,1} \tag{1.22}$$

Which yields the internally consistent table $\mathbf{OIT}^{t,1}$:

$$\mathbf{OIT}^{t,1} = \begin{bmatrix} \mathbf{Z}^{t,1} & \mathbf{Y}^{t,1} & \mathbf{e}^{t,1} \\ \mathbf{m}^{t,1} & 0 & 0 \\ \mathbf{t}^{t,1} & 0 & 0 \\ \mathbf{v}^{t,1} & 0 & 0 \end{bmatrix} \tag{1.23}$$

At this stage, each time period t has an *internally consistent* table from the first iteration that is still *temporally inconsistent*, i.e., summation of the same element in each time period does not equal its annual value. Thus, in the third step, a temporal adjustment is imposed so that every element adds up to the actual annual flow. Initially, adjust each element of the matrix $\mathbf{OIT}^{t,1}$ by its proportion in relation to the sum of both $\mathbf{OIT}^{1,1}$ and $\mathbf{OIT}^{2,1}$ tables:[15]

$$\mathbf{OIT}^{t,1} = {}^{\mathrm{E}}\mathbf{IOT}^{0} \otimes \left(\mathbf{OIT}^{t,1} \oslash (\mathbf{OIT}^{1,1} + \mathbf{OIT}^{2,1})\right) \qquad \forall t \tag{1.24}$$

With the application of this process, each new $\mathbf{OIT}^{t,1}$ is again *internally inconsistent*. By repeating the operations described in the second step above, we can obtain *internally consistent* $\mathbf{OIT}^{1,1}$ and $\mathbf{OIT}^{2,1}$, whose element-wise sum approaches the annual table. The difference between $(\mathbf{OIT}^{1,1} + \mathbf{OIT}^{2,1})$ and ${}^{\mathrm{E}}\mathbf{IOT}^{0}$ can be calculated by using some measure of matrix similarity (e.g., mean absolute percentage error (Butterfield & Mules, 1980), standardized weighted absolute difference (Lahr, 2001), psi statistic (Knudsen & Fotheringham, 1986), etc.), and based on a maximum error threshold, determine if a reiteration of the third step is needed.

Once *temporally* and *internally consistent* matrices are obtained, new shares ${}^{\mathrm{S}}\mathbf{V}^{t,2}$, ${}^{\mathrm{S}}\mathbf{Y}^{t,2}$ ${}^{\mathrm{S}}m^{t,2}$, ${}^{\mathrm{S}}t^{t,2}$ and ${}^{\mathrm{S}}e^{t,2}$ are calculated for this table in relation to the annual table:

$${}^{\mathrm{S}}\mathbf{V}^{t,2} = \hat{\mathbf{v}}^{t,1} \times \left({}^{\mathrm{E}}\hat{\mathbf{v}}^{0}\right)^{-1} \tag{1.25}$$

$${}^{\mathrm{S}}m^{t,2} = \mathbf{m}_{1*}^{t,1} \times \left({}^{\mathrm{E}}\mathbf{m}_{1*}^{0}\right)^{-1} \tag{1.26}$$

$${}^{\mathrm{S}}t^{t,2} = \mathbf{t}_{1*}^{t,1} \times \left({}^{\mathrm{E}}\mathbf{t}_{1*}^{0}\right)^{-1} \tag{1.27}$$

$${}^{\mathrm{S}}e^{t,2} = \mathbf{e}_{*1}^{t,1} \times \left({}^{\mathrm{E}}\mathbf{e}_{*1}^{0}\right)^{-1} \tag{1.28}$$

[15] As aforementioned, Hadamard (element-wise) multiplication is denoted by $\otimes$ and division by $\oslash$. Also, as any division by zero implies that the corresponding denominator is also zero (since the method never changes null elements in the annual table), the operation's result is set to zero.

$$ {}^{\mathrm{S}}\mathbf{Y}^{t,2} = \widehat{\mathbf{Y}}_{*j}^{t,1} \times \left({}^{\mathrm{E}}\widehat{\mathbf{Y}}_{*j}^{0} \right)^{-1} \tag{1.29} $$

Deviations from the "true" temporal shares ${}^{\mathrm{S}}\mathbf{V}^{t,1}$, ${}^{\mathrm{S}}\mathbf{Y}^{t,1}$ ${}^{\mathrm{S}}m^{t,1}$, ${}^{\mathrm{S}}t^{t,1}$ and ${}^{\mathrm{S}}e^{t,1}$ and the new ones are defined as d_{r}^{t} = (new share / true share), where r is a particular type of share. If deviations are above a certain error margin, the following correction factors are calculated through a convex adjustment function:

$$ c_{\mathrm{r}}^{t,2} = \begin{cases} 1 + (\Delta_{\mathrm{r}}^{t} \times 100)^{\varepsilon}/100 & \text{if } \Delta_{\mathrm{r}}^{t} > 0 \\ 1 - (-\Delta_{\mathrm{r}}^{t} \times 100)^{\varepsilon}/100 & \text{if } \Delta_{\mathrm{r}}^{t} < 0 \end{cases} \tag{1.30} $$

where $\Delta_{\mathrm{r}}^{t} = d_{\mathrm{r}}^{t} - 1$ and ε is the adjustment elasticity (usually 0.9).[16] This results in the shares' correction factors: $\mathbf{c}_{\mathbf{V}}^{t,2}$ $(1 \times n)$, $\mathbf{c}_{\mathbf{Y}}^{t,2}$ $(1 \times f)$, $c_{m}^{t,2}$, $c_{t}^{t,2}$, $c_{e}^{t,2}$. The first step of the next iteration ($k = 2$) is similar to the previous one, except that the correction factor is applied to the "true" shares:

$$ \mathbf{Z}^{t,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\mathbf{V}^{t,2} \times {}^{\mathrm{E}}\mathbf{Z}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{Z}^{0} \times {}^{\mathrm{S^C}}\mathbf{V}^{t,2} \right) \right] \tag{1.31} $$

$$ \mathbf{m}^{t,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}m^{t,2} \times {}^{\mathrm{E}}\mathbf{m}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{m}^{0} \times {}^{\mathrm{S^C}}\mathbf{V}^{t,2} \right) \right] \tag{1.32} $$

$$ \mathbf{t}^{t,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}t^{t,2} \times {}^{\mathrm{E}}\mathbf{t}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{t}^{0} \times {}^{\mathrm{S^C}}\mathbf{V}^{t,2} \right) \right] \tag{1.33} $$

$$ \mathbf{Y}^{t,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\mathbf{V}^{t,2} \times {}^{\mathrm{E}}\mathbf{Y}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{Y}^{0} \times {}^{\mathrm{S^C}}\mathbf{Y}^{t,2} \right) \right] \tag{1.34} $$

$$ \mathbf{e}^{t,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\mathbf{V}^{t,2} \times {}^{\mathrm{E}}\mathbf{e}^{0} \right) + \left({}^{\mathrm{E}}\mathbf{e}^{0} \times {}^{\mathrm{S^C}}e^{t,2} \right) \right] \tag{1.35} $$

$$ \mathbf{v}^{t,2} = {}^{\mathrm{E}}\mathbf{v}^{0} \times {}^{\mathrm{S^C}}\mathbf{V}^{t,2} \tag{1.36} $$

where,

$$ {}^{\mathrm{S^C}}\mathbf{V}^{t,2} = \hat{\mathbf{c}}_{\mathbf{V}}^{t,2} \times {}^{\mathrm{S}}\mathbf{V}^{t,1} \tag{1.37} $$

---

[16] This is the same elasticity used by Beutel (2002) in his exposition of the EURO method. It affects the speed in which Equation 1.30 adjusts the shares via the correction factor c. If $\varepsilon = 1$, the error in the rates is completely transferred to the correction factor. By letting $\varepsilon < 1$, the adjustment portrayed in Equation 1.30 becomes non-linear, implying a smoother convergence correction so that each iteration allows some error room for adjustment in the next round.

$$ {}^{\mathrm{S}^{\mathrm{C}}}m^{t,2} = c_m^{t,2} \times {}^{\mathrm{S}}m^{t,1} \tag{1.38} $$

$$ {}^{\mathrm{S}^{\mathrm{C}}}t^{t,2} = c_t^{t,2} \times {}^{\mathrm{S}}t^{t,1} \tag{1.39} $$

$$ {}^{\mathrm{S}^{\mathrm{C}}}e^{t,2} = c_e^{t,2} \times {}^{\mathrm{S}}e^{t,1} \tag{1.40} $$

$$ {}^{\mathrm{S}^{\mathrm{C}}}\mathbf{Y}^{t,2} = \hat{\mathbf{c}}_{\mathbf{Y}}^{t,2} \times {}^{\mathrm{S}}\mathbf{Y}^{t,1} \tag{1.41} $$

These adjusted matrices create an *internally inconsistent* table and, in the second step, they are modified to become *internally consistent* again. In the third step, *temporally* and *internally consistent* tables are created and new deviations and correction factors are calculated. In order to guarantee convergence, at the beginning of the third iteration, and in all subsequent iterations, the correction factors are multiplied with the previous ones. Hence, at iteration I the correction will be given by $\prod_{k=2}^{I} c_{\mathrm{r}}^{t,k}$.[17] The algorithm continues until the estimated variables are close to the official macroeconomic data for each time period, i.e., all deviations are below a given minimum precision level. This new method provides complete *intra-year* IO tables estimates that are consistent with the annual data.

The main advantages of the T-EURO are the same as the EURO method, with the addition of temporal consistency of the disaggregated tables. Note that by not assuming constant flow shares, the *intra-year* technical structure is implicitly adjusted in the method, thus capturing seasonal production structure variations.[18] In terms of limitations, the sign preserving property is an issue if change in inventories are disaggregated in the final demand vector as the sign structure of the annual matrix will be reproduced in intratemporal matrices.

1.3.2. A Comparison Between T-EURO and RAS

Given the wide use of the RAS procedure, adjusted tables recovered by both methods will be compared to demonstrate the advantages and disadvantages of the T-EURO for temporal

[17] For instance, in the case of value added, this implies: ${}^{\mathrm{S}^{\mathrm{C}}}\mathbf{V}^{t,I} = \left(\hat{\mathbf{c}}_{\mathbf{V}}^{t,2} \times \hat{\mathbf{c}}_{\mathbf{V}}^{t,3} \times \ldots \times \hat{\mathbf{c}}_{\mathbf{V}}^{t,I-1} \times \hat{\mathbf{c}}_{\mathbf{V}}^{t,I}\right) \times {}^{\mathrm{S}}\mathbf{V}^{t,1}$.

[18] The annual technical structure is taken as a first approximation of the *intra-year* **A** matrices, however it is modified at each time step in order to conform with balancing and consistency constraints of the IO table. This allows production structure variations to arise in each period.

disaggregation. Since the primary focus of IO analysis relies on the technical coefficient and Leontief Inverse matrices, they are the targets of this comparison.

The comparison between actual and estimated matrices is made using different measures of matrix closeness commonly used in the IO literature. Denoting by x_{ij} the estimated element and by $\tilde{x}_{ij}$ the true element, we can define:

(1) Mean Absolute Deviation (MAD): reflects the average error of an estimated coefficient (in any direction).

$$MAD = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|\left(x_{ij} - \tilde{x}_{ij}\right)\right| \tag{1.42}$$

(2) Mean Absolute Percentage Error (MAPE): reflects the average percentage error of an estimated coefficient (in any direction).

$$MAPE = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\left|\left(x_{ij} - \tilde{x}_{ij}\right)\right|}{\left|\tilde{x}_{ij}\right|} \times 100 \tag{1.43}$$

(3) Weighted Absolute Percentage Error (WAPE): reflects the average percentage error of an estimated coefficient weighted by the relative size of each coefficient in the true matrix.

$$WAPE = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(\frac{\left|\tilde{x}_{ij}\right|}{\sum_k \sum_l \tilde{x}_{kl}}\right) \times \frac{\left|\left(x_{ij} - \tilde{x}_{ij}\right)\right|}{\left|\tilde{x}_{ij}\right|} \times 100 \tag{1.44}$$

(4) Standardized Weighted Absolute Difference (SWAD): similar to WAPE but weighting the absolute error.

$$SWAD = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(\frac{\left|\tilde{x}_{ij}\right|}{\sum_k \sum_l \tilde{x}_{kl}{}^2}\right) \times \left|\left(x_{ij} - \tilde{x}_{ij}\right)\right| \tag{1.45}$$

(5) Psi Statistic: an information-based statistic.

$$\psi = \frac{1}{\sum_i \sum_j \tilde{x}_{ij}}\sum_{i=1}^{n}\sum_{j=1}^{n}\left[\left|\tilde{x}_{ij}\right| \times \left|\ln\left(\frac{\tilde{x}_{ij}}{\left(\left|x_{ij}\right| + \left|\tilde{x}_{ij}\right|\right)/2}\right)\right| + \left|x_{ij}\right| \times \left|\ln\left(\frac{x_{ij}}{\left(\left|x_{ij}\right| + \left|\tilde{x}_{ij}\right|\right)/2}\right)\right|\right] \tag{1.46}$$

Several previous papers (e.g., Temurshoev *et al*., 2011) have shown that the traditional EURO method is outperformed by the RAS method under perfect information. Nonetheless, because in practice the information required by the RAS method needs to be estimated (which is especially true for *intra-year* tables), embedded estimation errors need to be accounted for in the latter. In doing so, the suggestions of Tarancón and Río (2005) are adopted and three levels of error (2%, 5% and 10%) are randomly applied in the total intermediate sales and intermediate purchases vectors ($\mathbf{u}^t$ and $\mathbf{v}^t$ respectively). Due to the unavailability of actual *intra-year* tables, I use a series of Brazilian IO tables from 2002 to 2005.[19] The RAS estimates the interindustrial transaction table only, while the T-EURO recover the entire IO table for each period.[20]

Note that two options are available for the temporal disaggregation of more than two periods: a simultaneous disaggregation or a hierarchical disaggregation. In the former, all periods are solved in parallel, so they are derived from the same top base structure (the annual table). In the latter, the disaggregation is performed in pairs, i.e., semester tables are derived first and quarterly tables are derived from them. Hence, each level of tables uses as base the upper level structure. A comparison was made between these two options using the series of Brazilian IO tables (2002-2005, each year representing one "quarter") aggregated into a 4-year matrix (representing the "annual table"). Results are shown in Table 1.2 and highlight that the method is robust enough so both options yield similar results.

Table 1.2 shows the errors between the true 2004 IO table and the ones generated by T-EURO and RAS for both the technical coefficient matrix and the Leontief Inverse. As can be seen, the RAS outperforms the T-EURO method when full information is available. Nonetheless, at the standard 5% error level, the T-EURO for semester disaggregation consistently yields better results. And although quarterly disaggregation tends to induce larger errors, as a result of more variability of coefficients at lower aggregation levels, overall the T-EURO outperforms the RAS at the same 5% error (see Table 1.2 for 2004 and Tables A.1, A.2 and A.3 in the Appendix for 2002, 2003 and 2005 respectively).

[19] Benchmark IO tables for Brazil are only available for the years 1985, 1990-1996, 2000 and 2005. Hence a more recent series was estimated from the national accounts using Guilhoto and Sesso Filho (2005) methodology.
[20] No temporal consistency constraint is applied to the RAS, so besides projection errors there are some aggregation errors not considered in the analysis. In further works, comparisons with the CRAS procedure will be performed.

Table 1.1. Comparison between simultaneous and hierarchical disaggregation

	Technical Coefficient Matrix				Leontief Inverse Matrix			
	Q1 (2002)	Q2 (2003)	Q3 (2004)	Q4 (2005)	Q1 (2002)	Q2 (2003)	Q3 (2004)	Q4 (2005)
MAD	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
MAPE	0.148	0.173	0.253	0.239	0.125	0.191	0.280	0.313
WAPE	0.110	0.098	0.198	0.218	0.042	0.062	0.169	0.217
SWAD	0.001	0.001	0.002	0.002	0.000	0.000	0.001	0.001
PSI	0.001	0.001	0.002	0.002	0.000	0.001	0.002	0.002

Also, notice that when comparing weighted and unweighted errors (WAPE and MAPE respectively) for all T-EURO disaggregations (semester and quarter) they are consistently lower for WAPE. Thus, it indicates that the method performs better in the adjustment of larger coefficients in the matrix, which are usually the most significant from an economic perspective. Moreover, the average percent error is the lowest for the Leontief Inverse matrix.

In sum, in these simulation, the T-EURO yields better estimates under limited data situations when the minimal information required by RAS needs to be estimated, which tends to compound the errors from the econometric estimates and the adjustment itself. Although it is not possible to ascertain that the T-EURO will always outperform RAS, given that the data required for forecasting interindustrial sales and purchases by sector for each quarter are relatively scarcer *intra-year* than *inter-year* (as industrial surveys are not available), the T-EURO method offers a significant advantage by only requiring official data readily available with GDP releases and avoiding the estimation of additional econometric models which will, necessarily, carry over errors to RAS. Moreover, the T-EURO avoids the issue of hysteresis (Lenzen, Moura, Geschke, Kanemoto, & Moran, 2012) from the traditional RAS method, which could be significant if seasonality is strong within the year and superior data is unavailable to inform *intra-year* estimation.

Table 1.2. Results of temporal disaggregation via T-EURO and RAS, 2004

		Technical Coefficient Matrix				Leontief Inverse Matrix			
		No Error	**2% Error**	**5% Error**	**10% Error**	**No Error**	**2% Error**	**5% Error**	**10% Error**
MAD	**T-EURO $(Q)^S$**	0.002				0.002			
	T-EURO $(Q)^H$	0.002				0.002			
	RAS	0.001	0.001	0.002	0.002	0.001	0.002	0.004	0.005
MAPE	**T-EURO $(Q)^S$**	8.735				4.927			
	T-EURO $(Q)^H$	8.727				4.919			
	RAS	7.148	7.319	10.216	11.957	3.216	3.961	7.936	8.961
WAPE	**T-EURO $(Q)^S$**	4.949				1.600			
	T-EURO $(Q)^H$	4.947				1.601			
	RAS	3.238	4.142	6.123	8.217	0.916	1.492	2.784	3.367
SWAD	**T-EURO $(Q)^S$**	0.039				0.008			
	T-EURO $(Q)^H$	0.039				0.008			
	RAS	0.022	0.031	0.046	0.079	0.004	0.007	0.012	0.013
PSI	**T-EURO $(Q)^S$**	0.049				0.016			
	T-EURO $(Q)^H$	0.049				0.016			
	RAS	0.032	0.041	0.061	0.082	0.009	0.015	0.028	0.034

Notes: T-EURO $(Q)^S$: 2004 table derived from the 2002-2005 "annual table" via simultaneous disaggregation
T-EURO $(Q)^H$: 2004 table derived from the 2002-2005 "annual table" via hierarchical disaggregation
RAS: 2004 table derived from the 2002-2005 "annual table"

1.4. Application

To illustrate the application of the T-EURO method, annual Brazilian IO tables for the 2004-2006 period are used to derive quarterly intratemporal tables from official GDP statistics for each year. A simple structural economic analysis is performed to highlight the heterogeneity in the production structure in each period, via the multiplier product matrix (MPM) and economic landscapes.

The Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística, 2014) provides quarterly GDP data comprised of value added disaggregated into Agriculture, Industry and Services, Taxes, Household Expenditure, Government Expenditure, Gross Capital Formation, Change in Inventories, Exports and Imports. By combining these data with a series of quarterly GDP volume index, value added can be further disaggregated into 12 sectors (Table A.4 in the Appendix). The estimated 2004 quarterly tables are reported on Figures A.2-A.5 in the Appendix.

An important feature of the IO system is to portray linkages between sectors in the economy. Sectors both demand inputs (backward linkages) and supplies goods (forward linkages) to other sectors, allowing the identification of production chains. In an attempt to identify key sectors in the economy, several measures of connectedness have been proposed.[21] The most commonly used are the Rasmussen-Hirschman Indexes which measure the power and sensitivity of dispersion for a particular sector. From the basic IO model, we obtain the total requirement matrix (Leontief Inverse) $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1}$. Denote by $\bar{b} = \boldsymbol{\iota}'\mathbf{B}\boldsymbol{\iota}/n$ the average of all elements in $\mathbf{B}$. Hence, the power of dispersion index $\mathbf{BL} = \boldsymbol{\iota}'\mathbf{B}/\bar{b}$ and the sensitivity of dispersion $\mathbf{FL} = \mathbf{B}\boldsymbol{\iota}/\bar{b}$ imply that industries with $\mathbf{BL}_j > 1$ ($\mathbf{FL}_i > 1$) have above average direct backward (forward) linkages.

The multiplier product matrix (MPM) was devised to simultaneously account for both forward and backward linkages in the economy, reflecting the first order field of influence of a change in a particular input coefficient (Sonis & Hewings, 1999). It is defined as $\mathbf{M} = \|(\mathbf{B}\boldsymbol{\iota})(\boldsymbol{\iota}'\mathbf{B})\|/(n\bar{b})$ and measures a sector's connectedness to all other sectors. By sorting the matrix in a rank-size hierarchy, an "artificial economic landscape" is created and can be used to graphically portray structural changes in the economy.

Overall, in terms of the connectivity of production chains, the structure tends to be quite stable within the year, with the manufacturing sector exhibiting the strongest dependency in the economy (Figure 1.2). In terms of output multipliers, relatively more variability is observed within quarters and in its evolution over time (Table A.5 in the Appendix).

[21] For a more comprehensive treatment of measurements of economic linkages in the IO framework, the interested reader is referred to Miller and Blair (2009).

The Agriculture sector is the one that benefits the most from the temporal disaggregation because the size of its linkages and output multipliers vary significantly *intra-year*. As shown in Figure 1.3 and Figure 1.4, linkages portrayed in annual tables omit the typical seasonality of the industry. Stronger backward linkages arise in the second semester due to the start of the soybeans and corn cycles, requiring the acquisition of inputs. Conversely, their harvest in the first semester increase forward linkages as agriculture supplies the food production chain and exports.

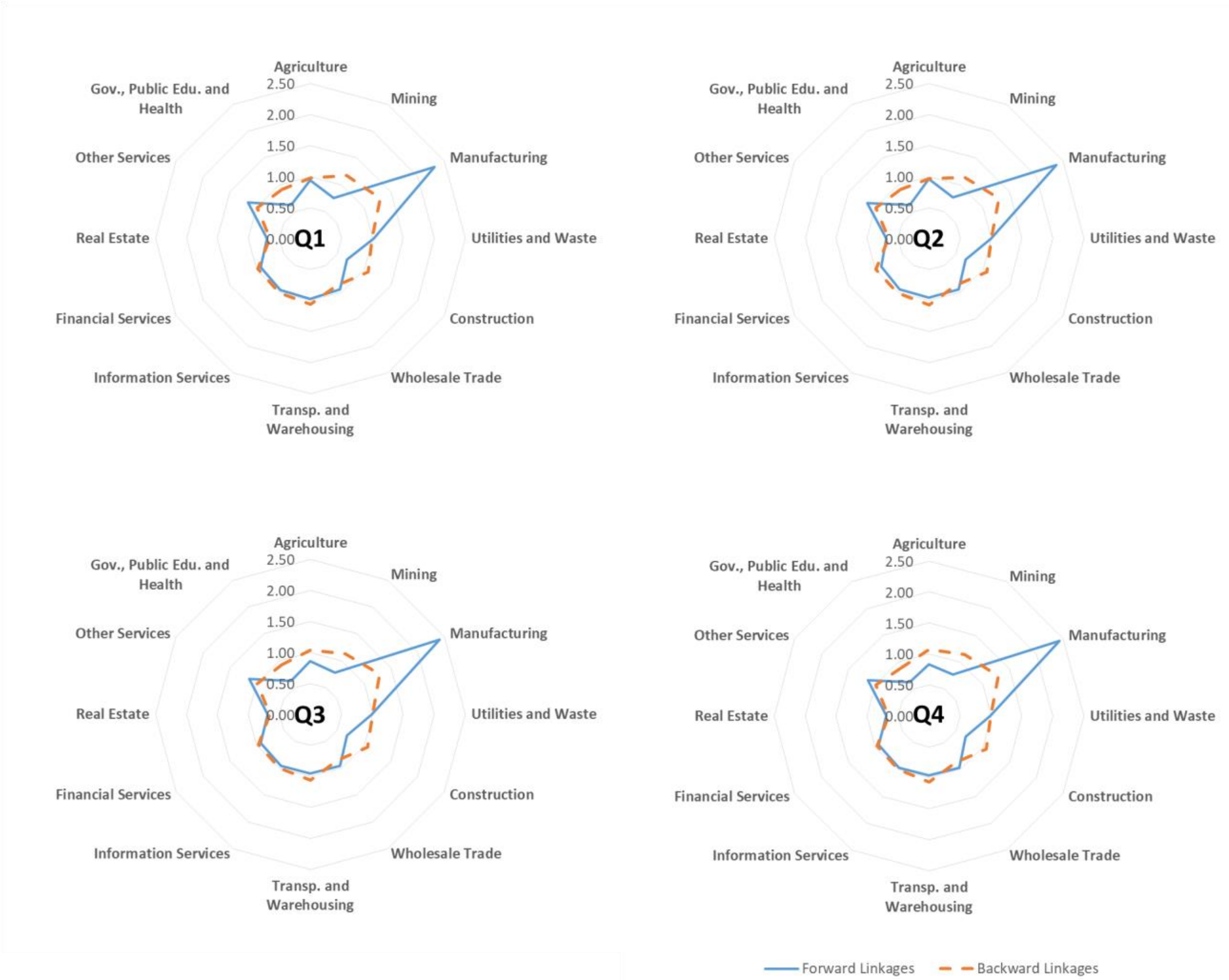


Figure 1.2. Hirschman/Rasmussen backward and forward linkages, 2004

The "economic landscape" portrayed in Figure A.6 is consistent with the previous observations, showing the Manufacturing as by far the most linked sector in the economy at any point in the year. Due to its usually initial position in the production chain, it has larger forward linkages than backward linkages. Moreover, a careful analysis of the MPM reveals that these forward linkages tend to strength towards the end of the year in response to increasing demand in the holiday season. Mining also exhibits marginal increases in forward linkages throughout the year, probably pulled by Manufacturing ahead in the production chain.

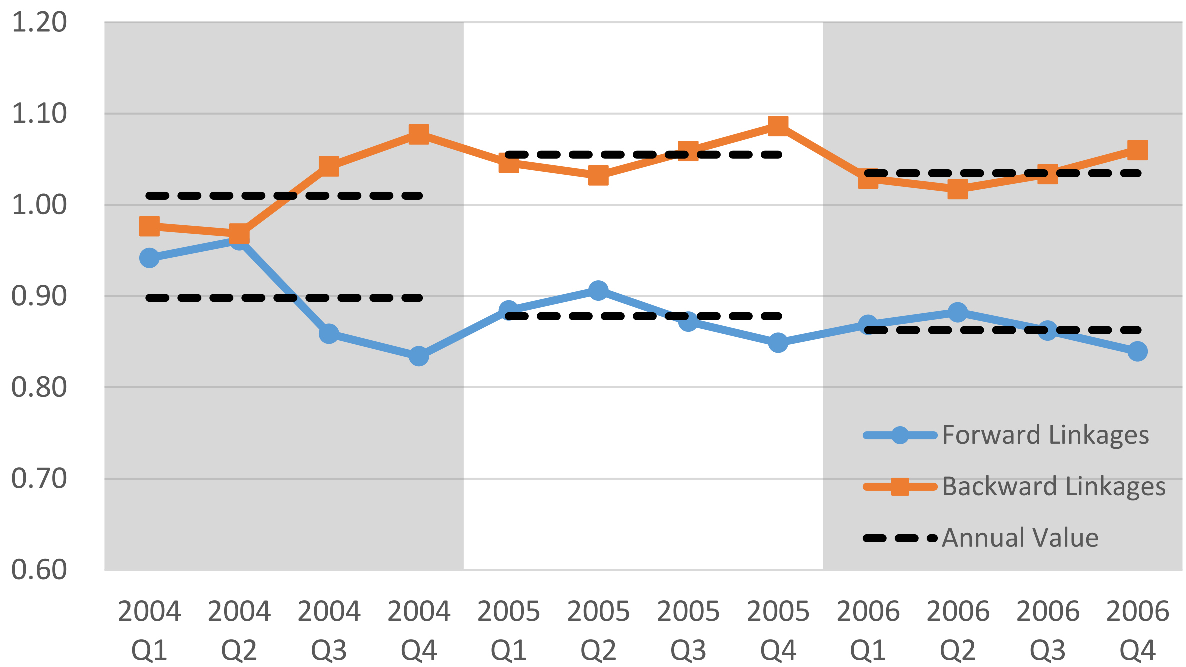


Figure 1.3. Comparison of quarterly linkages in relation to annual linkages, agriculture, 2004-2006

Notice, however, that the Agriculture sector's dynamics is unique in the landscape. In the first two quarters, forward linkages increase while backward linkages decrease, the opposite happening in the second half of the year. In the first semester, forward linkages with Manufacturing and Transportation increase the most due to food processing and export activities. Conversely, backward linkages with Manufacturing and the Financial Sector are the ones that increases the most in the second semester, consistent with the increase requirement of inputs and financing. The remaining sectors of the economy experience very small variations in the year. Overall, due to *intra-year* dynamics, disruptive events in a particular production chain can have more/less negative effects depending on its timing and duration, which may affect the optimal policy response devised. The use of annual tables abstracts from such dynamics, what can ultimately lead to incorrect assessments (see Chapter 4).

Figure 1.5 contrasts the use of the annual output multiplier instead of quarterly multipliers. Positive variations indicate overestimation and negative variations indicate underestimation. Agriculture, Mining, Financial Services and Government have the largest errors, the former in excess of 5%. Although for several industries errors for most quarters are below 1%, the total bias for a particular impact analysis can be low or high depending on the subset of sectors affected and the actual time period of the stimulus.

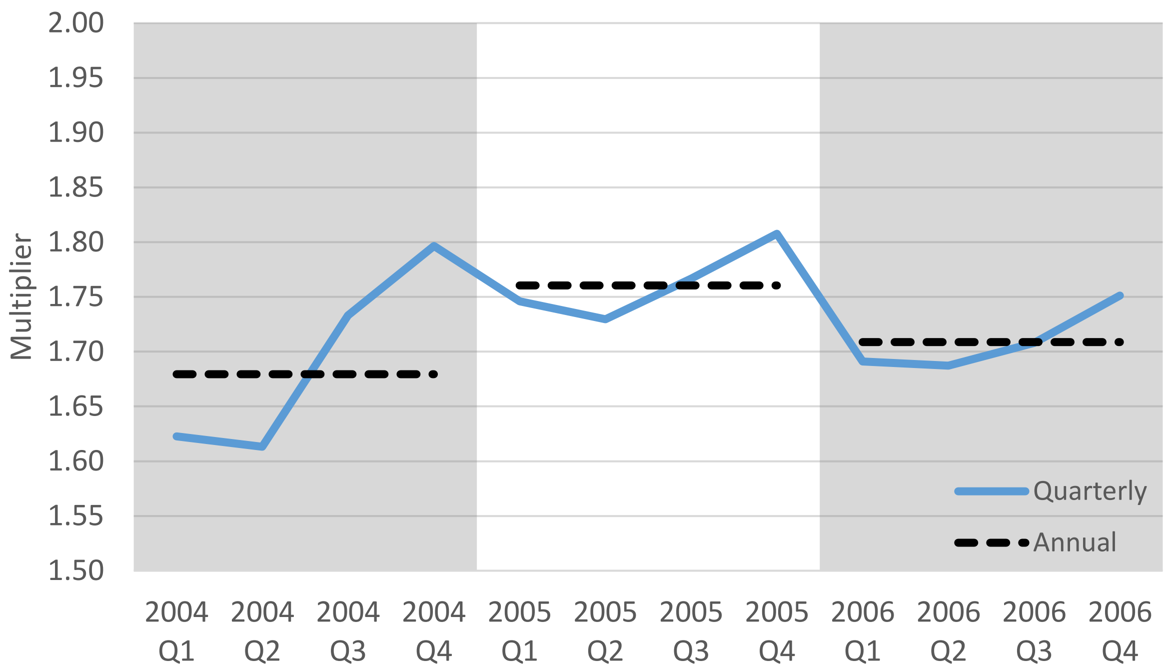


Figure 1.4. Comparison of output multipliers, Agriculture, 2004-2006

In sum, although most of the economy has a stable structure, some important sectors in the Brazilian economy as Agriculture and Manufacturing exhibit particular *intra-year* dynamics which may impose significant biases if the annual coefficients are used. Hence, *intra-year* tables should be preferred since they provide a more comprehensive picture of the economic dynamics.

Moreover, another advantage of a finer disaggregation of time is to smooth out technology transitions, revealing the dynamics of change and overall trends.

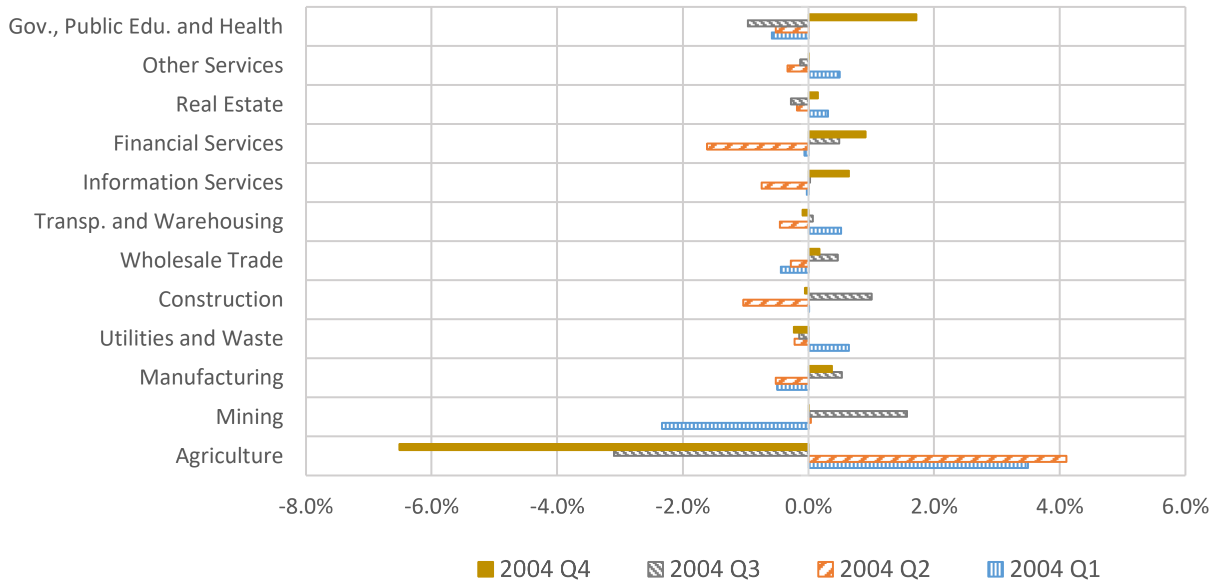


Figure 1.5. Estimation error due to annual vs. quarterly multipliers

1.5. Conclusions

Despite several methodological advances in terms of regional and industrial disaggregation, the IO literature regarding time dimension issues has focused on *inter-year* updating and dynamic models that still rely on annual tables as benchmarks. The structure portrayed in annual tables, however, ignores any nuances and seasonality of a particular sector *intra-year*, biasing the estimated results of transient phenomena such as unexpected disruptions. The disaggregation of the IO table temporally is, thus, essential to improve the accuracy of such models as well as to expose seasonal production chain patterns, explore structural dynamics within a year, determine optimal policy intervention timings and analyze environmental processes.

The T-EURO method proposed in this Chapter intends to fill this gap in the literature by disaggregating annual tables into *intra-year* matrices with distinct technical structure. Based on the EURO method, the T-EURO inherits the virtues of requiring only official macroeconomic data (*intra-year* GDP information that is readily available in most countries), adjusting the full IO system, avoiding arbitrary changes in flows and maintaining supply-demand consistency. In addition, the implemented modifications transform the updating method into a disaggregation method, guaranteeing the temporal consistency of estimates as well as its convergence. In terms of performance, the example for the Brazilian tables from 2002-2005 shows the T-EURO outperforming the RAS method, although a generalization of this result is not possible. However, given that detailed data to forecast interindustrial sales and purchases are relatively scarcer *intra-year,* the T-EURO has the advantage of relying only on official data, mitigating the issue of compounding errors from econometric estimates of the table's borders and the RAS rebalancing algorithm, as well as the issue of hysteresis from serial methods like RAS.

As an application example, the 2004-2006 annual Brazilian IO tables were disaggregated for each quarter and the resulting economic structure was analyzed. While sectors such as Manufacturing and Services tend to maintain a more stable linkage structure throughout the year, Agriculture is significantly affected by seasonality in production, altering its linkages and multipliers. As highlighted herein, the use of annual coefficients for this sector creates important biases in both directions in excess of 5%, since it cannot properly reflect the *intra-year* dynamics.

A few caveats of this method are its sign preserving property for particular components of the IO table (change in inventories and net taxes/subsidies), estimation of independent intratemporal tables, and inexistence of *intra-year* benchmark tables to contrast estimates. In further work, robustness checks and analysis using different IO datasets will be performed, as well as an evaluation of the accuracy of using *intra-year* tables as benchmarks for current dynamic models instead of annual ones.

Although methods focusing on the disaggregation of IO tables into its industry and regional dimensions have been largely explored, the temporal dimension has had limited attention. This Chapter aims to refocus on temporal issues by offering an initial method in the temporal disaggregation realm and highlighting its advantages, calling for a new wave of developments in this direction.

CHAPTER 2: THE SEASONAL STRUCTURE OF THE US ECONOMY: ESTIMATION OF INDUSTRIAL LINKAGES AT NATIONAL, STATE AND COUNTY LEVELS

2.1. Introduction

Seasonality is an inherent feature of economic systems, as supply and demand conditions fluctuate throughout the year driven by nature's cyclical patterns and societal rules (cultural, legal, institutional). These variations reflect the rearrangement of production systems to cope with scarce local resources and shifts in local demand by changing production lines, inventories, shipping modes and the spatial distribution of suppliers. Agriculture is a primal example of seasonal dynamics, particularly in the northern US states, where winter months prevents major commercial crops. For the Midwest, where corn and soybeans are the main crops, most of the agricultural activity is concentrated during growing season, usually from the second to early fourth quarter of the year (United States Department of Agriculture [USDA], 2010). The steel and iron scrap industry in the US is another seasonal industry that relies heavily on shipping availability for collection and distribution of products. During winter, frozen waterways in the Great Lakes force changes in freight mode to rail, affecting prices and supply. Moreover, demand drops in the end of the year, and surges in the first quarter (when steelmakers rebuild raw materials inventories) also induce high fluctuation in the industry (Albertson & Aylen, 1996).

These seasonal changes in input requirements alter the structure and connectivity of different production chains (both local and external) and consequently change the direct, indirect and induced impacts of these sectors on the local economy. For example, this implies that a flood event on a rural county can have significantly different effects for the community if it happens in the summer or in the winter. Hence, by ignoring this intra-year structural variation we might over or under estimate the impact of an event. Chapter 1 shows that annual multipliers can diverge by up to 6% when compared to quarterly multipliers estimated for the same period.

The major challenge in considering sub-year structural change is the limited availability of *intra-annual* multisectoral economic data, especially for finer geographical units such as states and counties. The source of much of these national data at annual level derive from the system of national accounts which is based on annual censuses and surveys of manufacturing, services and agriculture to estimate supply and demand flows among economic agents. This information is compiled in an input-output (IO) table that portrays the total annual transactions among industries and between industries and final demand. Chapter 1 tackles the temporal disaggregation issue at national level, by proposing a technique to estimate *intra-year* IO tables using only quarterly macroeconomic data (GDP by major component), which is readily available in most countries, and the annual table as a prior. Despite its low data requirements, this technique cannot be applied when data is even more limited, i.e., in finer scales such as states and counties. As the economic structure of lower geographical units can differ substantially from the national level, local communities still lack data to more accurately estimate the total impacts of local shocks.

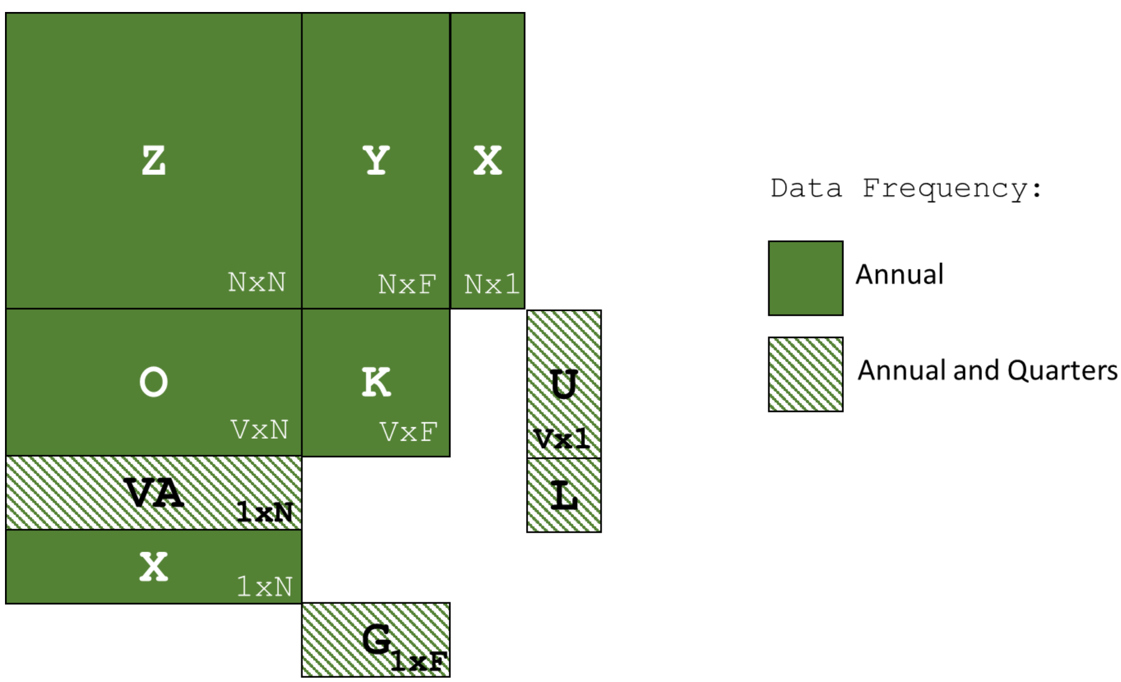
This Chapter introduces a solution based on information theory to estimate state and county level multisectoral data using only and all scarce information available. We propose a maximum cross-entropy program with multiple priors to recover quarterly IO tables from annual ones. A key feature of this approach is its flexibility in considering any additional information available for a particular region. We also provide a roadmap regarding data sources for the US that allows the estimation of these intra-year tables for any state and county between 2002-2016. To illustrate its practical application, we extract and analyze the quarterly tables for the US, State of Illinois, Cook County (IL) and Iroquois County (IL) for 2015.

The next Section discusses the data and methodologies used to estimate quarterly multisectoral data for the US at national, state and county levels. Section 2.3 presents and analyzes the intra-year IO tables for Illinois, and conclusions follow in Section 2.4.

2.2. Methods and Data

2.2.1. National Quarterly Tables

Although multisectoral *intra-year* data are notably scarce, at least at national level most countries have official quarterly GDP estimates by component. These data are the minimum requirements of the Temporal EURO (T-EURO) method proposed in Chapter 1 for quarterly disaggregation of symmetric input-output tables (Figure 2.1). The T-EURO is a modification of the EURO method (Beutel, 2002; Eurostat, 2008) that estimates intra-year IO tables (IOT) based on an annual IOT and quarterly GDP data by major component. Interested readers can see the full procedure in Chapter 1. In a nutshell, the GDP information is converted into quarterly shares of value added by industry, total value added, total imports, total exports and total final demand. These shares are then used to modify the structure of the annual IOT by rows and columns, similarly to the first iteration in a RAS adjustment, and these structures are averaged in each quarter. Because the resulting tables are internally unbalanced, we reestimate the total output by using this averaged input structure in a Leontief model, and then apply a quantity model to rebalance the flows. At this stage, each quarter is balanced but does not add up to the annual observed flows. Hence, according to the estimated quarterly values, the annual flows are redistributed in each quarter, guaranteeing their temporal consistency. The quarterly tables are again internally unbalanced, so we follow the previous steps to adjust the flows in each table. When both internal and temporal consistency are achieved, we check the estimated GDP shares by quarter with the true ones and apply marginal corrections in the next iteration.



Notes: **Z**: Interindustrial Flows; **Y**: Final Demand and Exports; **O**: Primary Inputs and Industrial Imports (except labor income); **VA**: Labor Income; **K**: Final Demand Imports; **X**: Total Industrial Output; **G**: Total Final Demand and Exports; **U**: Total Primary Inputs and Imports; **L**: Total Labor Income. Matrix dimensions indicated in the corners.

Figure 2.1: Data availability at national level, US

The main advantage of the T-EURO method is its low quarterly data requirements (only GDP by major component), which are readily available at national level in most countries. In the case of the US, however, the Bureau of Economic Analysis (BEA) currently[22] does not provide *not seasonally adjusted* estimates for quarterly GDP, except for Government expenditures (NIPA Tables 3.22 and 3.23 (Bureau of Economic Analysis [BEA], 2018c). As expected, for intra-year disaggregation purposes, seasonally adjusted series cannot be used. Hence, additional datasets are necessary to estimate the major components of GDP at higher frequency. We base most of our estimates on the main data sources outlined in BEA's NIPA Handbook (BEA, 2017) for the construction of quarterly estimates, relying solely on publicly available information.

Quarterly labor income by industry was based on the BLS' Quarterly Census of Employment and Wages (QCEW) (BLS, 2018b). The QCEW is a firm-level dataset based on information from unemployment insurance administrative files from each US state. Therefore, the scope of the data depends on each state's unemployment insurance system reporting requirements. Overall, the covered employment information represents 95% of all private-sector civilian jobs in the US. The main categories that are underrepresented in this dataset are: agriculture (it includes around 53% of employees in these activities) and parts of the public sector like federal, military and postal workers (BLS, 2018a).

Private companies' total wages were allocated to their respective sectors, while government-owned companies were aggregated in either the Federal, or State and Local Government Enterprises sector. These series were compiled for the 71-sector disaggregation scheme in the annual IOT for 1996-2016. We calculated the Pearson correlation between the annual series from BEA and BLS for both NAICS 2 and 3 digits aggregation, and the results are reported in Figures C.1 and C.2 in the Appendix, respectively. The BLS data track most sectors quite accurately, although a few sectors had to be aggregated due to low correlation resulting in a 60-sector disaggregation. The sum of wages for all industries in a given quarter is also used as proxy for total personal consumption expenditures.

[22] The BEA will release *not-seasonally* adjusted series starting in mid-2018 as part of a comprehensive update of the US National Income and Product Accounts. This is in part a response to a known issue of residual seasonality in the seasonally adjusted GDP series made available by the BEA (Rudebusch, Wilson, & Mahedy, 2015; Stark, 2015) that seems to persist even after changes in the methodology used (Lunsford, 2017).

Following BEA (2017), we use the US International Transactions Accounts (ITA) dataset as the main source for our estimates of total goods and services' imports and exports (BEA, 2018b). Some adjustments[23] are required to bridge ITA's and NIPA's trade values as described in the NIPA Handbook (BEA, 2017). Due to lack of information to perform an equivalent adjustment intra-year, our estimates are based on ITA's quarterly values available in its Table 1.1 (BEA, 2018b). The ITA annual estimates correlate well with NIPA's series as shown in Figure 2.2.

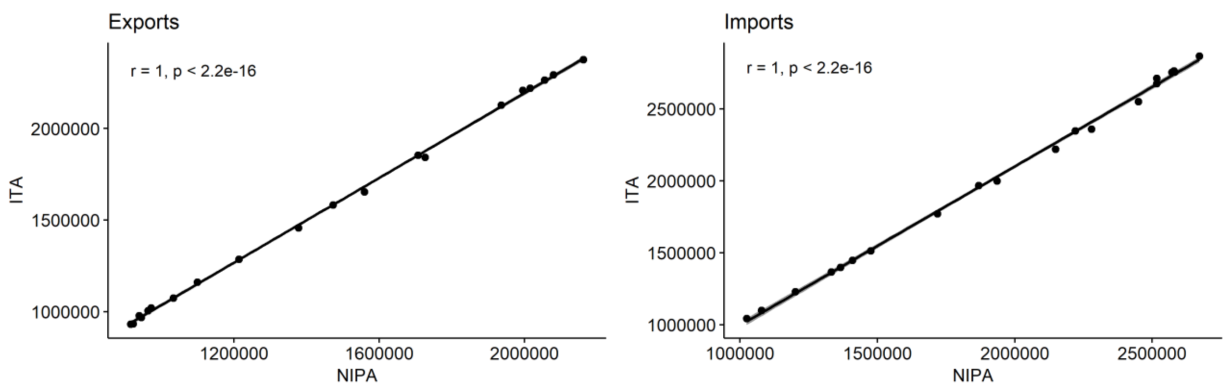


Figure 2.2: Correlation between import and export series NIPA/ITA

Quarterly estimates of total change in inventories are based on Census Bureau's monthly Manufacturing & Trade Inventories & Sales Report, using the series of inventories for total businesses (Census Bureau, 2018c). The report combines data from the Manufacturers' Shipments, Inventories, and Orders Survey as well as the Monthly Retail and Wholesale Trade Surveys, covering only nonfarm industries. The BEA uses annual data from the USDA on crop output, cash receipts and livestock to estimate agricultural inventories. Given the unavailability of quarterly data from USDA, we only use the Census data, which correlates well with the annual series (Figure 2.3).

[23] The values reported in the ITA's current account need to be adjusted to include only gold used for domestic industrial production, exclude trade with US territories and commonwealths to align with NIPA's geographic coverage, include imputed values for financial services furnished without payment, and other statistical adjustments. NIPA's Table 4.3B shows the adjustment process for the annual data.

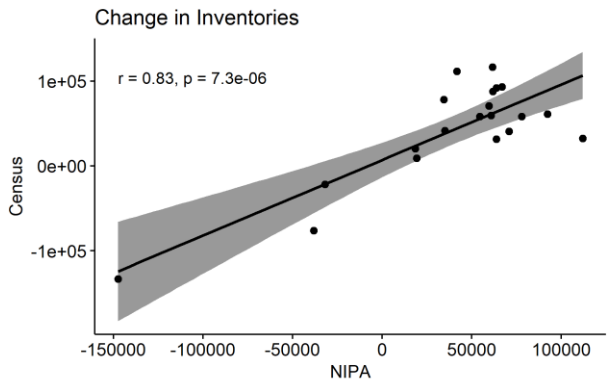


Figure 2.3: Correlation between total change in inventories series NIPA/Census

Residential and nonresidential investment in structures are based on Census Bureau's Value of Construction Put in Place Survey (Census Bureau, 2018a). The monthly values are aggregated to quarterly level for total residential and total nonresidential. Nonresidential investment in equipment and intellectual property products are based on the same total wages series as the one used for total personal consumption expenditures. Finally, government expenditure is the only GDP component currently available that is not-seasonally adjusted. The quarterly values are taken from NIPA's Tables 3.22 and 3.23 (BEA, 2018c) and aggregated into government expenditures and gross investments. Table 2.1 summarizes the data sources used for each GDP component.

For all components (except government expenditures), quarterly shares were calculated and the annual GDP values were distributed accordingly. This procedure guarantees that each component adds up to its annual value, but does not impose consistency within each quarter, i.e., the macroeconomic balance between income and expenditures might not hold. Denoting g_{ct} the GDP component $c = \{v_1, \dots, v_N, v_o, m, y_1, \dots, y_5, g_1, \dots, g_4, e\}$ (according to Table 2.1) at time period t , the macroeconomic consistency requires that:

$$\sum_{i=1}^{N} g_{v_i t} + g_{v_o t} = \sum_{i=1}^{5} g_{y_i t} + \sum_{i=1}^{4} g_{g_i t} + (g_{et} - g_{mt}) \quad \forall t \tag{2.1}$$

To establish this identity, we rebalance the estimated quarterly GDP components using the Generalized RAS method (Junius & Oosterhaven, 2003; Lenzen, Wood, & Gallego, 2007;

Termushoev, Miller, & Bouwmeester 2013). GRAS minimizes the distance between our current estimates of the GDP components (q_{ct}) and the new estimates (g_{ct}), subject to Equation 2.1 (in which government expenditures, $c = g_1, \dots, g_4$, are the exogenous data) and the temporal adding up constraint for each component. The nonlinear programming is given by:

$$\min_{\mathbf{G}} I(\mathbf{G} \,||\, \mathbf{Q}) = \sum_t \sum_c |q_{ct}| z_{ct} \ln\left(\frac{z_{ct}}{e}\right) \tag{2.2}$$

subject to

$$\sum_{i=1}^{N} g_{v_i t} + g_{tv_o} - \sum_{i=1}^{5} g_{y_i t} - (g_{et} - g_{mt}) = \sum_{i=1}^{4} g_{g_i t} \quad \forall t \tag{2.3}$$

$$\sum_{t=1}^{4} g_{ct} = g_c^{\mathrm{YEAR}} \quad \forall c \tag{2.4}$$

where $z_{ct} = g_{ct}/q_{ct}$ (such that $z_{ct} = 1$ if $q_{ct} = 0$) and e is the base of natural logarithms.

Once the quarterly GDP components are balanced, the T-EURO method can be applied to each year in order to estimate its intra-year tables. The final quarterly tables have the disaggregation presented in Table C.1 and span the period 2002:Q1-2016:Q4.

2.2.2. State and County Quarterly Tables

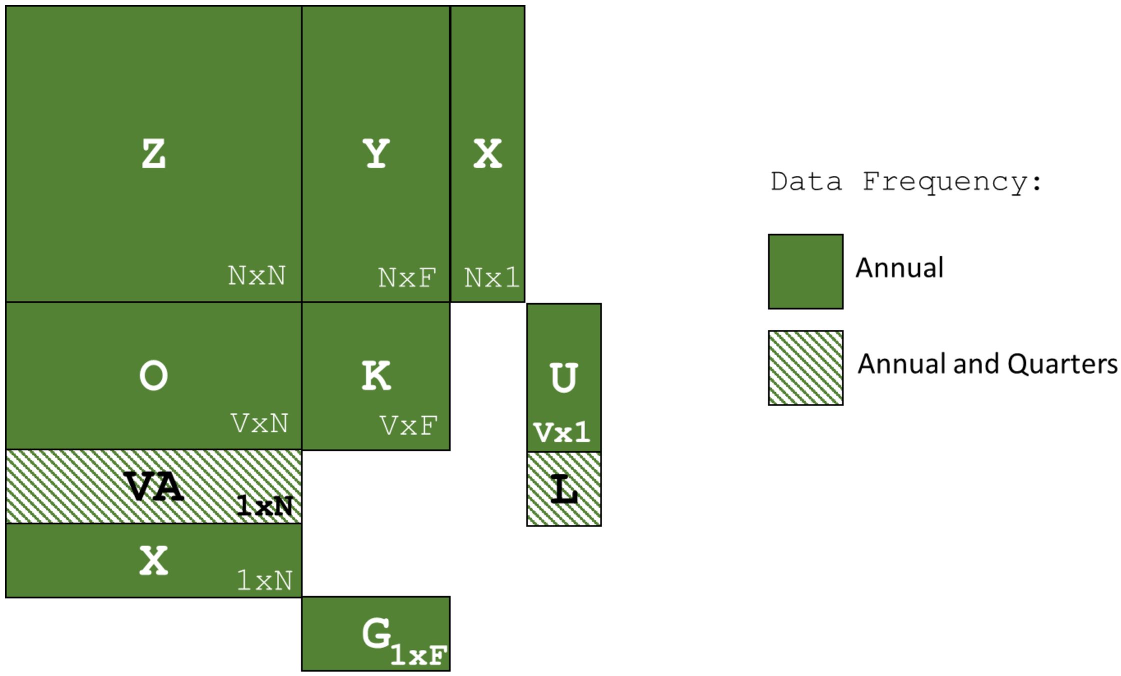
At finer geographical scales, as expected, *intra-year* data become scarcer. Information on final demand expenditure and trade are not widely available, and we could only identify labor income proxies that are publicly available for any state or county (Figure 2.4).

For states, quarterly labor income by industry can still be based on the BLS' QCEW (BLS, 2018b), although some industrial aggregation might be required to avoid issues of censored information. The QCEW, however, does not report quarterly wages at scales finer than state level and thus cannot be used to proxy labor income for counties. Instead, we use the Quarterly Workforce Indicators (QWI) dataset from Census, as it provides estimates of employment and earnings down to county and metro-areas (Census Bureau, 2018d).

Table 2.1: Data sources for the estimation of quarterly GDP components

			Source	Dataset	Variable	Freq.	Start Year
Value Added							
V001	$v_1 \ldots v_N$	**Compensation of employees**	BLS	QCEW	Total Wages	Q	1975
V000	v_o	**Total primary inputs (except V001)**	BLS	QCEW	Total Wages	Q	1975
Trade							
IMP	m	**Total imports of goods and services**	BEA	ITA - Table 1.1	Imports of goods and services	Q	1960
F040	e	**Total exports of goods and services**	BEA	ITA - Table 1.1	Exports of goods and services	Q	1960
Final Demand							
F010	y_1	**Personal consumption expenditures**	BLS	QCEW	Total Wages	Q	1975
F02S	y_2	**Nonresidential fixed inv. in structures**	Census	Value of Construction Put in Place Survey	Total Nonresidential	M	2002*
F02E **F02N**	y_3	**Nonresidential fixed inv. in equipment** **Nonresidential fixed inv. in IP products**	BLS	QCEW	Total Wages	Q	1975
F02R	y_4	**Residential private fixed investment**	Census	Value of Construction Put in Place Survey	Total Residential	M	2002*
F030	y_5	**Change in private inventories**	Census	Manufacturing & Trade Inventories & Sales	Inventories - Total Businesses	M	1992
F06C **F07C**	g_1	**Federal, defense: Consumption** **Federal, nondefense: Consumption**	BEA	NIPA - Table 3.22	Consumption expenditures	Q	1947
F06S **F06E** **F06N** **F07S** **F07E** **F07N**	g_2	**Federal, defense: Gross inv. in structures** **Federal, defense: Gross inv. in equipment** **Federal, defense: Gross inv. in IP products** **Federal, nondefense: Gross inv. in structures** **Federal, nondefense: Gross inv. in equipment** **Federal, nondefense: Gross inv.in IP products**	BEA	NIPA - Table 3.22	Gross government investment	Q	1947
F10C	g_3	**State and local: Consumption**	BEA	NIPA - Table 3.23	Consumption expenditures	Q	1947
F10S **F10E** **F10N**	g_4	**State and local: Gross inv. in structures** **State and local: Gross inv. in equipment** **State and local: Gross inv. in IP products**	BEA	NIPA - Table 3.23	Gross government investment	Q	1947

Notes: Q = Quarterly, M = Monthly, *Total construction (not disaggregated) is available from 1993.



Notes: **Z**: Interindustrial Flows; **Y**: Final Demand and Exports; **O**: Primary Inputs and Industrial Imports (except labor income); **VA**: Labor Income; **K**: Final Demand Imports; **X**: Total Industrial Output; **G**: Total Final Demand and Exports; **U**: Total Primary Inputs and Imports; **L**: Total Labor Income. Matrix dimensions indicated in the corners.

Figure 2.4: Data availability at state and county levels, US

The QWI is based on the Longitudinal Employer-Household Dynamics (LEHD) that integrates employer-employee microdata. The LEHD is a longitudinal dataset built on federal datasets (Social Security, IRS), administrative information from state agencies, the QCEW and other surveys, and covers 95% of US private sector jobs (Abowd *et al*., 2005). Unlike the QCEW, the QWI is based on job-level data by linking employees and employers in its framework. Such bridge is created by combining states' quarterly reports of unemployment insurance administrative files and QCEW records. As expected, because the QCEW is one of the primary sources of information for the QWI, they are comparable datasets.

The wages accounted for in the QWI are the ones reported as an unemployment insurance covered earning during a given quarter with similar scope as the QCEW. Notice that since the QCEW is collected at the state level, the QWI estimates the spatial distribution of jobs throughout the state based on commercial and residential addresses from QCEW records and other Census datasets (see Section 3.3 of Abowd *et al*. (2005)). This weighting was made consistent with the state-level QCEW statistics, so that the beginning of the quarter employment from QWI matches the state-wide employment on the first month of the quarter from the BLS.[24]

In this context, even the low data requirements of the T-EURO method are not met, so a different solution needs to be used. To recap, our goal is to recover $N^2 + V * N + N * F + V * F$ unknown elements for each quarter based on $N + 1$ exogenous variables. If we consider this underidentified inverse problem from the lenses of information theory, we can use the maximum entropy principle and use only and all information available to estimate the different IO tables.

Consider a random variable z with n possible realizations $(z_1, \dots, z_n)$ with unknown probabilities $(p_1, \dots, p_n)$ of occurrence such that $\sum_{i=1}^{n} p_i = 1$. Given no additional information, the distribution that best reflects the uncertainty about z (i.e., the least informative distribution) is uniform, as it assigns equal probability for any realization. From an Information Theory perspective, we can measure this uncertainty via Shannon's (1948) entropy measure:

$$H(\mathbf{P}) = -K \sum_{i=1}^{n} p_i \ln p_i \tag{2.5}$$

where K is a positive constant and $0 \ln(0) = 0$. Notice that the function H is bounded between$[0, K \ln n]$, the upper limited reached when $p_1, \dots, p_n$ follows a uniform distribution. The larger the entropy measure H, the more uncertain we are about the distribution of p.

Now consider that we know the *a priori* distribution of p from non-sample or pre-sample information and denoted it by $q_1, \dots, q_n$. If we want to departure from this prior knowledge to measure the uncertainty about a chosen distribution p, following Kullback and Leibler (1951), we can measure the convergence between the two distributions as:

$$-D(\mathbf{P}||\mathbf{Q}) = -\sum_{i=1}^{n} p_i \ln \frac{p_i}{q_i} = -\sum_{i=1}^{n} p_i \ln p_i + \sum_{i=1}^{n} q_i \ln q_i \tag{2.6}$$

[24] The QWI uses several processes to comply with confidentiality protection, especially at finer geographical scales, by introducing noise to the measures, aggregating or suppressing data. Payroll indicators are not suppressed, but are influenced by some noise that does not affect their time-series or cross-section analytic validity (Abowd *et al*., 2005). In instances where the data distortion is substantial (due to small number of firms/employers, etc.) the observation is flagged accordingly.

where $D(\mathbf{P}||\mathbf{Q})$ measures the distance between $\mathbf{p}$ and $\mathbf{q}$, and is known as the Kullback and Leibler (K-L) cross-entropy measure. When $\mathbf{p}$ and $\mathbf{q}$ are identical, $D(\mathbf{P}||\mathbf{Q})$ reaches its minimum. Notice that Shannon's entropy measure (Equation 2.5) is a special case of K-L when the prior distribution $\mathbf{q}$ is uniform.

Now, consider that we have some additional information about the random variable (say, a moment condition), and we want to use this limited knowledge to *infer* its posterior distribution. Following Jaynes (1957), we can use the maximum entropy principle and set up a programming problem that maximizes the entropy of the posterior distribution subject to the additivity constraint ($\sum_{i=1}^{n} p_i = 1$) and any additional data constraint available. Equivalently, if we have a prior distribution, we can use the K-L measure and solve for the posterior distribution that minimizes the divergence ($D(\mathbf{P}||\mathbf{Q})$) with the prior and is consistent with the information provided.[25]

The application of the entropy principle in IO analysis was introduced by Theil in the 1960s. Tilanus and Theil (1965) used the K-L measure to determine the information inaccuracy of forecasts of input coefficients in different industries. Theil (1967) analyzes the information loss from aggregating sectors in the IO table by studying how a measure of matrix information content varies across different scales. These papers were followed by the works of Wilson (1970a, 1970b) and Batten (1981) looking at the estimation of interregional IO models through maximum entropy. Golan, Judge and Robinson (1994) propose an alternative to the RAS rebalancing algorithm using a cross entropy formulation. The authors consider the column standardized coefficients of the table as probabilities and use the same row and column constraints as the RAS to update the base matrix (used as prior).[26] This work was later extended by Robinson, Cattaneo and El-Said (2001) in the context of social accounting matrices (SAM) incorporating additional constraints to capture errors in variables. Fernández-Vázquez (2015) uses generalized maximum entropy to resolve the issue of estimating the multipliers of non-linear IO models, given the small amount of data points available from harmonized time-series

[25] For example, considering the moment condition $\sum p_i z_i = y$, a maximum cross-entropy program would be:

$$\min_{\mathbf{P}} D(\mathbf{P}||\mathbf{Q}) = \sum_{i=1}^{n} p_i \ln \frac{p_i}{q_i} \qquad s.t. \qquad \sum_{i=1}^{n} p_i z_i = y \;\; and \; \sum_{i=1}^{n} p_i = 1$$

[26] Notice that both the GRAS formulation presented in Equations 2.2-2.4 and the RAS formulation presented in Equations 1.1-1.4, although grounded on information theory are not equivalent to the Kullback-Leibler cross-entropy criterion unless all variables are non-negative (Lemelin, 2009).

of IO tables. More recently, Fernández-Vázquez (2010) and Fernández-Vázquez, Hewings and Ramos (2015) have proposed the use of multiple priors in the adjustment of IO tables based on early works from Golan (2001) and Bernadini (2008). This data-weighted priors (DWP) approach allows us to use a mixture of *a priori* information that are endogenously weighted by the maximum cross-entropy program.

We depart from this DWP framework to set up our cross-entropy (CE) specification: each element of the IO matrix is assumed to be a discrete random variable with support vector $\mathbf{b}' = (b_1, \dots, b_M)$ and associated probabilities $\mathbf{p}' = (p_1, \dots, p_M)$. The prior distribution is denoted $\mathbf{q}' = (q_1, \dots, q_M)$ and data weights per industry in each quarter by γ_{jt} with $\mathbf{b}^{\boldsymbol{\gamma}\prime} = \left(b_1^{\gamma}, \dots, b_H^{\gamma}\right)$ and $\mathbf{p}^{\boldsymbol{\gamma}\prime} = \left(p_1^{\gamma}, \dots, p_H^{\gamma}\right)$, so that $\gamma_{jt} = \sum_h b_h^{\gamma} p_{hjt}^{\gamma}$.

Our target is to estimate the dark shaded matrices in Figure 2.4 by using the exogenous quarterly labor income information by industry (va_j) and the annual totals by element. We also have assumed two priors: the state's (county's) annual table and the national (state) quarterly tables. Since we do not know the total output nor the total final demand per quarter, we column standardize the matrices annually, according to the total output per industry j (x_j^{YEAR}) or total final demand per component f (g_f^{YEAR}). Hence, each element is now bounded [0,1] and we use the same support vector for all elements $\mathbf{b}' = (0, 0.5, 1)$. The notation used is shown in Table 2.2.

Table 2.2: Notation used in the maximum entropy program

Matrix	Standardized Element	Associated Probabilities	Estimated Element
Z	$a_{ijt} = z_{ijt}/x_j^{\text{YEAR}}$	p_{mijt}^{A}	$\tilde{a}_{ijt} = \sum_M b_m \tilde{p}_{mijt}^{\text{A}}$
Y	$c_{ift} = y_{ift}/g_f^{\text{YEAR}}$	p_{mift}^{C}	$\tilde{c}_{ift} = \sum_M b_m \tilde{p}_{mift}^{\text{C}}$
O	$w_{vjt} = o_{vjt}/x_j^{\text{YEAR}}$	p_{mvjt}^{W}	$\tilde{w}_{vjt} = \sum_M b_m \tilde{p}_{mvjt}^{\text{W}}$
K	$d_{vft} = k_{vft}/g_f^{\text{YEAR}}$	p_{mvft}^{D}	$\tilde{d}_{vft} = \sum_M b_m \tilde{p}_{mvft}^{\text{D}}$

The basic DWP cross-entropy program is specified in Equations 2.7-2.17:

$$
\begin{aligned}
\min_{\mathbf{P}^{\mathrm{A}},\mathbf{P}^{\mathrm{P}},\mathbf{P}^{\mathrm{C}},\mathbf{P}^{\mathrm{D}},\mathbf{P}^{\gamma}} & D\left(\mathbf{P}^{\mathrm{A}},\mathbf{P}^{\mathrm{P}},\mathbf{P}^{\mathrm{C}},\mathbf{P}^{\mathrm{D}},\mathbf{P}^{\gamma} \,||\, \mathbf{Q}^{\mathrm{AA}},\mathbf{Q}^{\mathrm{AQ}},\mathbf{Q}^{\mathrm{P}},\mathbf{Q}^{\mathrm{C}},\mathbf{Q}^{\mathrm{D}},\mathbf{Q}^{\gamma}\right) \\
&= \sum_{j=1}^{N}\sum_{t=1}^{T}\gamma_{jt}\sum_{m=1}^{M}\sum_{i=1}^{N} p_{mijt}^{\mathrm{A}} \ln\left(\frac{p_{mijt}^{\mathrm{A}}}{q_{mij}^{\mathrm{AA}}}\right) \\
&+ \sum_{j=1}^{N}\sum_{t=1}^{T}\left(1-\gamma_{jt}\right)\sum_{m=1}^{M}\sum_{i=1}^{N} p_{ijtm}^{\mathrm{A}} \ln\left(\frac{p_{mijt}^{\mathrm{A}}}{q_{mijt}^{\mathrm{AQ}}}\right) \\
&+ \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{f=1}^{F}\sum_{t=1}^{T} p_{mift}^{\mathrm{C}} \ln\left(\frac{p_{mift}^{\mathrm{C}}}{q_{mift}^{\mathrm{C}}}\right) + \sum_{m=1}^{M}\sum_{v=1}^{V}\sum_{j=1}^{N}\sum_{t=1}^{T} p_{mvjt}^{\mathrm{W}} \ln\left(\frac{p_{mvjt}^{\mathrm{W}}}{q_{mvjt}^{\mathrm{W}}}\right) \\
&+ \sum_{m=1}^{M}\sum_{v=1}^{V}\sum_{f=1}^{F}\sum_{t=1}^{T} p_{mvft}^{\mathrm{D}} \ln\left(\frac{p_{mvft}^{\mathrm{D}}}{q_{mvft}^{\mathrm{D}}}\right) + \sum_{h=1}^{H}\sum_{j=1}^{N}\sum_{t=1}^{T} p_{hjt}^{\gamma} \ln\left(\frac{p_{hjt}^{\gamma}}{0.5}\right)
\end{aligned}
\tag{2.7}
$$

subject to:

$$\sum_{t=1}^{T}\left(\sum_{m=1}^{M} b_m p_{mijt}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} = z_{ij}^{\mathrm{YEAR}} \quad \forall i,j \tag{2.8}$$

$$\sum_{t=1}^{T}\left(\sum_{m=1}^{M} b_m p_{mift}^{\mathrm{C}}\right) g_f^{\mathrm{YEAR}} = y_{if}^{\mathrm{YEAR}} \quad \forall i,f \tag{2.9}$$

$$\sum_{t=1}^{T}\left(\sum_{m=1}^{M} b_m p_{mvjt}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} = o_{vj}^{\mathrm{YEAR}} \quad \forall v,j \tag{2.10}$$

$$\sum_{t=1}^{T}\left(\sum_{m=1}^{M} b_m p_{mvft}^{\mathrm{D}}\right) g_f^{\mathrm{YEAR}} = k_{vf}^{\mathrm{YEAR}} \quad \forall v,f \tag{2.11}$$

$$
\begin{aligned}
&\sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijt}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjt}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jt} \\
&\quad = \sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mjit}^{\mathrm{A}}\right) x_i^{\mathrm{YEAR}} + \sum_{f=1}^{F}\left(\sum_{m=1}^{M} b_m p_{mjft}^{\mathrm{C}}\right) g_f^{\mathrm{YEAR}} \quad \forall j,t
\end{aligned}
\tag{2.12}
$$

$$\sum_{m=1}^{M} p_{mijt}^{\mathrm{A}} = 1 \quad \forall i,j,t \tag{2.13}$$

$$\sum_{m=1}^{M} p_{mift}^{\mathrm{C}} = 1 \quad \forall i, f, t \tag{2.14}$$

$$\sum_{m=1}^{M} p_{mvjt}^{\mathrm{W}} = 1 \quad \forall v, j, t \tag{2.15}$$

$$\sum_{m=1}^{M} p_{mvft}^{\mathrm{D}} = 1 \quad \forall v, f, t \tag{2.16}$$

$$\sum_{h=1}^{H} p_{hjt}^{\gamma} = 1 \quad \forall j, t \tag{2.17}$$

The minimand (Equation 2.7) is the K-L cross-entropy measure and is divided into five terms. The first term measures the divergence between the posterior probabilities for matrix **Z** and the annual prior (q_{mij}^{AA}), each column in each quarter weighted by γ_{jt}. The second term is the divergence with respect to the quarterly prior (q_{mijt}^{AQ}), each column in each quarter weighted by $1 - \gamma_{jt}$ (notice that the weights ($\gamma_{jt} = \sum_{h=1}^{H} b_h^{\gamma} p_{hjt}^{\gamma}$) are endogenously estimated). The next three terms quantify the divergence of the posterior probabilities for matrices **Y**, **O** and **K** with their respective annual priors. The last term quantifies the divergence for the weights from the uniform distribution. We chose this uninformative prior as we do not have any preference among the two matrices, similarly to Fernández-Vázquez *et al*. (2015).

Equations 2.8-2.11 are the temporal consistency constraints, and they assure that the sum of each element throughout the quarters adds up to its annual value. Equation 2.12 is an internal consistency constraint and guarantees the balance between total sales and total purchases by industry. Finally, Equations 2.13-2.17 are the probability consistency constraints and bound the sum of probabilities to 1.

This nonlinear program estimates the optimal probabilities that minimize the dissimilarity with the weighted prior distributions and are consistent with the limited information in the data. We can then recover the coefficients following the last column of Table 2.2. The estimated

Lagrange multipliers indicate the impact of each constraint to the solution, and the data weights reflect the preferred prior for each industry in each quarter.[27]

Following Golan *et al.* (1994), we can also obtain a normalized measure of uncertainty associated with each estimated matrix value. For instance, taking $\tilde{a}_{ijt}$, we have:

$$S(\tilde{a}_{ijt}) = \left(-\sum\nolimits_{M} \tilde{p}^{\mathrm{A}}_{mijt} \ln \tilde{p}^{\mathrm{A}}_{mijt}\right) / \ln M \tag{2.18}$$

$S(\tilde{a}_{ijt})$ is the Shannon's entropy measure normalized by the size of the support vector, so that it reflects the randomness (uncertainty) of the probability distribution attached to a given matrix element (in this case $\tilde{a}_{ijt}$). Moreover, we can also calculate the variance of an estimated element by (Golan *et al.*, 1994):

$$\sigma^2(\tilde{a}_{ijt}) = \sum_{m=1}^{M} (b_m)^2 p^{\mathrm{A}}_{mijt} - \left(\sum_{m=1}^{M} b_m p^{\mathrm{A}}_{mijt}\right)^2 \tag{2.19}$$

The advantage of the maximum entropy framework is its flexibility in including additional exogenous constraints if the researcher has more information from a particular region. In our case, we proxy the total household expenditure with the total labor income from either QCWE or QWI. Denoting the rescaled total expenditure for each quarter as u_t, we have:

$$\left(\sum_{m=1}^{M} b_m p^{\mathrm{C}}_{mi\mathrm{H}t}\right) g^{YEAR}_{\mathrm{H}} + \left(\sum_{m=1}^{M} b_m p^{\mathrm{D}}_{mv\mathrm{H}t}\right) g^{\mathrm{YEAR}}_{\mathrm{H}} = u_t \quad \forall t \tag{2.20}$$

Also, for some regions in which there is information on the agricultural growing season, a constraint about the trend in this sector's output can be added. In the case of Illinois, for example, corn and soybeans represented more than 93% of total harvested acres in 2009 (USDA, 2010). Given their similar growing seasons (Figure 2.5), we can add three constraints on total output:

---

[27] Notice that the objective function and constraints are continuously differentiable and convex for $\forall p_i > 0$, which satisfy the sufficient conditions for a global minimum (Golan, Judge, & Miller, 1996).

$$\sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ1}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ1}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ1} \leq \sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ2}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ2}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ2} \tag{2.21}$$

$$\sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ2}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ2}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ2} \leq \sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ3}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ3}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ3} \tag{2.22}$$

$$\sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ3}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ3}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ3} \leq \sum_{i=1}^{N}\left(\sum_{m=1}^{M} b_m p_{mijQ4}^{\mathrm{A}}\right) x_j^{\mathrm{YEAR}} + \sum_{v=1}^{V}\left(\sum_{m=1}^{M} b_m p_{mvjQ4}^{\mathrm{W}}\right) x_j^{\mathrm{YEAR}} + va_{jQ4} \tag{2.23}$$

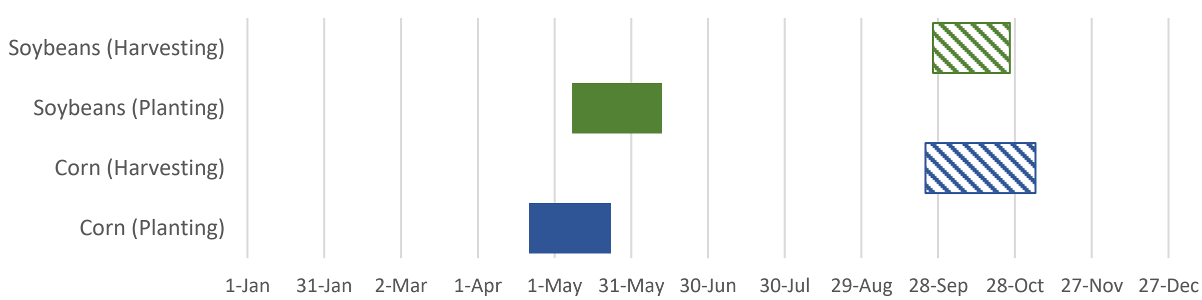


Figure 2.5: Most active periods for planting and harvesting, Illinois 2010 (USDA, 2010)

Finally, at the county level we have the possibility of using three different priors for the interindustrial transaction matrix: the county's annual table ($\mathbf{Q}^{\mathrm{AA}}$), the state's quarterly tables ($\mathbf{Q}^{\mathrm{AQs}}$) or the national quarterly tables ($\mathbf{Q}^{\mathrm{AQn}}$). Therefore, we do a straightforward modification of the K-L cross-entropy measure in Equation 2.7 to consider more than two priors:

$$\min_{\mathbf{P}^{\mathrm{A}},\mathbf{P}^{\mathrm{P}},\mathbf{P}^{\mathrm{C}},\mathbf{P}^{\mathrm{D}},\mathbf{P}^{\gamma}} D(\mathbf{P}^{\mathrm{A}},\mathbf{P}^{\mathrm{P}},\mathbf{P}^{\mathrm{C}},\mathbf{P}^{\mathrm{D}},\mathbf{P}^{\gamma}\ ||\ \mathbf{Q}^{\mathrm{AA}},\mathbf{Q}^{\mathrm{AQs}},\mathbf{Q}^{\mathrm{AQn}},\mathbf{Q}^{\mathrm{P}},\mathbf{Q}^{\mathrm{C}},\mathbf{Q}^{\mathrm{D}},\mathbf{Q}^{\gamma})$$

$$\begin{aligned}
&= \sum_{j=1}^{N}\sum_{t=1}^{T}\gamma_{1jt}\sum_{m=1}^{M}\sum_{i=1}^{N} p_{mijt}^{\mathrm{A}} \ln\left(\frac{p_{mijt}^{\mathrm{A}}}{q_{mij}^{\mathrm{AA}}}\right) \\
&+ \sum_{j=1}^{N}\sum_{t=1}^{T}\gamma_{2jt}\sum_{m=1}^{M}\sum_{i=1}^{N} p_{ijtm}^{\mathrm{A}} \ln\left(\frac{p_{mijt}^{\mathrm{A}}}{q_{mijt}^{\mathrm{AQs}}}\right) \\
&+ \sum_{j=1}^{N}\sum_{t=1}^{T}\gamma_{3jt}\sum_{m=1}^{M}\sum_{i=1}^{N} p_{ijtm}^{\mathrm{A}} \ln\left(\frac{p_{mijt}^{\mathrm{A}}}{q_{mijt}^{\mathrm{AQn}}}\right) \\
&+ \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{f=1}^{F}\sum_{t=1}^{T} p_{mift}^{\mathrm{C}} \ln\left(\frac{p_{mift}^{\mathrm{C}}}{q_{mift}^{\mathrm{C}}}\right) + \sum_{m=1}^{M}\sum_{v=1}^{V}\sum_{j=1}^{N}\sum_{t=1}^{T} p_{mvjt}^{\mathrm{W}} \ln\left(\frac{p_{mvjt}^{\mathrm{W}}}{q_{mvjt}^{\mathrm{W}}}\right) \\
&+ \sum_{m=1}^{M}\sum_{v=1}^{V}\sum_{f=1}^{F}\sum_{t=1}^{T} p_{mvft}^{\mathrm{D}} \ln\left(\frac{p_{mvft}^{\mathrm{D}}}{q_{mvft}^{\mathrm{D}}}\right) + \sum_{u=1}^{3}\sum_{h=1}^{H}\sum_{j=1}^{N}\sum_{t=1}^{T} p_{uhjt}^{\gamma} \ln\left(\frac{p_{uhjt}^{\gamma}}{q_{uhjt}^{\gamma}}\right)
\end{aligned} \tag{2.24}$$

The probabilities for each weight are still bounded between 0 and 1 and are subject to the modified probability consistency constraint $\sum_{h=1}^{H} p_{uhjt}^{\gamma} = 1 \quad \forall u, j, t$ (similar to the one in Equation 2.17). We also include the constraint that the weights themselves sum to 1:

$$\sum_{u=1}^{3}\gamma_{ujt} = \sum_{u=1}^{3}\left(\sum_{h=1}^{H} b_h^{\gamma} p_{uhjt}^{\gamma}\right) = 1 \qquad \forall j, t \tag{2.25}$$

In sum, the basic DWP CE program for states is composed of Equations 2.7-2.17 (Model 1), and for counties of the objective function in Equation 2.24, constraints 2.8-2.17 and 2.25 (Model 2). A simple application using the standard datasets and procedures aforementioned is presented next.

2.3. Application

To illustrate the applicability of the methodology presented in Section 2.2, we perform the quarterly temporal disaggregation of the 2015 IO tables for the US, State of Illinois, Cook County (where the city of Chicago is located) and Iroquois County (a rural county in Central Illinois). To reduce loss of data fidelity at county level, we use NAICS 2-digit aggregation at all geographical levels, although a disaggregation up to 60 sectors is possible at the national level. Data sources are the same presented in Section 2.2. The annual IO table for the US was obtained from BEA's Input-Output Accounts Data (BEA, 2018a), and the tables for Illinois and its counties were obtained from IMPLAN (2018). We use MATLAB to run the T-EURO algorithm for the US, and GAMS[28] to solve the following non-linear programs: Model 1 plus constraints in Equations 2.20-2.23 for Illinois; Model 2 plus constraint in Equation 2.20 for Cook County (urban); and Model 2 plus constraints in Equations 2.20-2.23 for Iroquois County (rural).

We expect to observe strong seasonality in agriculture and construction industries, in which activity should reduce significantly during winter months (especially in the first quarter). For agriculture in particular, planting/growing periods should generate higher backward linkages, while harvest periods should induce more forward linkages, similar to the results found for Brazil in Chapter 1. We also expect accentuated seasonality in utilities and mining/oil extraction due to peak in energy use for heating during the winter and tourism related sectors (NAICS 71 and 72) with higher activity during the end of the year holiday season.

For each region, we report its quarterly GDP, its quarterly output by industry, the spread of the quarterly output multipliers (the direct and indirect output necessary to supply $1 increase in final demand), the weighted type I income multiplier (the direct and indirect labor income impact of an increase of 1% in the final demand of a given sector), and the contribution of the sector to the regions' total value added (using a Hypothetical Extraction Method). A complete description and discussion of these measures are available in Miller and Blair (2009).

The estimated quarterly GDP by region is reported in Table 2.3. For the US, Illinois and Cook County, the GDP has a U-shaped pattern throughout the quarters, mainly driven by manufacturing and service activities. In Iroquois County, where agriculture is the dominant sector, the evolution of the GDP follows the growing pattern of corn and soybeans with the lowest value added in the first quarter, and the highest in the fourth quarter.

[28] We use the CONOPT3 solver, version 3.14T.

Table 2.3: Quarterly GDP (Million dollars), not seasonally adjusted, 2015

	Adm. Unit	Q1	Q2	Q3	Q4	Annual
US	National	4,529,684	4,346,978	4,387,557	4,856,480	18,120,700
Illinois	State	197,407	189,225	189,559	205,003	781,193
Cook	County	96,809	91,497	91,964	100,187	380,456
Iroquois	County	190	209	210	223	832

The output evolution in the quarterly IO tables for the US follows the overall expected seasonality pattern described earlier. The fourth quarter is the strongest for most activities, although the first quarter also shows a significant role in Manufacturing (NAICS 31-33), Information (NAICS 51) and FIRE[29] sectors (Table 2.4). The output multiplier varies on average 2.1% intra-year, with the largest variation concentrated in service activities (Figure 2.6). Among those, Healthcare (NAICS 62) and tourism related sectors (NAICS 71 and 72) change the most (3.7%, 2.7% and 2.8% respectively).

Agriculture (NAICS 11) follows its expected seasonal pattern, with output growing throughout the quarters but concentrated in the middle of the year when several crops are growing simultaneously in the US. As shown ahead, this pattern will differ in Illinois and in particular Iroquois county due to climate conditions, with output peaking in Q4 following the growing season of corn and soybeans. In the US, backward linkages are the highest in Q1 when inputs are purchased for the planting period, while forward linkages increase in Q3 and Q4 during harvesting when crops are pushed downstream in the food industry chain. Another interesting pattern to notice is the increase in forward linkages in mining and oil extraction during Q1 and Q4, driven mainly by utilities during the winter months.

A more significant indicator of the impact of a sector in the economy is its effect on local income weighted by the sector' size, presented in Figure 2.7. These income multipliers show high variance within the year. Public Administration (NAICS 92), Healthcare and Manufacturing have the largest effects throughout the quarters, with Healthcare exhibiting the largest variance in Q4, and Construction (NAICS 23) and Finance and Insurance (NAICS 52) the largest in Q1. The deviation from the annual multiplier is also the largest for Construction and Finance and Insurance. The widest spread in output multipliers is the greatest for the latter (50% intra-year).

[29] FIRE: Finance, Insurance, Real Estate, and Rental and Leasing (NAICS 52-53).

Table 2.4: Total quarterly output by industry in the US, 2015, million dollars

NAICS	Description	Q1	Q2	Q3	Q4
11	Agriculture, Forestry, Fishing and Hunting	99850	111392	117062	121946
21	Mining, Quarrying, and Oil and Gas Extraction	121993	106548	104745	104953
22	Utilities	112156	94231	93213	103793
23	Construction	305367	361278	392181	388143
31-33	Manufacturing	1431398	1360247	1361160	1482486
42	Wholesale Trade	385581	366352	369281	412568
44-45	Retail Trade	368180	364799	369393	413585
48-49	Transportation and Warehousing	267447	260292	263425	289521
51	Information	395766	355347	367612	400143
52	Finance and Insurance	700238	523971	521520	595921
53	Real Estate and Rental and Leasing	839262	773553	786350	911223
54	Professional, Scientific, and Technical Services	566426	546659	550838	636980
55	Management of Companies and Enterprises	175779	141861	138531	156053
56	Adm. and Sup. and Waste Mmgt.	214561	214320	218828	242785
61	Educational Services	69611	69632	70122	76043
62	Health Care and Social Assistance	524010	516596	528904	596461
71	Arts, Entertainment, and Recreation	69444	71779	75733	89926
72	Accommodation and Food Services	249562	252624	258987	275836
81	Other Services (except Public Administration)	198955	197968	200748	220107
92	Public Administration	823641	833350	830662	851647

At national level, Manufacturing has the largest contribution to GDP throughout the year, Mining, Utilities, FIRE and Management Services have the most significant effect on Q1's GDP, Public Administration on Q2-Q3, while margins (Transportation, Wholesale and Retail sectors), FIRE and health activities drive the growth in Q4 (Figure 2.8).

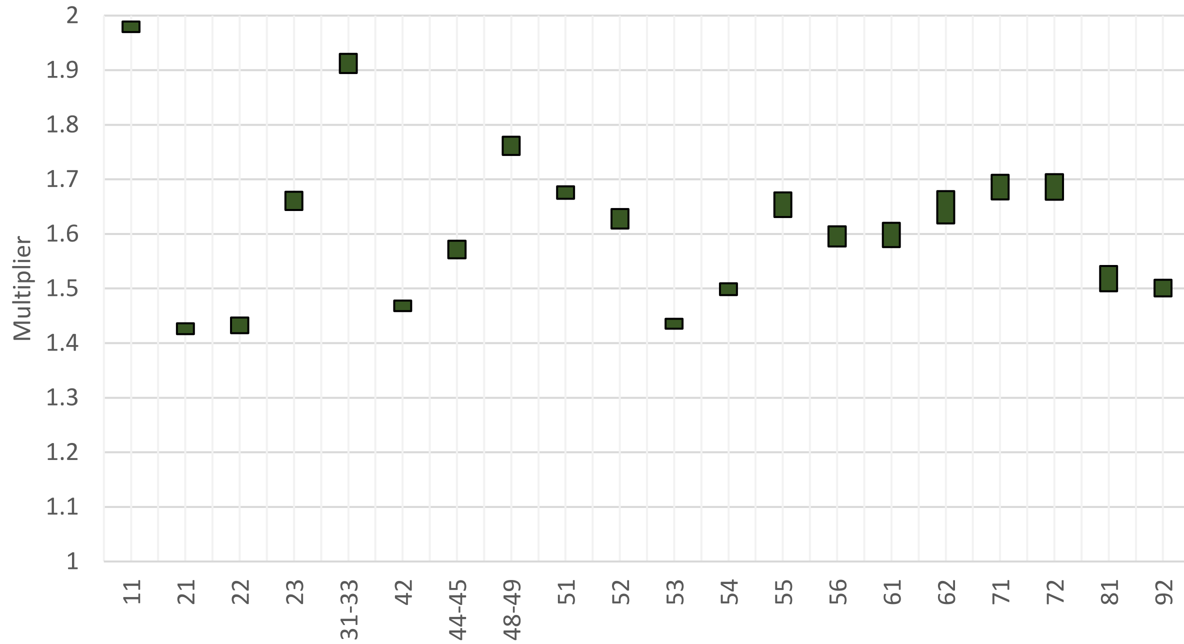


Figure 2.6: Output multiplier spread throughout the year by industry, US, 2015

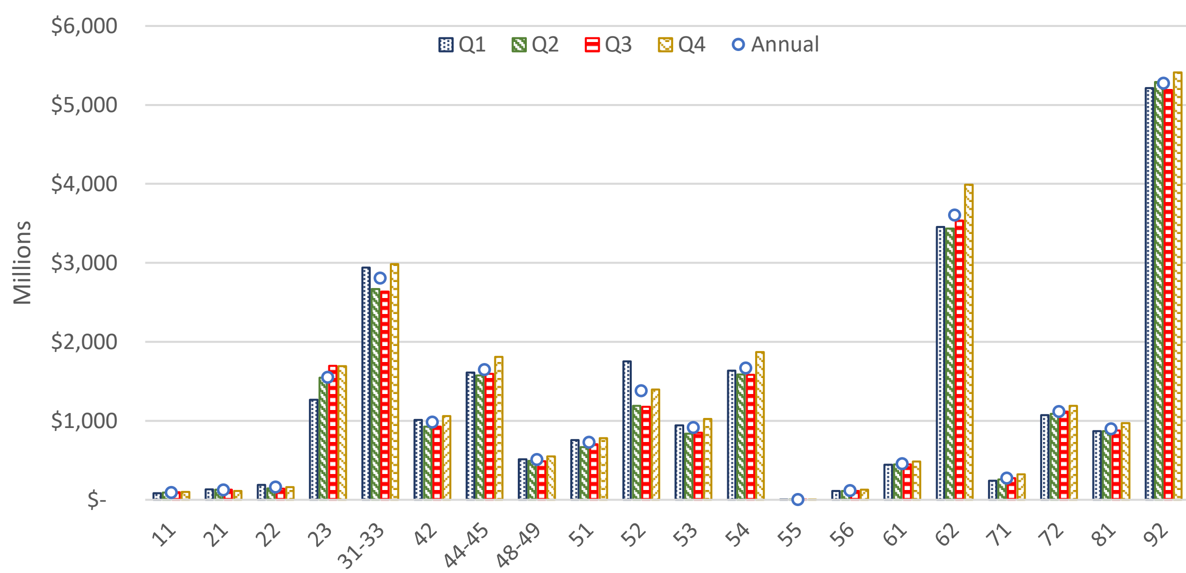


Figure 2.7: Weighted type I income multiplier, US, 2015

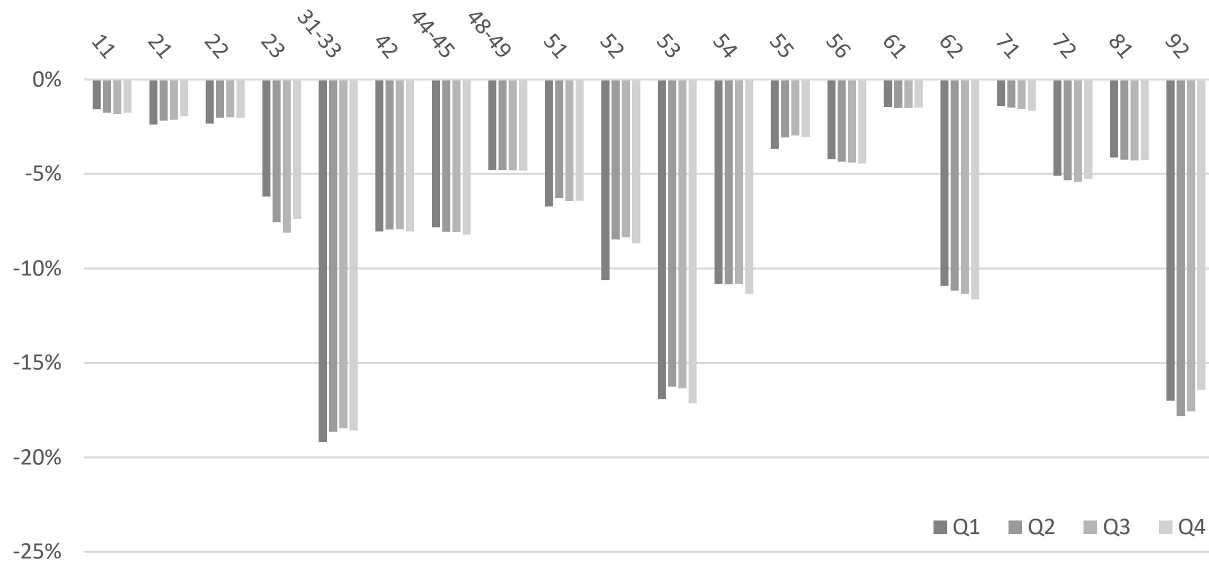


Figure 2.8: Quarterly sectoral contribution to the GDP, US, 2015

In 2015, Manufacturing, FIRE and Public Administration represented 44% of the annual GDP in the State of Illinois, varying between 43 and 46% during the year. Although Illinois is a large grain producer (corn and soybeans), the agricultural industry is relatively small regarding its GDP participation. Nonetheless, this sector follows the expected pattern for midwestern states with growing output and multiplier effects from Q1 to Q4 (Table 2.5), and a significant spread in income multiplier (27%, Figure 2.10). As noted for the national level, agriculture has declining backward linkages and growing forward linkages throughout the year, reflecting the major planting and harvesting periods in the state (see Figure 2.5). Construction also tracks the expected pattern of higher activity from Q2 onwards.

The rest of the sectors have a similar intra-year pattern as the national one, but with lower variance. Overall the output multipliers are lower than the nation's (as we should expect of a smaller economy) with also lower average spread intra-year (1.7%), although there is significantly higher spread (4.2%) for Management Services (NACIS 55) (Figure 2.9). Manufacturing, Public Administration and Healthcare have the highest income multipliers and follow the intra-year dynamics for the US (Figure 2.10). Manufacturing shows a stable GDP contribution throughout the quarters, while Finance and Insurance varies the most, being particularly important in Q1 during pre-harvest when loans, insurance and other financial instruments are contracted (Schnitkey & Coppess, 2018). Professional Services (NAICS 54) and Healthcare have an increasing participation in the state's value added in the year (Figure 2.11).

Table 2.5: Total quarterly output by industry in Illinois, 2015, million dollars

NAICS	Description	Q1	Q2	Q3	Q4
11	Agriculture, Forestry, Fishing and Hunting	3909	4082	4204	4379
21	Mining, Quarrying, and Oil and Gas Extraction	1462	1400	1392	1415
22	Utilities	7898	7398	7276	7545
23	Construction	13979	14941	15574	15947
31-33	Manufacturing	82769	80451	80873	83317
42	Wholesale Trade	21874	21247	21194	22521
44-45	Retail Trade	13628	13527	13735	14826
48-49	Transportation and Warehousing	15332	14824	14953	15733
51	Information	15100	14304	14367	14992
52	Finance and Insurance	37918	31116	30886	33279
53	Real Estate and Rental and Leasing	33590	32344	32583	34190
54	Professional, Scientific, and Technical Services	26887	26117	26676	29858
55	Management of Companies and Enterprises	7342	5995	5930	6635
56	Adm. and Sup. and Waste Mmgt.	9649	9567	9674	10422
61	Educational Services	3441	3492	3527	3659
62	Health Care and Social Assistance	20893	20996	21108	23543
71	Arts, Entertainment, and Recreation	2972	3068	3162	3261
72	Accommodation and Food Services	8965	9194	9328	9761
81	Other Services (except Public Administration)	13125	12666	12828	13749
92	Public Administration	19173	19795	17956	19743

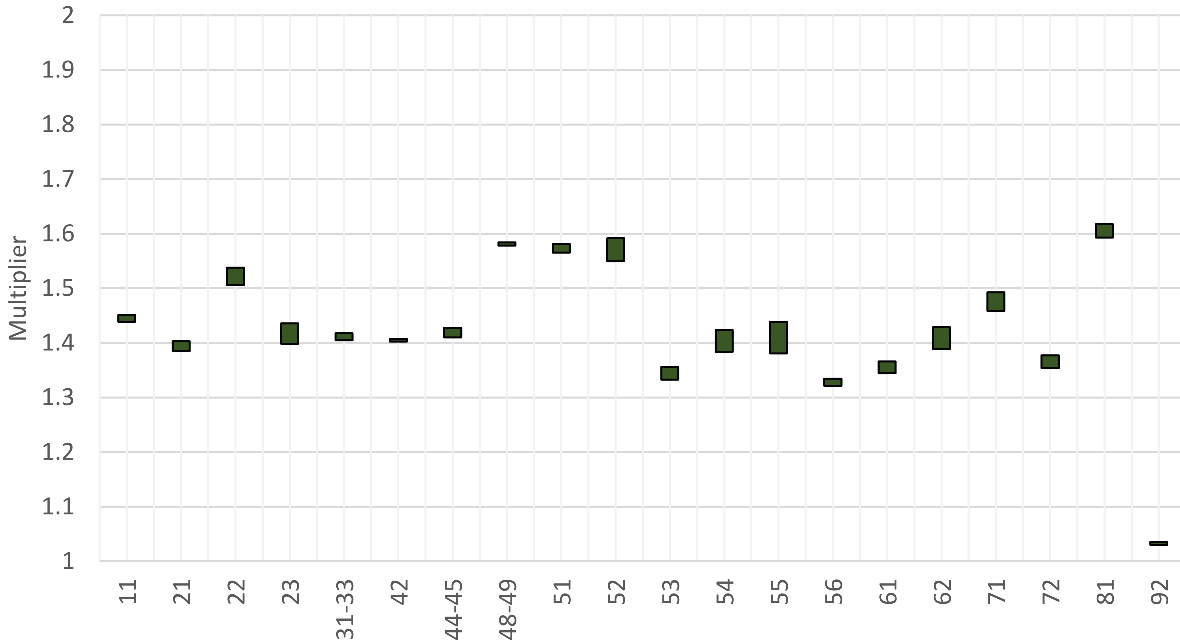


Figure 2.9: Output multiplier spread throughout the year by industry, Illinois, 2015

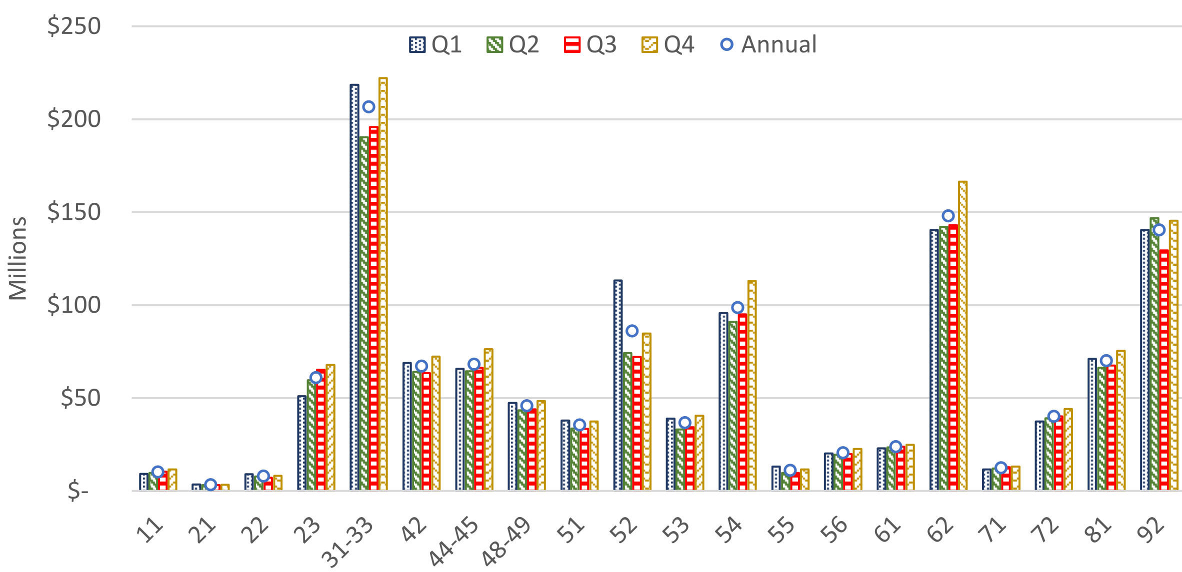


Figure 2.10: Weighted type I income multiplier, Illinois, 2015

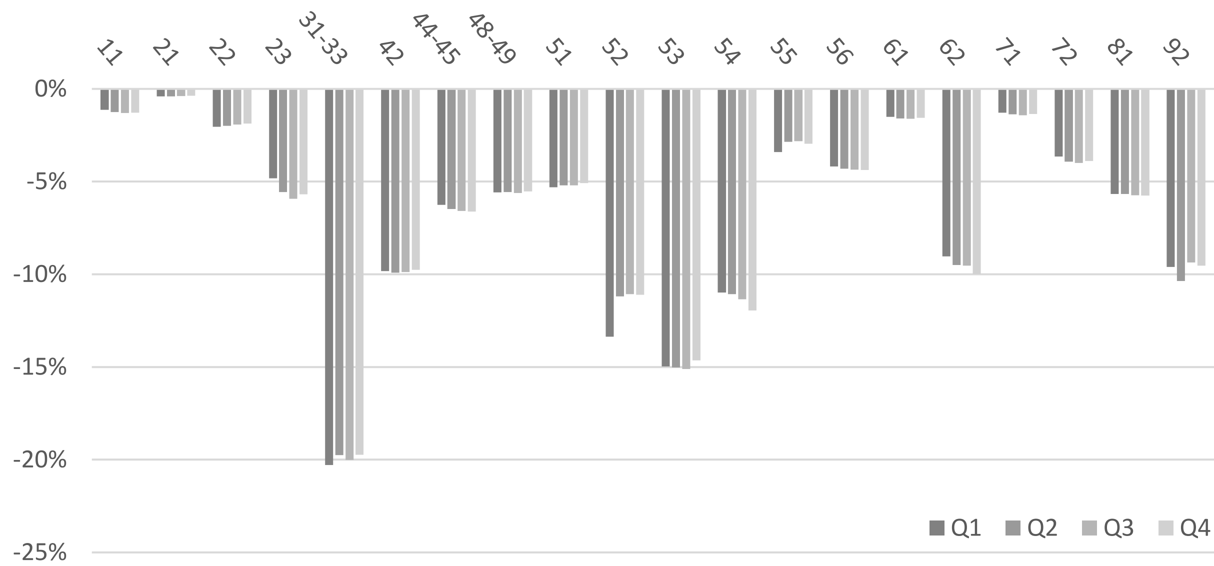


Figure 2.11: Quarterly sectoral contribution to the GDP, Illinois, 2015

Cook County is characterized by large Manufacturing, Finance and Professional Services sectors which output tend to follow a U-shape curve intra-year (Table 2.6). The first quarter is particularly strong for Finance and Insurance activities, while the last quarter is stronger for Professional Services. Output multipliers have a higher spread than the state and the US, especially in service sectors, the largest observed in Educational Services (Figure 2.12). When we look at the income multiplier accounting for the sector size (Figure 2.13), Finance and Insurance, Professional Services and Healthcare activities have the largest impacts in the local labor income, largely concentrated in Q4 for the latter two. Their multipliers vary 66%, 46% and 47% respectively over the year. In terms of contributions to the local GDP, Information (NAICS 51) and FIRE sectors affect almost 50% of the local economy, with the highest impact on Q1 and lowest in Q2 (Figure 2.14). Manufacturing has a more stable contribution throughout the year.

The county also concentrates 55% of tourism activities' GDP in Illinois. These activities exhibit an interesting pattern in the region with accommodation growing consistently from Q1 to Q4 and recreational activities peaking during the summer months in Q2 and Q3. Their multipliers also vary considerably intra-year: 5.3% and 1.6% for output and 37% and 20% for labor income respectively, and their importance in the GDP peaks in the middle of the year.

Table 2.6: Total quarterly output by industry in Cook County, 2015, million dollars

NAICS	Description	Q1	Q2	Q3	Q4
11	Agriculture, Forestry, Fish. and Hunt.	5	6	7	7
21	Mining, Quarrying, and Oil and Gas Extraction	100	118	120	129
22	Utilities	1454	1409	1396	1424
23	Construction	5760	6156	6294	6502
31-33	Manufacturing	23181	22769	22807	23561
42	Wholesale Trade	8418	8079	8004	8438
44-45	Retail Trade	5485	5481	5552	6009
48-49	Transportation and Warehousing	8669	8506	8521	8856
51	Information	9609	9172	9159	9488
52	Finance and Insurance	21619	17575	17460	18694
53	Real Estate and Rental and Leasing	17765	17168	17188	17976
54	Professional, Scientific, and Technical Services	16425	16272	16602	18636
55	Management of Companies and Enterprises	3565	2908	2845	3034
56	Adm. and Sup. and Waste Mmgt.	4981	4984	5064	5482
61	Educational Services	2457	2622	2038	2631
62	Health Care and Social Assistance	9676	9765	10035	11052
71	Arts, Entertainment, and Recreation	1592	1823	1862	1748
72	Accommodation and Food Services	4497	4654	4697	4940
81	Other Services (except Public Administration)	6635	6487	6579	6974
92	Public Administration	8497	7720	8018	8264

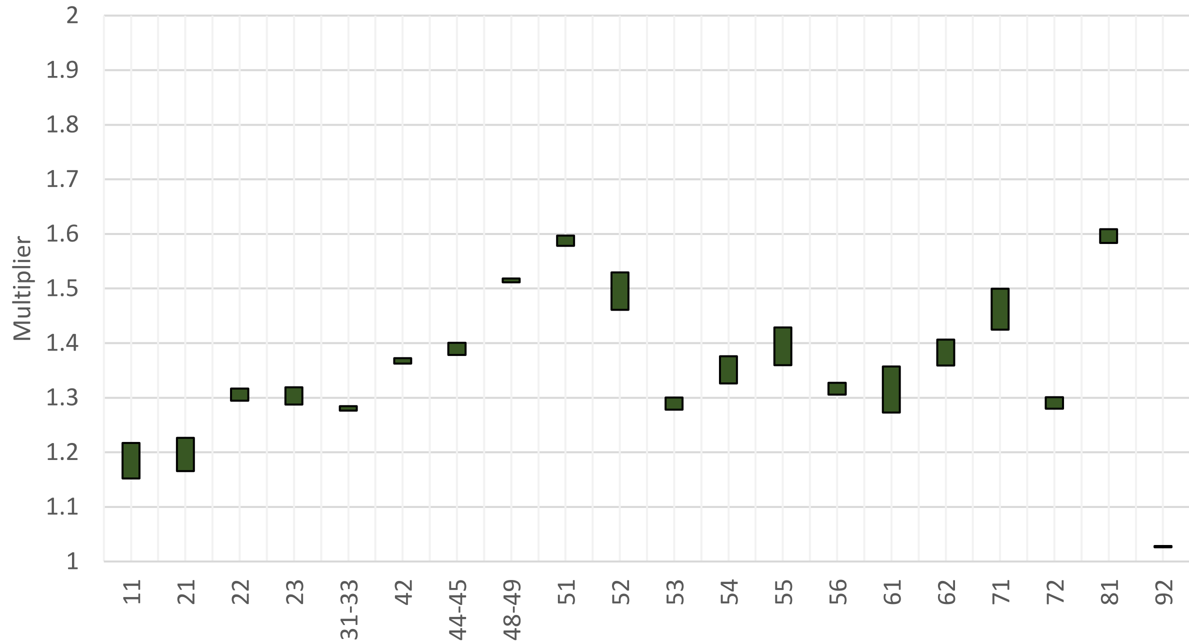


Figure 2.12: Output multiplier spread throughout the year by industry, Cook County, 2015

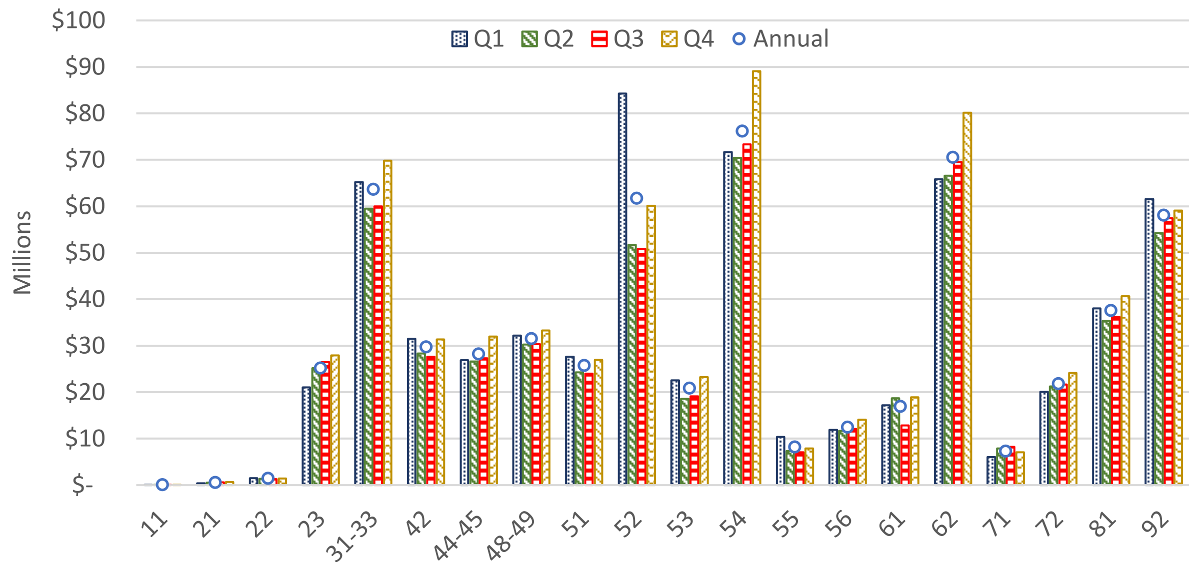


Figure 2.13: Weighted type I income multiplier, Cook County, 2015

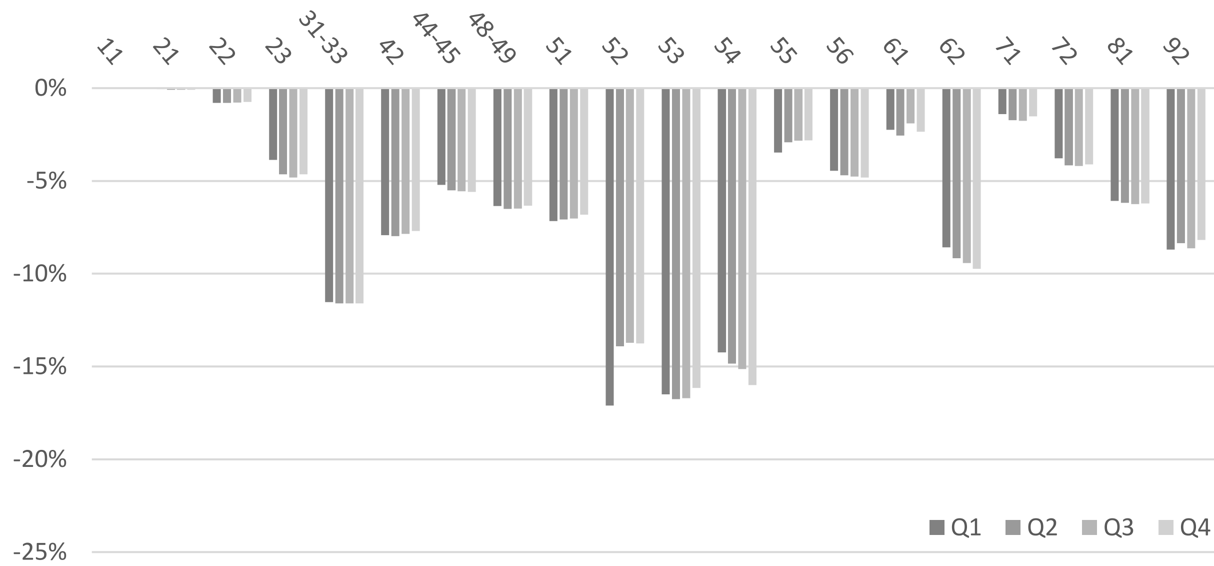


Figure 2.14: Quarterly sectoral contribution to the GDP, Cook County, 2015

Iroquois is a small, predominantly agricultural county in east central Illinois. Hence, we should expect to observe a higher intra-year seasonality than in the other regions (Table 2.7). Indeed, from Figures 2.16 and 2.17, one can note the significant impact of Agriculture to the local community besides the strong variation in terms of income impacts and GDP contribution throughout the year. The income multiplier grows 54% from winter (Q1) to harvest season in Q4 when the contribution to the region's GDP reaches 25%. This variation exerts significant error if we use annual income multipliers instead of quarterly ones: the effects of a shock in this sector would be overestimated by 27% in Q1 and underestimated by 18% in Q4. Directly connected to Agriculture is Food Manufacturing which is the major component of sector 31-33, in which backward linkages increase in the Q4. Forward linkages for Agriculture do not vary significantly intra-year since most of the production is exported and processed outside of the county.

Table 2.7: Total quarterly output by industry in Iroquois County, 2015, million dollars

NAICS	Description	Q1	Q2	Q3	Q4
11	Agriculture, Forestry, Fishing and Hunting	107	112	113	119
21	Mining, Quarrying, and Oil and Gas Extraction	1	1	1	1
22	Utilities	14	14	14	14
23	Construction	33	37	37	37
31-33	Manufacturing	92	92	92	93
42	Wholesale Trade	40	41	41	43
44-45	Retail Trade	27	28	29	29
48-49	Transportation and Warehousing	26	27	27	28
51	Information	8	8	8	8
52	Finance and Insurance	23	23	23	24
53	Real Estate and Rental and Leasing	37	37	37	38
54	Professional, Scientific, and Technical Services	10	10	10	11
55	Management of Companies and Enterprises	3	3	3	3
56	Adm. and Sup. and Waste Mmgt.	2	3	3	3
61	Educational Services	1	1	1	1
62	Health Care and Social Assistance	29	30	31	32
71	Arts, Entertainment, and Recreation	1	2	2	2
72	Accommodation and Food Services	9	9	9	9
81	Other Services (except Public Administration)	13	13	14	15
92	Public Administration	20	22	21	22

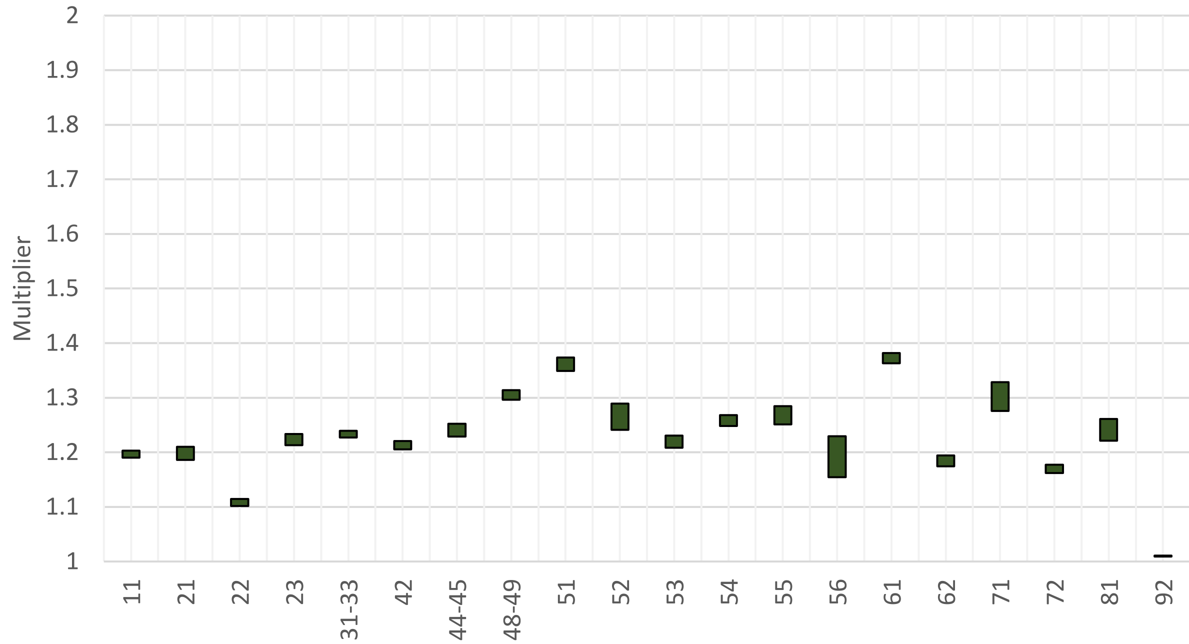


Figure 2.15: Output multiplier spread throughout the year by industry, Iroquois County, 2015

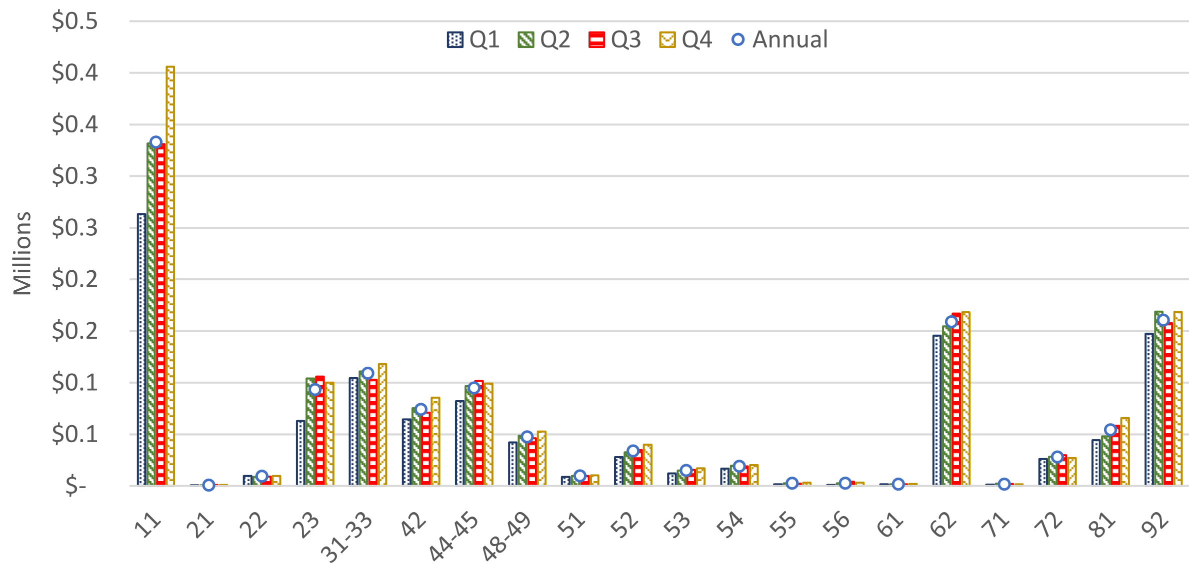


Figure 2.16: Weighted type I income multiplier, Iroquois County, 2015

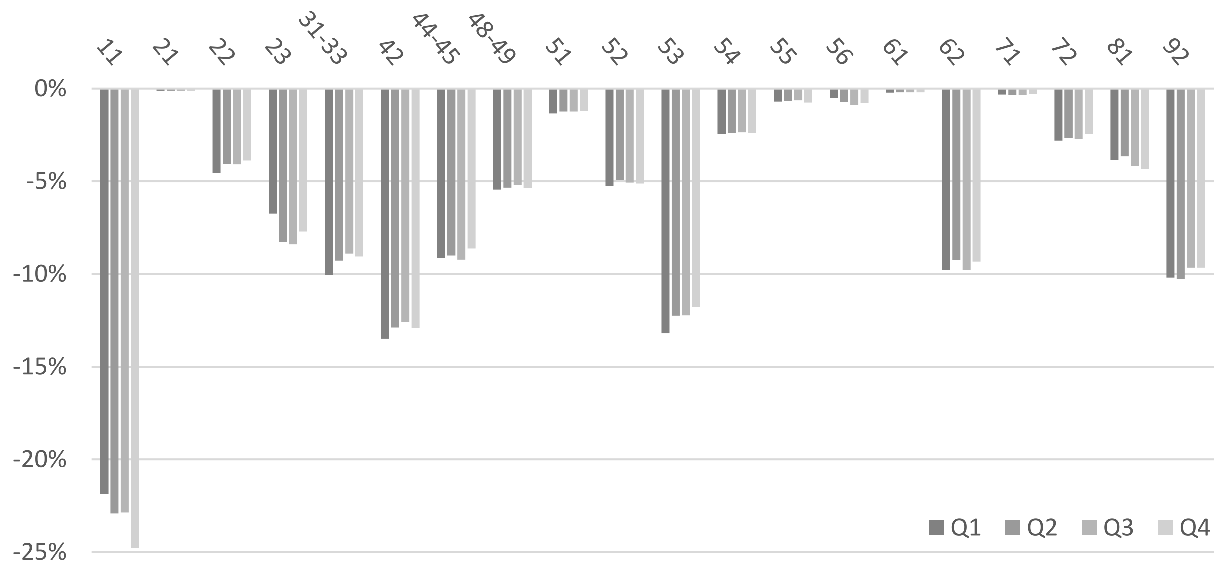


Figure 2.17: Quarterly sectoral contribution to the GDP, Iroquois County, 2015

2.4. Conclusions

In this Chapter, we provide a roadmap of procedures and public data sources to estimate quarterly multisectoral tables for any US state and county, taking the annual IO table for the region as given.[30] The advantage of the maximum entropy program proposed is its flexibility in including additional idiosyncratic information available for a particular region, complementing the common value added dataset available to all states/counties. We recommend using all information pertaining to the intra-year dynamics of the community, as it will improve the accuracy of the estimates. This maximum entropy program can also be adapted for the national level if the minimum information requirements for the T-EURO method are not met.

The disaggregation of the IO tables presented in Section 2.3 shows the ability of this approach in reflecting seasonal patterns, which is particularly important for small economies that rely on seasonal industries. The application for Iroquois County exemplifies the need for quarterly data when assessing shocks in local communities, as annual indicators would significantly mismeasure the effects on the regional labor income of the agricultural sector throughout the year.

[30] Annual state and county tables can be obtained commercially from IMPLAN (http://www.implan.com/) or IO-Snap (https://www.io-snap.com).

Three important caveats need to be considered when applying the procedures presented in this Chapter: first, a high sectoral aggregation might have a dampening effect on seasonal patterns and obfuscate which sector is driving this effect; second, the datasets provided constitute a consistent source to temporally disaggregate any state/county in the US, but the use of specific local information is essential to improve the estimates of the CE program. In the application on Section 2.3, there is still considerable uncertainty in sectors 51 to 54 (Figures C.3-C.5 in the Appendix); third, both the T-EURO method and the DWP CE program proposed were designed for non-negative entries and, thus, any value that can lead to a negative share (such as change in inventories and subsidies) needs to be aggregated before using these procedures. Allowing both positive and negative entries is subject of ongoing research.

This Chapter aims at providing the tools and inputs to allow researchers and practitioners to better capture the effects of intra-year interventions in regional economies. We hope that future research and analysis benefit from a better snapshot of the local economic structure at different points in time, and acknowledge that the timing of the shock is critical for the size and scope of its outcomes.

CHAPTER 3: THE CHALLENGE OF ESTIMATING THE IMPACT OF DISASTERS: MANY APPROACHES, MANY LIMITATIONS AND A COMPROMISE

3.1. Introduction

Disasters have unique features and effects that pose challenges to traditional economic modeling techniques. Most of them derive from a time compression phenomenon (Olshansky, Hopkins, & Johnson, 2012) in which, instead of a gradual transition phase after the steady-state is disrupted, an accelerated adjustment process (due to recovery efforts) brings the economy to a new steady-state.[31] Even though some activities compress better than others (e.g., money flows in relation to construction), it creates an intense transient economic shock (non-marginal) that is spatially heterogeneous and simultaneous, and that depends on the intensity of damages, the local economic structure, and the nature and strength of interregional linkages. As a result of the speed of disaster recovery, there is significant uncertainty, simultaneous supply constraints with different forward and backward linkages effects due to production chronology and schedules, and behavioral changes that affect both the composition and volume of demand (Okuyama, 2009). Timing is, therefore, fundamental in determining the extent of impacts since capacity constraints, inventories and production cycles vary throughout the year (see Chapters 1 and 2).

In terms of economic modeling, the aforementioned features translate into a series of effects for which the net outcome (positive/negative) is unknown, as it depends on the idiosyncrasies of the region. In the aftermath of a disaster, the previous steady-state of the economy is disrupted by changes in both supply and demand. Household displacement, income loss, structural changes in expenditure patterns, diminished government expending, and reconstruction efforts imply positive and negative effects to final demand. Industrial response to the latter, in terms of output scheduling, affects intermediate demand. Conversely, supply may be locally constrained due to physical damage to capital and loss of inventory, or externally constrained by limited input availability for production (due to accessibility issues or disruptions in the production chain). Whether the net effect on the region is positive or negative will depend on the characteristics of the disaster, the resilience of local industries, the volume of

[31] E.g., a large amount of damaged assets is intensely replaced during recovery, moving the dynamics of capital depreciation and replacement to a new steady-state in the region or across regions.

reconstruction funds made available and the size of interregional linkages. Spillover effects spread through supply chains' disruptions and resource allocations for reconstruction in different regions at different times.

Hence, modeling efforts are essential to understand the role of different constraints in the post-disaster recovery path and to better inform mitigation planning. Regional industrial linkages topologies have a key role in spreading or containing disruptions, as well as sectoral robustness in terms of inventories, excess capacity, and trade flexibility (Rose & Wei, 2013). Supply chain disruptions can have significant impacts on the financial health of firms by constraining sales, diminishing operating income and increasing share price volatility (Hendricks & Singhal, 2005). Nonetheless, most firms do not properly quantify these risks, with few developing backup plans for production shutdowns due to physical damage or alternative suppliers in case of disruptions (University of Tennessee, 2014). Assessing the dynamics of dissemination and identifying crucial industrial nodes can lead to more resilient economic systems.

As highlighted by Oosterhaven and Bouwmeester (2016), ideally, the assessment of regional impacts should be based on an interregional computable general equilibrium (CGE) framework. However, as a set of such models is required to account for both short-run (when substitution elasticities are minimal) and long-run impacts, the cost-time effectiveness of this approach is usually problematic (Rose, 2004; Pan & Richardson, 2015). The widely used alternative has been input-output (IO) models due to their rapid implementation, easy tractability and integration flexibility with external models that are essential in the estimation of impacts post-disaster. The tradeoff between its CGE counterpart is more rigid assumptions on substitutability of goods, price changes and functional forms, which make IO more appropriate for short-term analysis. A variety of IO models has been proposed to deal with disruptive situations, most of them built upon the traditional demand-driven Leontief model (Okuyama, 2007; Okuyama & Santos, 2014). Nevertheless, these contributions are fragmented in different models, many of which either fail to incorporate the aforementioned constraints or do so in an indirect way that may be inconsistent with the assumptions of the IO framework (Oosterhaven & Bouwmeester, 2016; Oosterhaven, 2017).

In this Chapter, we offer a compromise that encompasses the virtues of *intertemporal* dynamic IO models with the explicit *intratemporal* modeling of production and market clearing, thus allowing for supply and demand constraints to be simultaneously analyzed. The Generalized Dynamic Input-Output (GDIO) framework is presented and its theoretical basis derived. The GDIO synthetizes many of the early contributions in the disaster literature, especially those contained in the Inventory Adaptive Regional IO Model (Hallegatte, 2014), complementing them with the Sequential Interindustry Model, a demo-economic extension and seasonality effects. We integrate in a single model inventory dynamics, expectations' adjustment, timing of the event, impacts of displacement, unemployment and reconstruction. The GDIO provides insights into the role of pivotal production chain bottlenecks, population dynamics and interindustrial flow patterns that can guide the formulation of better recovery strategies and mitigation planning.

In the next Section, we present a concise literature review of models focused on disruptive events using the IO framework. Section 3.3 describes the intuition, mathematical formulation and solution of the GDIO model. Section 3.4 presents a simple 3-sector example to show the basic feedbacks in the model and compares these results with the recovery paths of other models in the literature. Conclusions follow.

3.2. Literature Review

The input-output literature on natural disasters is vast, and although a comprehensive review is outside the scope of this Chapter, it is available in Okuyama (2007), Przyluski and Hallegatte (2011) and Okuyama and Santos (2014). In this Section, we briefly highlight the main contributions and some of the pitfalls from the current literature.

In explicitly considering supply, demand and trade constraints, and their sources inside the framework, Cochrane (1997), Oosterhaven and Bouwmeester (2016) introduced rebalancing algorithms for squared IO tables, which were later extended by Koks and Thissen (2016) and Oosterhaven and Többen (2017) to supply and use tables (SUT). Alternatively, Rose and Wei (2013) use both supply- and demand-driven models to capture backward and forward spillovers from shortfalls in intermediate inputs. These approaches, however, rely on an implicit assumption of perfect information to rebalance the economy and calculate total multiplier effects. A way to incorporate the increase in uncertainty in the aftermath of a disaster – arising from information asymmetries (Okuyama & Santos, 2014) – is to include these constraints in the IO framework by explicitly modeling the market clearing process (in a Marshallian sense). In the Adaptive Regional IO Model (ARIO) model (Hallegatte, 2008), sectors produce according to an expected demand level that might differ from the actual demand resulting in over- or under-supply (a reflection of highly uncertain environments).

For *ex-ante* analyses, it is also essential to consider the interaction between local demand-production conditions and the evolution of these constraints instead of imposing an exogenous recovery trajectory. Lian and Haimes (2006) provide an alternative in the Dynamic Inoperability Input-Output Model (DIIM) by transforming the Leontief Dynamic growth model into a recovery model.[32] The DIIM determines the speed with which the production gap post-disaster closes in each period according to supply-demand unbalances.

In terms of dynamics, a few studies have proposed formulations focused on industrial chronologies and production sequencing in order to capture intertemporal disruption leakages. The time-lagged model proposed by Cole (1988, 1989)[33] and the Sequential Interindustry Model (SIM) by Romanoff and Levine (1981) relax the assumption of production simultaneity, instead accounting for production timing. This is essential, as production delays can have ripple effects in different industrial chains, and perpetuate in the economy for several periods, influencing output *intertemporally* (Okuyama, Hewings, & Sonis, 2002; 2004). However, the role of seasonality in the economic structure is still unaccounted for in the available dynamic models. Although some sectors have more stable production structures over the course of a year, the bias of using annual multipliers in seasonal sectors such as agriculture can be significant, as highlighted in Chapters 1 and 2. Hence, fluctuations in production capacity and interindustrial linkages *intra-year* have a significant impact on the magnitude, spread and duration of unexpected disruptive events, which affect sectoral adaptive responses.

---

[32] The DIIM is the dynamic version of the Inoperability Input-Output Model (IIM) (Santos, 2003; Santos & Haimes, 2004). Despite its wide application in the literature, it offers no methodological advances in relation to the traditional IO model. In fact, as shown in Dietzenbacher and Miller (2015) and Oosterhaven (2017), it is just a normalization of the Leontief model.

[33] The time-lagged model has been criticized in a series of papers by Jackson, Madden and Bowman (1997), Jackson and Madden (1999) and Oosterhaven (2000), due to Cole's assumption of a fully endogenized system which is theoretical inconsistent and non-solvable. No other disaster applications are available.

The important role of inventories in mitigating short-term effects of disruptions has also been incorporated in the dynamic literature: the Inventory-SIM (Romanoff & Levine, 1990; Okuyama & Lim, 2002), the Inventory-DIIM (Barker & Santos, 2010) and the Inventory-ARIO (Hallegatte, 2014). However, there is still limited consideration of different types of inventories (materials and supplies, work-in-progress, finished goods) and their formation in the same framework. Besides inventories, Rose and Wei (2013) also consider other mitigation strategies such as using goods destined for export in the local economy, input conservation and production recapture. Further, Koks and Thissen (2016)'s MRIA model allows increasing local production of by-products to reduce inoperability.

Natural disasters also tend to change expenditure patterns both in the affected region (due to layoffs, reduced production, governmental assistance programs) and outside of it (relief aid). These have been incorporated in Okuyama *et al.* (1999) and Li, Crawford-Brown, Syddall and Guan (2013), but the main issue is to properly identify and quantify such behavioral changes. Another important challenge is the application of a systems approach to disaster modeling, i.e., the integration of regional macro models with physical networks (transportation, utilities, etc.) that operate at different scales and frequencies. There are temporal mismatches between low frequency economic models (monthly, quarterly, yearly basis) and high frequency physical networks (day, hourly intervals), as well as spatial mismatches in terms of systems boundaries and granularity (economic models usually defined over administrative boundaries at macro level versus micro level larger/smaller networks). Efforts in integrating physical networks include the Southern California Planning Model (Pan & Richardson, 2015), the National Interstate Economic Model (Park & Richardson, 2014) combining a MRIO with transportation networks, and the work of Rose and Benavides (1998) who focused on electricity supply.

In sum, several alternatives have been proposed, but their contributions are fragmented in several models without a common synthesis framework. The Inventory-ARIO model introduces many of the aforementioned contributions, such as modeling supply-demand in a dynamic context to explicitly incorporate constraints, consideration of inventory formation (materials and supplies only), and some adaptation behavior from agents, but such model is still incomplete. Missing are a more comprehensive accounting of production scheduling, seasonality in the production structure, and demographic dynamics post-event. The next Section introduces a new model that departs from the Inventory-ARIO model and integrates these points in a consistent and theoretically sound way.

3.3. Methodology

When dynamics are introduced in the IO framework, the economic system becomes a combination of *intratemporal* flows and *intertemporal* stocks. Intertemporal stocks are key to exploit such dynamics and are essential to fulfill both reproducibility (conditions for production in the next period) and equilibrium conditions (market clearing) across time periods. Inventories assure irreversibility of production (i.e., inputs need to be available before output is produced) and the feasibility of free disposal in a consistent accounting sense (by absorbing unused inputs/outputs) (Debreu, 1959). Therefore, as echoed by Aulin-Ahmavaara (1990), a careful definition of flows and stocks is paramount to avoid theoretical inconsistencies in the model.

Following the past literature (Leontief, 1970; Romanoff & Levine (1977); ten Raa, 1986), time is discretized into intervals $t \in \mathrm{T}$, $\mathrm{T} \supset \mathbb{Z}$, of length h. The discretization of a continuous process (production), requires that any flow $\mathbf{Z}_{ij}$ occurring during the length h be time-compressed, as $\nexists\, \mathbf{Z}_{ij}(t^*), \forall t^* \mid t < t^* < t + 1$. Moreover, since the production process is not explicitly modeled *per se*, production begins and ends simultaneously and synchronously within h for all industries, and output is sold at the end of the period to final demand or inventories (stocks).[34]

Flows and stocks need to be organized in a certain way in order to comply with time-relevant neoclassical assumptions on production sets. If production is to occur in period t, *irreversibility* mandates that all required inputs be available in advance and, therefore, input purchases occur in $t - 1$. Note that the discretization displaces all interindustrial flows that would occur within h to a single purchase event in the previous period, i.e., industries cannot purchase inputs during production. In addition, *free disposal* requires the existence of inventories, so that unused materials and finished goods can be consistently accounted for and transferred intertemporally.

[34] This includes both finished and work-in-progress goods.

Based on these assumptions, the length h can be divided into a sequence of events that starts with the formation of supply from production, and ends with demand being realized, markets cleared and goods allocated, thus creating the necessary conditions for production in the next period.[35] We assume intratemporal asymmetric information between producers and consumers and, hence, production schedules cannot be changed in response to demand shifts within h, but they can and will be adjusted between periods.

An overview of the model is presented in Figure 3.1. The intuition behind it is straightforward: producers determine the feasibility of their production schedules for the period, given the current availability of industrial inputs, capital and labor. Assuming non-substitutability between finished goods for intermediate and final consumptions, if the total schedule is not feasible, producers use a rationing rule to set how much to offer in each market in excess of any inventories from the previous period (Section 3.3.1). Therefore, final demand, influenced by reconstruction efforts, displacement, labor conditions and income, might be under- or over-supplied. Industries react to this supply-demand unbalance by adjusting their expectations for the next production cycle and by attempting to purchase the necessary level of inputs (Section 3.3.2). Because this interindustrial demand may also be under- or over-supplied, after markets clear, each sector determines a feasible production schedule for the upcoming period (Section 3.3.3). The stock losses of a disaster occur between periods, diminishing inputs, capital and displacing population, thus affecting production feasibility and demand level/composition for the next period.

[35] It follows from ten Raa (1986): all outputs for the period are assumed to form together at the end of h.

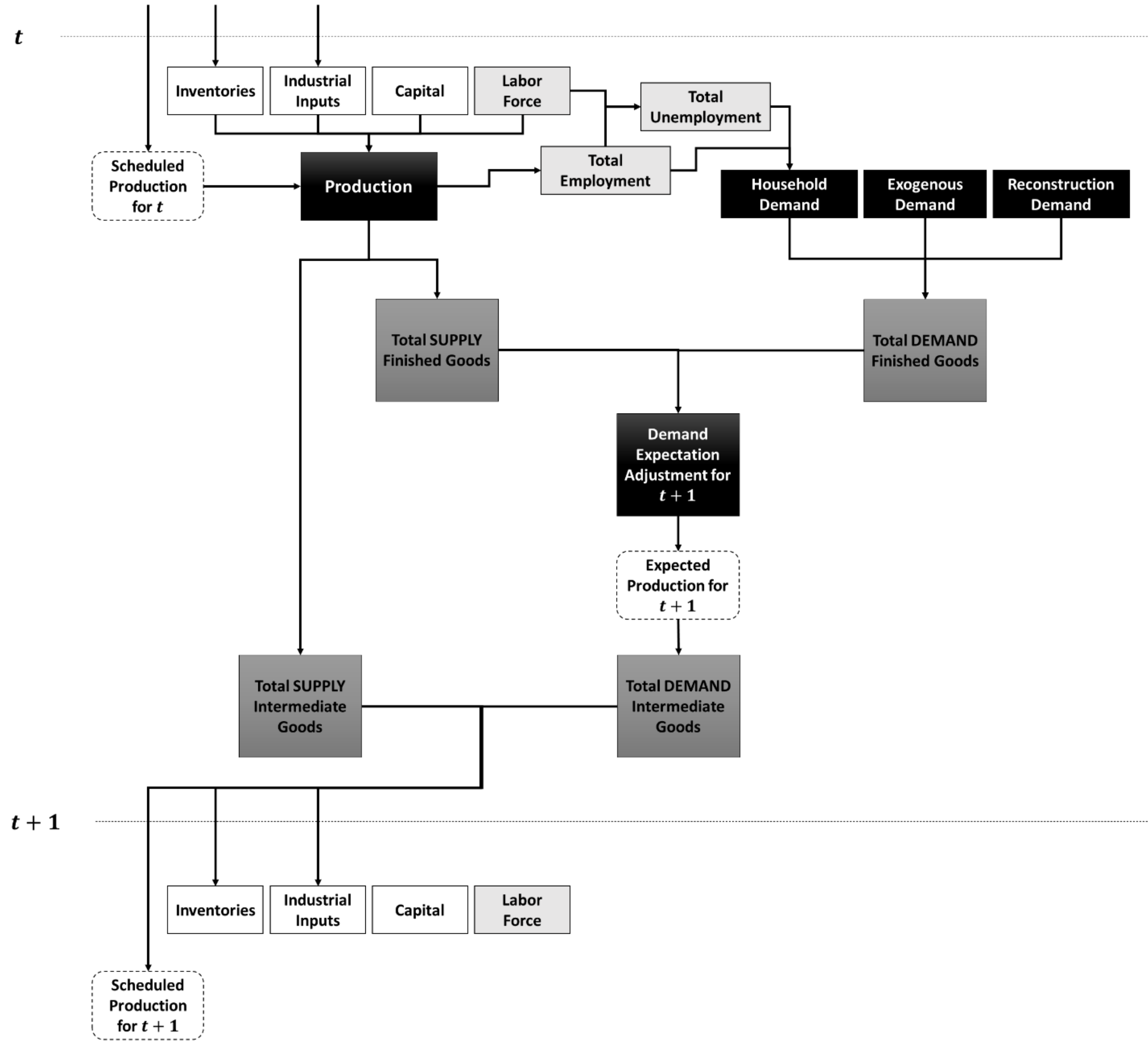


Figure 3.1: Overview of the Generalized Dynamic Input-Output Model (GDIO)

The generic formulation of the GDIO model is detailed in Figure 3.2,[36] so no specific functional forms are presented where there is flexibility (although examples are provided).

[36] The standard IO notation is used in this Chapter. Moreover, matrices are named in bold capital letters, vectors in bold lower-case letters (except inventories denoted by **I**) and scalars in italic lower-case letters. The Greek letter $\boldsymbol{\iota}$ (*iota*) denotes a unitary row vector of appropriate dimension. Finally, a hat sign over a vector indicates diagonalization, a prime sign transposition, $\times$ standard multiplication, and $\otimes$, $\oslash$ indicate element-wise multiplication and division respectively.

Assume an economy with n industries and T production periods of length h. An industry $\mu \in 1, \dots, n$ and time period $t \in 1, \dots, T$ are taken as reference points for expositional purposes.

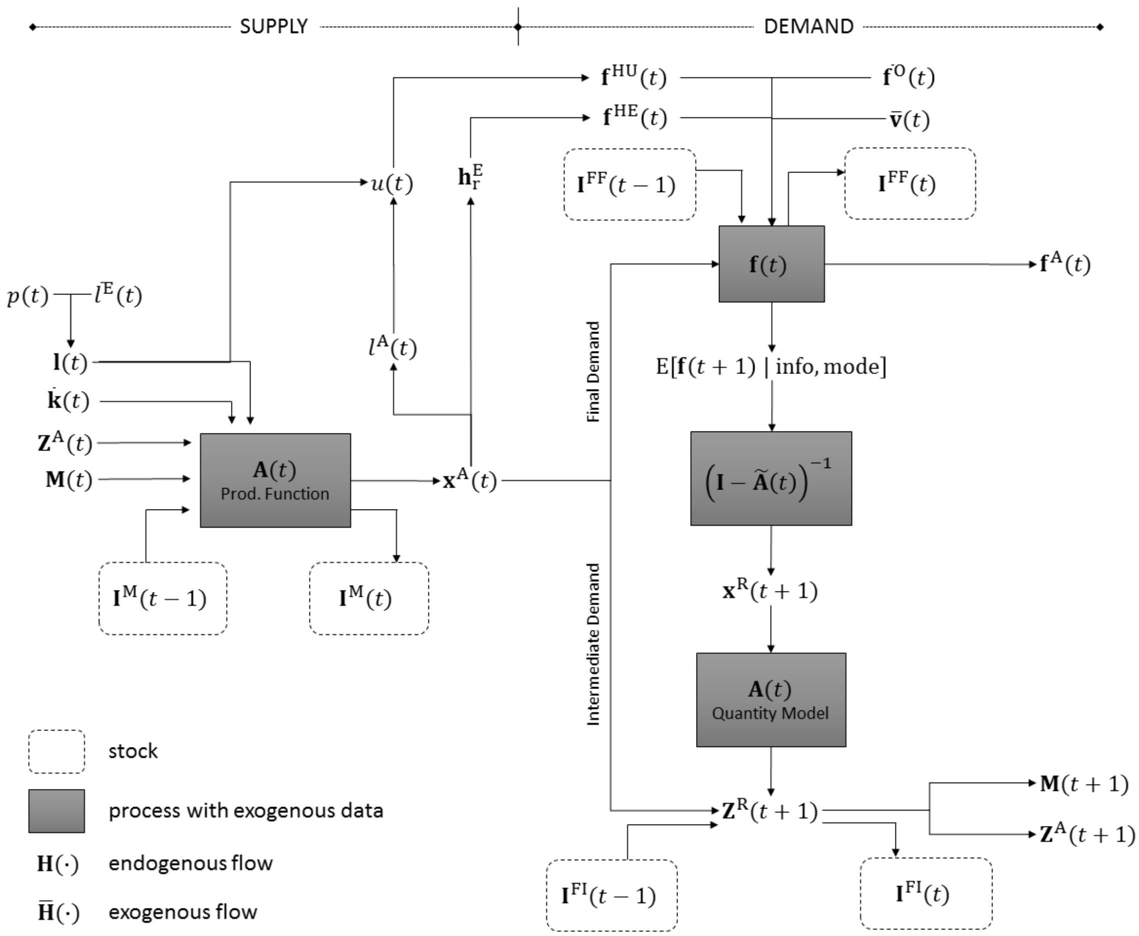


Figure 3.2: Detail view of the Generalized Dynamic Input-Output Model (GDIO)

3.3.1. Supply Side

It is imperative to distinguish between a local direct input requirement matrix ($\tilde{\mathbf{A}}$) and a proper technical coefficient matrix ($\mathbf{A}$), as the terminology has often been indiscriminately used in the literature. The former is derived from locally purchased inputs only, while the latter arises from *all* inputs required for production, both local and imported, thus reflecting the structure of a Leontief production function. Local direct input requirement matrices change when regional purchase coefficients (RPC) vary since $\widetilde{\mathbf{A}}(t) = \mathbf{RPC}(t) \otimes \mathbf{A}$, i.e., when there is a change in the share of domestic/external suppliers. This is quite frequently the case in disaster situations as local supply plunges. Conversely, technical coefficient tables are stable and may only change due to seasonality – if *intra-year tables* are used (Chapters 1 and 2) – or due to the adoption of alternative production technologies, the choice of which might depend on the availability of local supply.[37]

In contrast to traditional IO specifications, the Leontief production function is extended to include primary inputs (**l**) and assets/capital (**k**), besides industrial inputs (**Z**). This modification introduces supply constraints due to limited input availability, physical damage to capital or displacement of the workforce. Hence, production capacity in industry μ is given by available industrial inputs, and by the coefficients $\mathbf{a}_{\mu}^{\mathrm{L}}(t)$ and $\mathbf{a}_{\mu}^{\mathrm{K}}(t)$, which reflect primary inputs and assets requirements per unit of output respectively.[38]

Total available industrial inputs from industry i for production of industry μ at time t is the sum of locally purchased inputs ($\mathbf{Z}^{\mathrm{A}}$), imports ($\mathbf{M}^{\mathrm{I}}$) and *materials and supplies inventories* ($\mathbf{I}^{\mathrm{M}}$) from the previous period:[39]

$$\mathbf{Z}_{i\mu}^{\mathrm{T}}(t) = \mathbf{Z}_{i\mu}^{\mathrm{A}}(t) + \mathbf{M}_{i\mu}^{\mathrm{I}}(t) + \mathbf{I}_{i\mu}^{M}(t-1) \quad \forall i \tag{3.1}$$

Total labor supply $l^{T}(t)$ is determined endogenously as a fixed share τ of the current resident population $p(t)$, which in itself depends on total net migration ($\bar{n}(t)$) for the period, plus any external commuting labor $\bar{l}^{\mathrm{E}}(t)$.[40]

$$p(t) = p(t-1) - \bar{n}(t) \tag{3.2}$$

---

[37] Technology choice with constraints could be modeled using Duchin and Levine's (2011) framework.

[38] E.g., suppose an industry μ relies on a 10,000 sqft factory to produce \$10 million of output. Given the traditional linearity assumption, $\mathbf{a}_{\mu}^{\mathrm{K}}(t) = 10^3$ sqft/million \$. These coefficients change with the economic structure, i.e., due to seasonality, labor and capital requirements might change to accommodate different production functions.

[39] The inventory strategy in the GDIO is quite different from the Inv-ARIO model. The latter is based on the premise that all industries seek to maintain a target level of M&S inventories similar to "order-point systems" used in managing inventories prior to the 1970s (Ptak & Smith, 2011). The issue with such approach is that modern inventory management relies on "material requirement planning" systems that consider the full supply chain conditions when a firm re-orders inputs, not only its own inventory position (Ptak & Smith, 2011). In the GDIO, priority is given to attend demand in the post-disaster period, instead of rebuilding inventories.

[40] In a multiregional specification, external labor availability would be bounded by unemployed individuals in other regions. Also, if housing data is available, net migration can be endogenous: the amount of in- (out-)migration as a proportion φ of added (lost) residential squared footage in the previous period ($n(t) = \varphi * \Delta sqft^{\mathrm{RES}}(t-1)$).

$$l^{\mathrm{T}}(t) = \tau \times p(t) + \overline{l}^{\mathrm{E}}(t) \tag{3.3}$$

The labor supply can have different degrees of substitutability between industries depending on available information on skills, age, and/or education (Kim, Kratena, & Hewings, 2014; Kim & Hewings, 2018). In the simplest case, it can be assumed perfectly substitutable so that $\mathbf{l}(t) = l^{\mathrm{T}}(t) \times \mathbf{l}(0) \times (\boldsymbol{\iota} \times \mathbf{l}(0))^{-1}$.

Given available industrial inputs ($\mathbf{Z}^{\mathrm{T}}(t)$), primary inputs ($\mathbf{l}(t)$) and capital ($\mathbf{k}(t)$), industries produce in the current period following a Leontief production function, up to a total potential output $\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t)$:

$$\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t) \ = f(\mathbf{Z}^{\mathrm{T}}, \mathbf{l}, \mathbf{k}) = \min\left\{\frac{\mathbf{Z}_{1\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{1\mu}(t)}, \dots, \frac{\mathbf{Z}_{\mu\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{\mu\mu}(t)}, \dots, \frac{\mathbf{Z}_{n\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{L}}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{K}}(t)}\right\} \tag{3.4}$$

As aforementioned, the only reason for $\mathbf{A}_{ij}(t-1) \neq \mathbf{A}_{ij}(t)$ is a change in production technology. If regional purchase coefficients change from $t-1$ to t, they may not affect $\mathbf{A}_{ij}(t)$.

The actual total output $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ depends on the scheduled total output for the period $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$ (which is further discussed in Section 3.3.3) and any available *inventory of finished goods for intermediate demand* $\mathbf{I}_{\mu}^{\mathrm{FI}}$ from the last period (inventories of finished goods for final demand $\mathbf{I}_{\mu}^{\mathrm{FF}}$ were already embedded in $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$):

$$\mathbf{x}_{\mu}^{\mathrm{A}}(t) = \min\left\{\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t),\ \ \mathbf{x}_{\mu}^{\mathrm{S}}(t) \ - \mathbf{I}_{\mu}^{\mathrm{FI}}(t-1)\right\} \tag{3.5}$$

After production is completed, unused inputs enter the stock of *materials and supplies inventories* ($\mathbf{I}^{\mathrm{M}}$) at period t. We assume that imported inputs are used first in the production process and then local inputs are consumed.[41] In addition, note that $\mathbf{I}_{i\mu}^{\mathrm{M}}(t) \geq 0$, although $\Delta\mathbf{I}_{i\mu}^{\mathrm{M}}(t)$ can be either positive or negative:

$$\mathbf{I}_{i\mu}^{\mathrm{M}}(t) = \left[\mathbf{Z}_{i\mu}^{\mathrm{T}}(t)\right] - \left[\mathbf{A}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{A}}(t)\right] \quad \forall i \tag{3.6}$$

[41] In this way, there is no change in inventory for external industries.

3.3.2. Demand Side

On the demand side, a semi-exogenous final demand vector ($\mathbf{f}_{\mu}(t)$) and endogenous intermediate demands ($\mathbf{Z}^{\mathrm{R}}_{\mu j}(t)$) are locally supplied by $\mathbf{x}^{\mathrm{A}}_{\mu}(t)$ and any available *finished goods inventory*. We assume that there is non-substitutability between finished goods for final demand and finished goods for intermediate demand (analogous to the use of the Armington assumption for local versus imported goods in most CGE models), although there is perfect substitution of the latter among industries.[42] The amount of $\mathbf{x}^{\mathrm{A}}_{\mu}(t)$ destined for each type of demand is determined by the scheduled total output $\mathbf{x}^{\mathrm{S}}_{\mu}(t)$ and scheduled demands $\mathbf{Z}^{\mathrm{S}}_{\mu i}(t)\ \forall i$, $\mathbf{f}^{\mathrm{S}}_{\mu}(t)$ that were set when purchasing inputs in $t-1$. In the case when $\mathbf{x}^{\mathrm{S}}_{\mu}(t) \neq \mathbf{x}^{\mathrm{A}}_{\mu}(t)$, a rationing scheme $\mathbf{r}(t) \mid \sum_i \mathbf{r}_i(t) = 1$ must be applied (Bénassy, 2002). This scheme can reflect a uniform or proportional rationing, or an industrial prioritization, for example considering the production chronology in the sequential interindustry model and prioritizing supply to those flows closer to final demand (Li *et al.*, 2013; Hallegatte, 2014). Notice that it is still possible to model such imbalance between supply and demand in an IO framework as long as t is not too large, since prices may not be able to adjust rapidly. The rationing rule is constrained by:

$$\mathbf{x}^{\mathrm{A}}_{\mu}(t) = \sum_i \mathbf{Z}^{\mathrm{S}}_{\mu i}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{f}^{\mathrm{S}}_{\mu}(t) \times \mathbf{r}_{\mu}(t) \tag{3.7}$$

The composition and mix of final demand ($\mathbf{f}_{\mu}(t)$) are usually affected during the recovery period due to displacement of households, changes in income distribution, financial aid, government reconstruction expenditures and investment in capital formation. Most studies model final demand change exogenously with a recovery function that gradually returns it to the pre-disaster conditions (Okuyama *et al.*, 1999; Li *et al.*, 2013), and a few attempt to endogenize it in the core modeling framework by closing the system regarding households (Bočkarjova, 2007).

However, the simple endogenization of households to estimate induced effects implies strong assumptions: it assumes a linear homogeneous consumption function, i.e., there is a constant proportional transmission of changes in income to/from changes in consumption; that

[42] Thus the existence of two types of finished goods inventories: $\mathbf{I}^{\mathrm{FF}}_{\mu}(t)$ and $\mathbf{I}^{\mathrm{FI}}_{\mu}(t)$ respectively.

all employed individuals have the same wage and consumption pattern (consumption of unemployed individuals is exogenous); and it ignores the source of new workers (Batey & Weeks, 1989; Batey, Bazzazan, & Madden, 2001). Of particular interest for disaster analysis is the fact that Type II multipliers artificially inflate induced effects by excluding the expenditure of workers who are unemployed in the region. As highlighted in Batey (2018), when the consumption of unemployed individuals is ignored, any change in labor requirements results in a significant change in the level of final demand as new hires suddenly "enter" the local economy. Thus, in negative growth scenarios this technique overstates the impact of the regional decline. Further, there is the additional problem, noted by Okuyama *et al.* (1999), that households may delay purchases of durable goods in the aftermath of an unexpected event, confining expenditures to immediate needs (necessity goods).

A way to mitigate these issues is to build upon the demo-economic framework that has been developed in the last thirty years. These integrated (demographic) models attempt to relax some of the previous assumptions by explicitly considering indigenous and in-migrant wages and consumption responses, as well as unemployment, social security benefits and contractual heterogeneity (van Dijk & Oosterhaven, 1986; Madden, 1993).

The demo-economic framework will be used to capture part of the change in level/mix post-disaster and its implication in terms of induced effects. We focus on the impact of displacement, unemployment, and shifts in income distribution and expenditure patterns between households within the final demand. The other components of final demand are still considered to be exogenous ($\bar{\mathbf{f}}^{\mathrm{O}}$) and reconstruction demand is treated as an external shock ($\bar{\mathbf{v}}$).[43] We build upon a simplified version of Model IV proposed in Batey and Weeks (1989), by aggregating the intensive and extensive margins (see Equation D.1 in the Appendix).[44]

Therefore, once the actual total output of industry ($\mathbf{x}^{\mathrm{A}}$) is determined, the model estimates total employment for the period ($l^{\mathrm{A}}(t)$) using Equation 3.8, and the total final demand

[43] In many Regional Econometric IO models, state and local government expenditures are assumed to be endogenous with the revenues coming from a variety of direct and indirect taxes. After an unexpected event, this relationship might be uncoupled as disaster relief, funded by the federal government, pours into the region. Further, the allocation of these funds is likely to be different from the "average" portfolio of state and local government expenditures.

[44] We use this simplified version for expositional purposes only. Empirical applications should include a further demographic disaggregation, considering the number of individuals displaced and the expenditure pattern change of those rebuilding.

from employed *residents* ($\mathbf{f}^{\mathrm{HE}}(t)$) using Equation 3.9. Total unemployment determines the amount of final demand for these households ($\mathbf{f}^{\mathrm{HU}}(t)$) according to Equation 3.10.

$$l^{\mathrm{A}}(t) = \mathbf{a}^{\mathrm{L}} \times \widehat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) \tag{3.8}$$

$$\mathbf{f}^{\mathrm{HE}}(t) = \mathbf{h}_{\mathrm{c}}^{\mathrm{E}} \times (\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} \times \widehat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) + f_{\mathrm{H}}(t)) \tag{3.9}$$

$$\mathbf{f}^{\mathrm{HU}}(t) = s \times \mathbf{h}_{\mathrm{r}}^{\mathrm{U}} \times \left(l^{\mathrm{T}}(t) - l^{\mathrm{A}}(t)\right) \tag{3.10}$$

Total final demand for the period ($\mathbf{f}(t)$) is estimated by combining *resident* households' expenditures, other final demand components (exogenous) and reconstruction stimulus (exogenous).

$$\mathbf{f}(t) = \mathbf{f}^{\mathrm{HE}}(t) + \mathbf{f}^{\mathrm{HU}}(t) + \bar{\mathbf{f}}^{\mathrm{O}}(t) + \bar{\mathbf{v}}(t) \tag{3.11}$$

Given this semi-exogenous final demand, the actual demand supplied locally ($\mathbf{f}_{\mu}^{\mathrm{A}}(t)$) depends on finished goods produced in the period and any inventory from the previous period:

$$\mathbf{f}_{\mu}^{\mathrm{A}}(t) = \min\left(\mathbf{f}_{\mu}(t)\,, \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1)\right) \tag{3.12}$$

In the case where local supply is insufficient for final demand, imports ($\mathbf{m}^{\mathrm{FD}}$) are required. The amount of available imports can be exogenously imposed in a single region setting, or it can be endogenized in a multiregional setting, where firms produce to satisfy both local and external final demand. In the latter case, spatio-temporal disruption spillover effects can be assessed. Availability can also be linked to *accessibility* through an additional transportation model (Sohn, Hewings, Kim, Lee, & Jang, 2004).[45] In our single region exposition, we assume an external import constraint $\mathbf{T}_{\mu}^{\mathrm{FD}}(t)$ that determines how much trade

[45] Such extension is not included in the model's exposition. Moreover, accessibility could also consider commuting to/from the region, constraining available labor force.

flexibility there is in terms of finished goods for final demand consumption in the external industry μ.[46]

$$\mathbf{m}_{\mu}^{\mathrm{FD}}(t) = \min\left(\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t), \mathbf{T}_{\mu}^{\mathrm{FD}}(t)\right) \tag{3.13}$$

Sectors that can hold finished goods inventories[47] update their stocks:

$$\mathbf{I}_{\mu}^{\mathrm{FF}}(t) = \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) \tag{3.14}$$

Next, industries form expectations regarding final demand in the following period in order to purchase the required inputs at t. Industries do so by means of an expectation function $\mathrm{E}\left[\mathbf{f}_{\mu}(t+1)|\ \mathrm{info}\right]$, whose form is to be defined by the modeler, and may include an inventory strategy that varies according to the uncertainty in the system.[48] At this point, the GDIO intersects with the SIM, allowing sectors to behave as anticipatory, responsive or just-in-time (JIT). Anticipatory industries forecast final demand and, thus, their expectation function may or may not match the actual final demand in the next period. Just-in-time industries are a particular case which $\mathrm{E}\left[\mathbf{f}_{\mu}(t+1)\ |\ \mathrm{info}, \mathrm{JIT}\right] = \mathbf{f}_{\mu}(t+1)$, because they produce according to actual demand next period. Finally, responsive industries react to orders placed in previous periods (for a discussion on this terminology see Romanoff & Levine, 1981).[49]

The required output for $t+1$ ($\mathbf{x}^{\mathrm{R}}(t+1)$) is determined by its expected final demand via the Leontief model (Equation 3.15). After accounting for any labor or capital constraints (Equation 3.16), and any available materials and supplies inventory, industries determine the

[46] In case there is an upper bound to imports, final demand not supplied in some sectors can be accumulated to next period (e.g., construction demand), reflecting a backlog in orders: $\bar{\mathbf{f}}^{\mathrm{O}}(t+1) = \bar{\mathbf{f}}^{\mathrm{O}}(t+1) + [\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) - \mathbf{m}_{\mu}^{\mathrm{FD}}(t)]$.

[47] See Section 3.3.6 for notes on inventories.

[48] Such strategy could be included either as a deterministic (see Hallegate, 2014) or a stochastic component.

[49] An example of a SIM formulation with a simple inventory formation mechanism sensitive to the uncertainty in the system is:

$$\mathrm{E}\left[\mathbf{f}_{\mu}(t+1)|\ \mathrm{info}, \mathrm{mode}\right] = \begin{cases} \mathbf{f}_{\mu}(t) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if anticipatory} \\ \mathbf{f}_{\mu}(t+1) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if just in time} \\ \mathbf{f}_{\mu}(t-1) + \sigma \times \left[\mathbf{f}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t)\right], \text{if responsive} \end{cases}$$

where the adjustment parameter σ reflects the reaction of the sectors to such uncertainty. Therefore, we relax the assumption of perfect knowledge for production scheduling, a critique raised by Mules (1983) on the original SIM.

total intermediate input requirements in the period $\mathbf{Z}_{i\mu}^{\mathrm{R}}(t)$ (that includes both local and imported goods) (Equation 3.17).[50]

$$\mathbf{x}^{\mathrm{R}}(t+1) = \left(\mathbf{I} - \widetilde{\mathbf{A}}(t)\right)^{-1} [\mathrm{E}[\mathbf{f}(t+1) \mid \mathrm{info}, \mathrm{mode}] - \mathbf{I}^{\mathrm{FF}}(t)] \tag{3.15}$$

$$\mathbf{x}_{\mu}^{\mathrm{R}}(t+1) = \min\left(\mathbf{x}_{\mu}^{\mathrm{R}}(t+1), \mathbf{l}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{L}}(t+1), \mathbf{k}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{K}}(t+1)\right) \tag{3.16}$$

$$\Longrightarrow \quad \mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1) = \mathbf{A}_{i\mu}(t+1) \times \mathbf{x}_{\mu}^{\mathrm{R}}(t+1) - \mathbf{I}_{i\mu}^{\mathrm{M}}(t) \quad \forall i \tag{3.17}$$

Each industry then attempts to purchase its required inputs from other industries in the economy. Input supply of industry i to industry μ depends on the scheduled production, on any imposed rationing scheme, and on inventory of finished goods for intermediate demand of i. Since there is perfect substitutability of finished goods for intermediate demand among sectors, an inventory distribution scheme $\mathbf{d}(t)$ is required to allocate any available inventories between industries that are undersupplied. In its simplest form, this scheme may distribute equally within those demands that exceed current supply, or it can prioritize certain industries. The actual amount of inputs purchased locally is given by:

$$\mathbf{Z}_{i\mu}^{\mathrm{A}}(t+1) = \min\left(\mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1), \mathbf{Z}_{i\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{i}(t) + \mathbf{I}_{i}^{\mathrm{FI}}(t-1) \times \mathbf{d}_{i}(t)\right) \quad \forall i \tag{3.18}$$

In case local supply is insufficient for intermediate demand, imports are required. Besides possible trade constraints, for consistency we need to account for the production modes of external industries. In this single region exposition, the lag in production for anticipatory industries and foreign inventories is embedded in the constraint $\mathbf{T}_{i\mu}^{\mathrm{I}}(t)$ that provides import flexibility.[51] In a multiregional framework, external adjustments are explicitly modeled in the other region.

$$\mathbf{m}_{i\mu}^{\mathrm{I}}(t+1) = \min\left(\mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1) - \mathbf{Z}_{i\mu}^{\mathrm{A}}(t+1), \mathbf{T}_{i\mu}^{\mathrm{I}}(t)\right) \quad \forall i \tag{3.19}$$

[50] If an industry is just-in-time, for the model to be consistent with perfect foresight under discretization, labor and capital availability in Equation 3.16 would be indexed $t+1$.

[51] This constraint can be endogenized. A simple example would be a logistic function $\mathbf{T}_{i\mu}^{\mathrm{I}}(t) = f(\alpha, k) = \left(\alpha_i \times \mathbf{M}_{i\mu}^{\mathrm{I}}(0)\right)/\left(1 + e_i^{-k_i t}\right)$, where α_i indicates the amount of underutilized external capacity and k_i an industry specific speed of production increase. $\mathbf{T}_{i\mu}^{\mathrm{I}}(t)$ can also be a constant number that represents external inventories.

Inventories of finished goods for intermediate demand are updated, allowing free disposal for industries that cannot hold inventories:

$$\mathbf{I}_{\mu}^{\mathrm{FI}}(t) = \begin{cases} \sum_j \mathbf{Z}_{\mu j}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FI}}(t-1) - \sum_j \mathbf{Z}_{\mu j}^{\mathrm{A}}(t+1) \ , & \text{if } \mu \text{ can hold inventories} \\ 0 \ , & \text{o.w.} \end{cases} \tag{3.20}$$

3.3.3. Production Scheduling for the Next Period

Finally, given the amount of inputs effectively purchased, industries determine the production schedule for the next period:[52]

$$\mathbf{x}_{\mu}^{\mathrm{S}}(t+1) = \min\left\{\frac{\mathbf{Z}_{1\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{1\mu}(t)}, \dots, \frac{\mathbf{Z}_{\mu\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{\mu\mu}(t)}, \dots, \frac{\mathbf{Z}_{n\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{L}}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{K}}(t)}\right\} \tag{3.21}$$

$$\mathbf{Z}_{i\mu}^{\mathrm{S}}(t+1) = \widetilde{\mathbf{A}}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{S}}(t+1) \quad \forall i \tag{3.22}$$

$$\bar{\mathbf{f}}_{\mu}^{\mathrm{S}}(t+1) = \min\left(\mathrm{E}[\mathbf{f}(t+1) \mid \text{info, mode}],\ \mathbf{x}_{\mu}^{\mathrm{S}}(t+1) - \sum_j \mathbf{Z}_{\mu j}^{\mathrm{S}}(t+1) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t)\right) \tag{3.23}$$

Equations 3.21-3.23 create the necessary conditions for production in the next period. Note that the disaster significantly impacts anticipatory industries, since they base decisions about the level of future production on previous final demands. Inventories, thus, have an essential role in smoothing production mismatches due to asymmetric information.

Regional purchase coefficients for the period are, therefore, implicitly determined as a function of local supply capacity (see Section 3.3.5). The assumption of price stability is adequate in disruptions arising from unexpected events, as prices are slower to adjust. Also, if the analysis is performed in a small region, the assumption of price taking can be effective.

[52] See footnote 49 regarding the time indexes for JIT industries.

3.3.4. Solution Procedure

Recall that the SIM assumes that, in any period, JIT and responsive industries have perfect information on current and future final demands. If we assumed complete exogeneity of the latter, this requirement is easily satisfied and the model could be solved sequentially. With the demo-economic extension, however, households' final demand is endogenous and an iterative correcting approach is necessary. The SIM assumption is satisfied by reiterating periods in which the expected final demand and the actual final demand differ for responsive and JIT industries. For instance, at the first iteration of period t, expected final demand for these industries is set to a *prior* (the pre-disaster household's final demand) in Equation 3.15 and the model is solved until $\mathbf{f}(t+1)$ is calculated via Equation 3.11. If there is a mismatch between $\mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, JIT or Responsive}\right]$ and $\mathbf{f}_{\mu}(t+1)$ for $\forall \mu \mid \text{JIT or Responsive}$, the *prior* is updated according to the convex adjustment function:

$$\mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, J or R}\right] = \begin{cases} (1+(\Delta(t+1)\times 100)^{\varepsilon}/100) * \mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, J or R}\right] & \text{if } \Delta(t+1) > 0 \\ (1-(-\Delta(t+1)\times 100)^{\varepsilon}/100) * \mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, J or R}\right] & \text{if } \Delta(t+1) < 0 \end{cases} \quad (3.24)$$

where $\Delta(t+1) = \left(\mathbf{f}(t+1) / \mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, J or R}\right]\right) - 1$ and $\varepsilon = 0.9$ is the adjustment elasticity.[53] The current process halts and period t is reiterated with the adjusted *prior*. Period $t+1$ is finally allowed to proceed when $\mathrm{E}\left[\mathbf{f}_{\mu}(t+1) \mid \text{info, JIT or Resposive}\right] = \mathbf{f}_{\mu}(t+1)$.[54]

3.3.5. Recovering the Input-Output Table for the Period

An IO table reflecting actual flows can be extracted for each period according to Figure 3.3. Most of the vectors are determined directly from the previous equations. Interindustrial flows are determined by $\mathbf{Z}(t) = \left(\mathbf{A}(t) \times \hat{\mathbf{x}}^{\mathrm{A}}(t)\right) - \mathbf{M}^{\mathrm{I}}(t)$, since imported inputs are consumed first. Hence, total change in inventories is derived as:

[53] By letting $\varepsilon < 1$, the adjustment portrayed in Equation 3.24 becomes non-linear, implying a smoother convergence correction so that each iteration allows some error room for adjustment in the next round.
[54] In case of responsive industries with forward lags > 1, the algorithm requires reiterating previous periods when the forward lag is reached.

$$\Delta\mathbf{I}(t) = \{[\mathbf{Z}(t+1) + \mathbf{I}^{\mathrm{M}}(t)] \times \boldsymbol{\iota} + \mathbf{I}^{\mathrm{FI}}(t) + \mathbf{I}^{\mathrm{FF}}(t)\} \\ - \{[\mathbf{Z}(t) + \mathbf{I}^{\mathrm{M}}(t-1)] \times \boldsymbol{\iota} + \mathbf{I}^{\mathrm{FI}}(t-1) + \mathbf{I}^{\mathrm{FF}}(t-1)\} \tag{3.25}$$

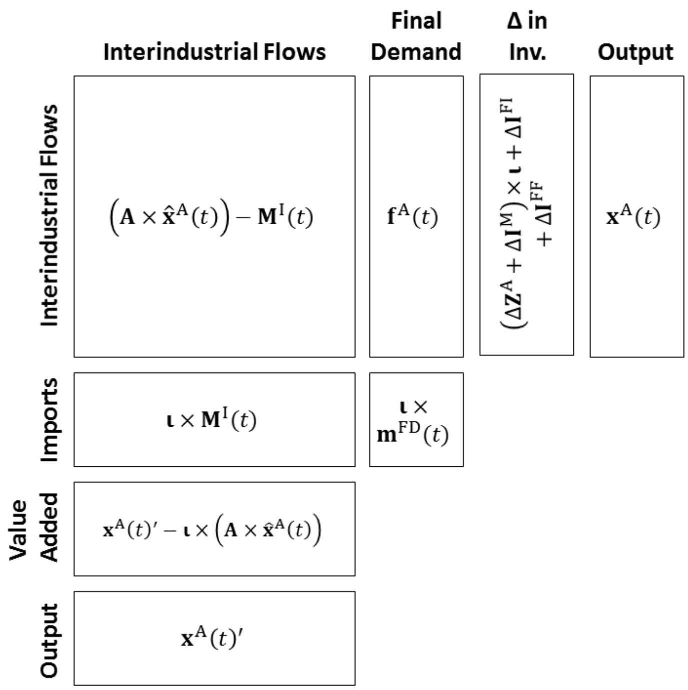


Figure 3.3: Extracted input-output table for period t

3.3.6. A Note on Inventories

First, recall that we assumed that besides relative prices, nominal prices do not change intertemporally. If they did, it would be necessary to account for holding gains/losses in inventories from period to period. Second, service sectors are assumed not to hold any finished goods inventory. It could be argued that they hold work-in-progress inventories (in case of consulting, entertainment, etc.), but it is assumed that these can be compartmentalized and produced in each time period. Unless h is very short (say, a day), one would expect finished services to be delivered in each time period.

Finally, the concept of partitioning transactions adopted in the System of National Accounts (which directly translates to the definition of distribution sectors – retail, wholesale and transportation – in the IO framework) needs to be accounted for when defining inventories. Transactions of retailers, wholesalers and transportation are recorded as their respective margins and, thus, represent services provided and not goods sold *per se* (United Nations, 2009). They do not hold any finished goods inventory, and material and supplies inventories consist only of operating expenses (rent, electricity, packaging, etc.) without purchases for resale.

3.4. Application Example

We illustrate the GDIO with a 3-sector example for a small economy. The pre-disaster IO table for the region is presented in Figure 3.4 and its parametrization in Tables 3.1 and 3.2. The model runs for 36 periods and we assume an unexpected event in period 13, when 15% of manufacturing becomes inoperable. There is no population displacement. Recovery happens during the subsequent 5 periods (Table 3.2). In this example, we compare the effects of trade restrictions to losses in the region, simulating a fully flexible scenario and a restricted one. These import constraints are implemented using the amount of foreign inventories / external available capacity at each period as proxies ($\theta = 100$ and $\theta = 1.5$ respectively).[55]

					Final Demand			
		Agriculture	Manufacturing	Services	Employed	Unemployed	Exports	Output
	Agriculture	5,129	27,147	788	13,107	713	5,917	52,801
	Manufacturing	9,192	121,491	38,735	127,063	3,959	42,109	342,549
	Services	3,084	44,835	76,574	233,534	4,043	13,367	375,436
Imports	Agriculture	387	2,459	743	1,724	57	-	
Imports	Manufacturing	967	7,378	5,940	7,760	257	-	
Imports	Services	580	14,757	743	7,760	257	-	
	Taxes	1,632	16,353	12,535	24,527	1,180	4,067	
	Value Added (Labor)	31,831	108,130	239,378				
	Output	52,801	342,549	375,436				
	Employment	4,906	3,700	11,905				
	Area (thousand sqft)	817	812	823				

Figure 3.4: Pre-disaster IO table, flow values in thousands of dollars

[55] The code and data for this example are available upon request.

Table 3.1: Regional characteristics

Variable	Description	Value
τ	Labor force participation rate	0.60
σ	Expectations' adjustment parameter	0.05
σ^{M}	Foreign sectors expectations' adjustment parameter	0.01
ε	Error allowed for JIT and responsive industries	0.01
p	Resident population	40,000
$\bar{l}^{\mathrm{E}}$	External labor force available	1,000
s	Unemployment benefits per period	$3,000

Table 3.2: Industrial characteristics

	Agriculture	**Manufacturing**	**Services**
Production Mode	Long Anticipatory (2 months)	Short Anticipatory (1 month)	Just-in-Time
Hold Inventories	Yes	Yes	No
ρ	0.99	0.98	0.98
Wages (per period)	$ 6,488	$ 29,224	$ 20,107
Capital Inoperability	0%	15%	0%
Capital Recovery Time	-	5	-

Figures 3.5-3.7 compare the results of both scenarios. Overall, under full trade flexibility, production losses are lower and recovery occurs faster than in the second scenario, since imports mitigate part of the supply restrictions in the economy. The model illustrates the major role that inventories and uncertainty have on losses and, especially, on their duration.

The initial periods post-disaster follow a similar pattern in both scenarios: first, manufacturing production declines due to capacity constraints, causing a reduction in local income (due to layoffs) and a subsequent small impact on Services. Agriculture maintains the same level of production since it is anticipatory, thus overproducing and building up inventories. In the next period, a substantial decline is observed in all sectors due to supply constraints from manufacturing (indirect effects), available inventories in Agriculture, and lower final demand. Lower outputs also translate into increasing unemployment in the region, shifting the final demand mix towards less services and more agricultural goods.

Capacity restoration, expectation adjustments and enough inventories of intermediate goods allow a reduction in losses in periods 15-16, during which most of the inventory created in the previous two periods is consumed. The depletion of inventories, however, leads to insufficient intermediate local supply to support production from the service sector in the next period (when capacity is almost fully restored in the manufacturing sector). The negative impact in Services is exacerbated by the increase in unemployed residents who spend a significantly smaller share of their income than employed residents in this sector. As the most labor-intensive sector in the economy, this leads to a negative inertial effect that exacerbates output losses until period 17. The two scenarios diverge from this point forward. The flexibility in trade in the first scenario, combined with the recovery experienced by Agriculture and Manufacturing, allows the Service sector to overcome local input supply restrictions and break its inertial effect, rebounding in the next periods. Conversely, trade restrictions in the second scenario slow such adjustment, especially for anticipatory industries in which supply-demand unbalances increase the uncertainty in the economy, compromising their expectations' correction. This longer realignment process permeates the system for several periods, feeding the negative inertial effect in Services, expanding unemployment and reducing final demand. In time, inventory and final demand heteroscedasticity decline, allowing the economy to rebound.

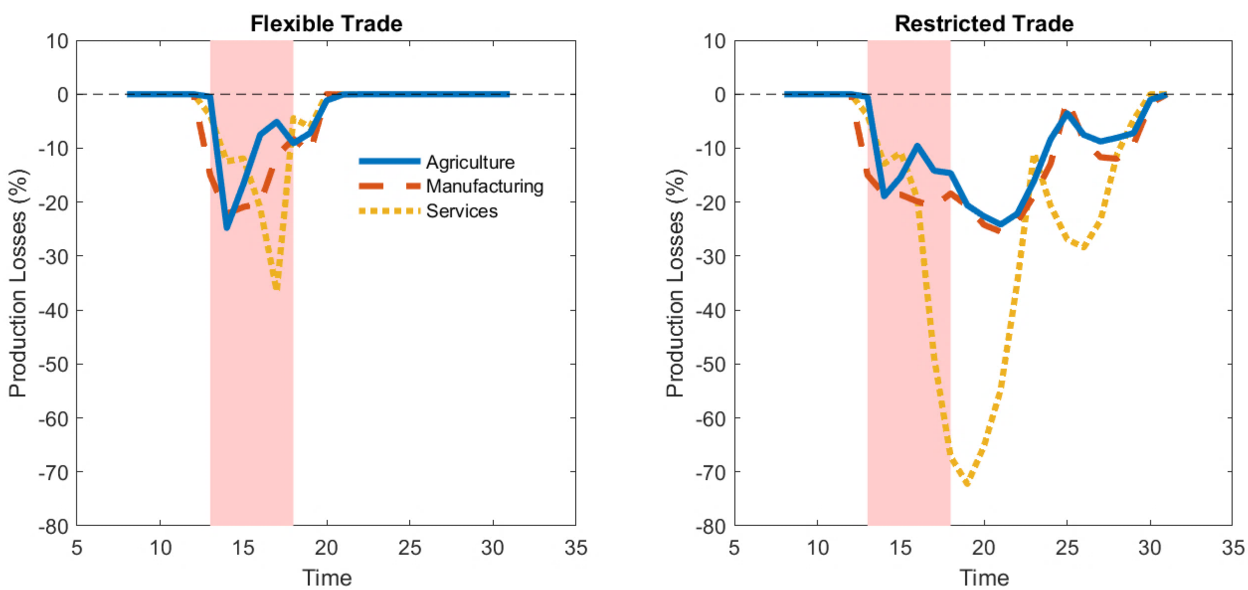


Figure 3.5: Production losses by industry

Services is the most sensitive sector in this example due to 2/3 of its output being consumed by the local final demand. Hence, changes in the composition and volume of household's demand have a crucial role in the dynamics of this sector.

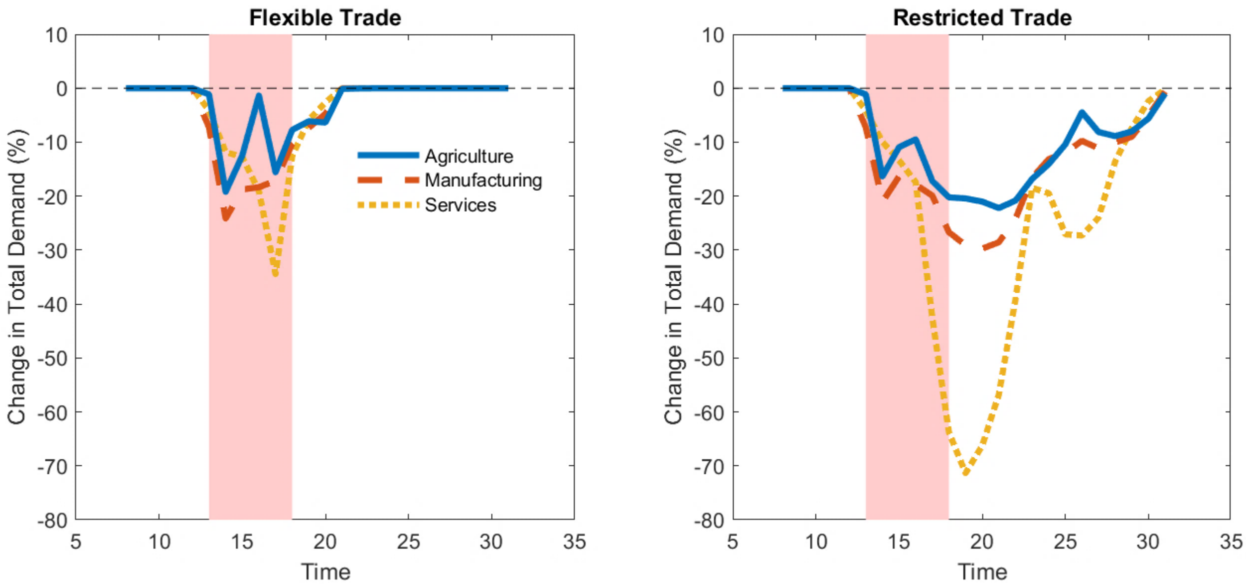


Figure 3.6: Evolution of total demand (intermediate + final) by industry

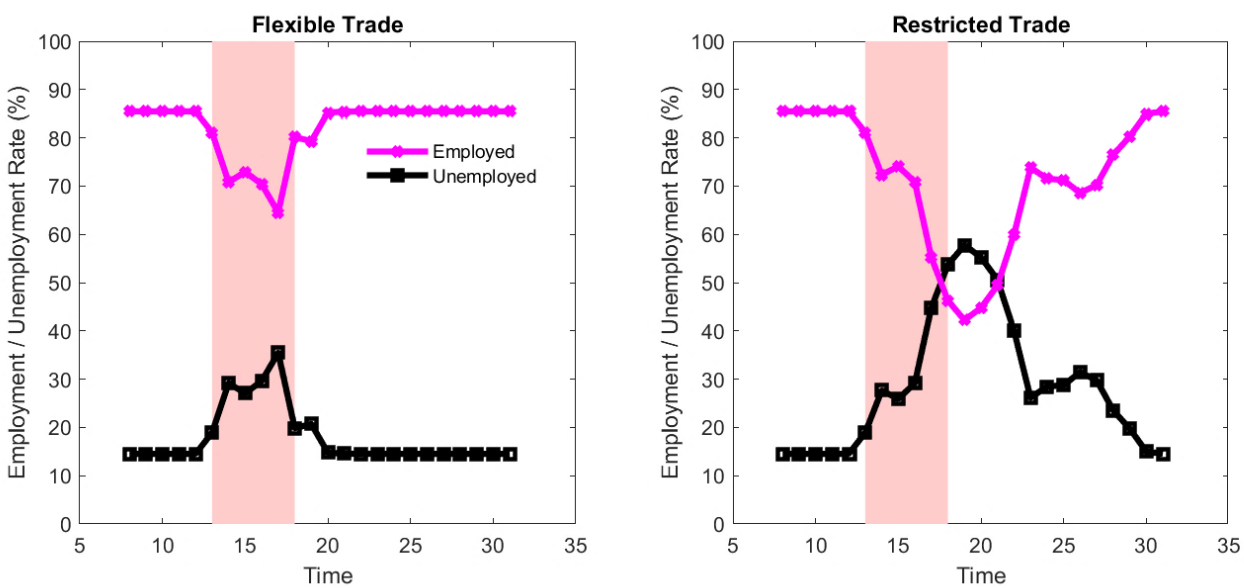


Figure 3.7: Evolution of demographic indicators

By embedding intertemporal expectation adjustments via the SIM, and the demo-economic framework, this model reflects a non-smooth recovery process in contrast to other models currently available. We compare our estimates in the "flexible trade" scenario with four commonly used single-region models in the literature: the traditional Leontief model, a simplified version of Cochrane's rebalancing model, the Inventory-DIIM, and the Inventory-ARIO model (see Table D.1 in the Appendix for details on their specifications. Induced effects are not considered).

Overall, the recovery curve is monotonic increasing and similarly smooth across all models (Figure 3.8). Since there is no change in demand composition nor heterogeneous production chronology, the recovery path is very homogeneous between sectors, which is in clear contrast with Figure 3.5, in which the SIM framework, combined with the explicit consideration of labor market changes, influences the amount and timing of impacts. Moreover, by not considering labor market conditions and their effect on final demand, Services is the least impacted sector in these models. The simulations shown in Figure 3.8 do not consider induced effects, however, which may partially explain the smaller total losses in relation to our model.

Because of their static formulations, both the Leontief and rebalancing models have no disruption spillovers beyond the 5-period recovery time for Manufacturing. Since each period's inoperability is contained within itself, the resulting recovery path is completely dependent on the exogenous recovery timing imposed, and therefore linear. The rebalancing model shows larger losses than the Leontief model, as it captures part of the forward effects besides backward impacts.

Conversely, both dynamic models portrayed in the bottom of Figure 3.8 account for intertemporal inoperability, resulting in longer recovery paths. In the Inventory-DIIM, the restoration pace is endogenously determined by the size of unbalance between supply-demand in each period, as well as the resilience and repair coefficient of the sectors. The Inventory-ARIO model operates in a somewhat similar fashion as the GDIO, however without considering final demand mix changes nor different types of production modes. It is the model that generates the closest amount of total losses to ours[56], although it overestimates them by 18.8% mainly because the GDIO corrects the induced effect for unemployed households.

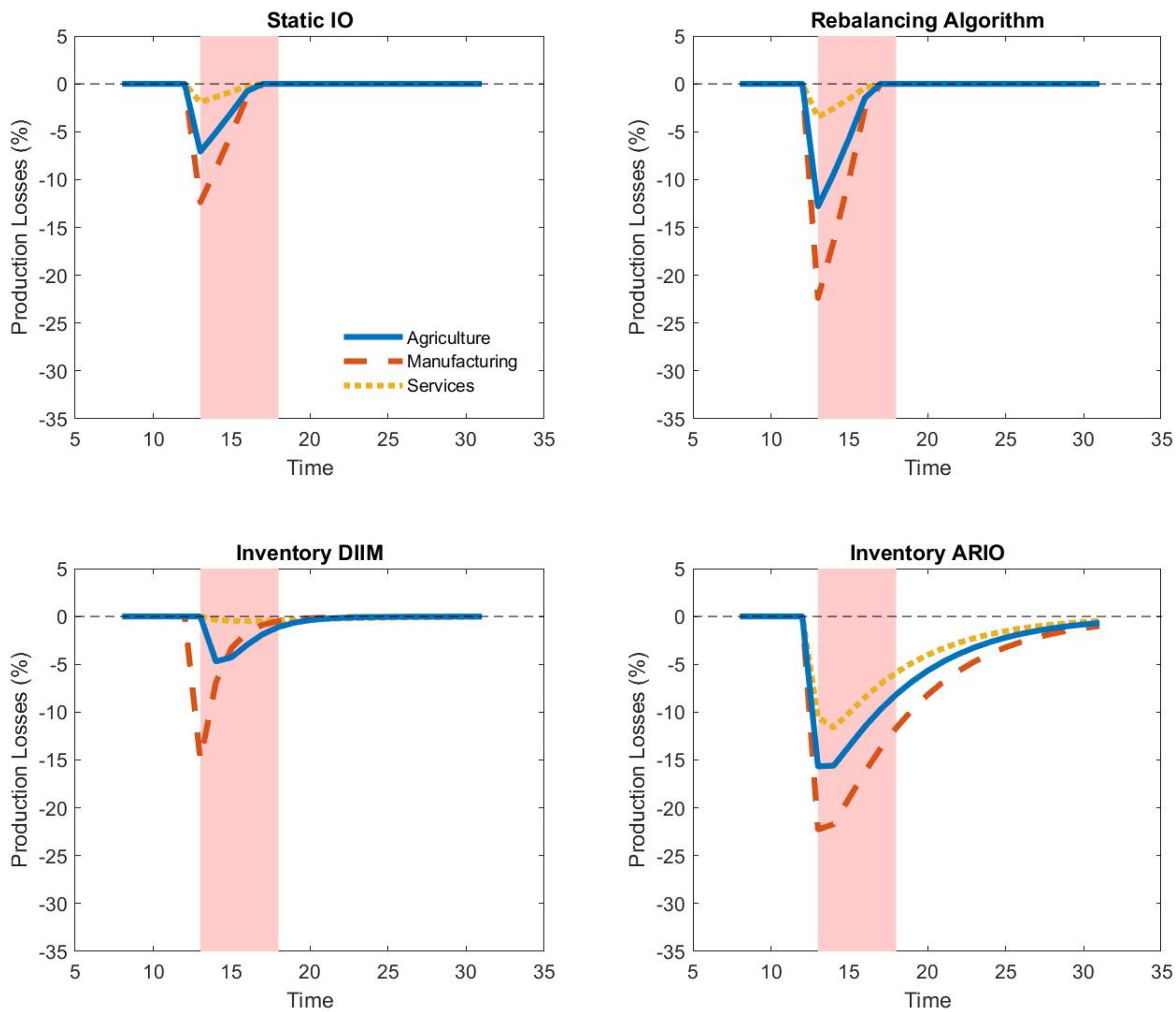


Figure 3.8: Production losses and final demand, other models

3.5. Conclusions

Disaster events present unique challenges to economic assessment due to its time-compression characteristic, i.e., a non-marginal negative shock followed by simultaneous and

[56] Total losses from the other models amount to 15.5% (Leontief), 28.6% (rebalancing) and 16.2% (Inv-DIIM) of the total estimates for the GDIO.

intense recovery efforts in the affected areas. Due to modern "lean" production systems with high specialization, little spare capacity (to exploit scale economies), and longer production chains, disruptions and subsequent production delays in one node of a network can quickly spread to other chains and create lingering disruptive effects. Thus, there is a need to assess these transient phenomena in an industrial network perspective, accounting for the spatio-temporal spillovers within and between affected and unaffected regions.

Modeling such industrial linkages' interdependence has been the main advantage of the IO framework, especially due to its relatively low data requirements, tractability and connectivity to external models. Given the simplicity and inadequacy of some of the assumptions in the traditional Leontief demand-driven model, several extensions have been proposed to address issues of supply constraints, dynamics and spatio-temporal limitations, but these contributions are still fragmentation in different models.

In a step towards a more complete methodology, this Chapter proposes the GDIO model. It combines insights from the past literature, building upon the Inventory-ARIO model, while also accounting for production scheduling, seasonality and demographic changes in a single framework. The GDIO, thus, encompasses the virtues of intertemporal dynamic models with the explicit intratemporal modeling of production and market clearing, which allows for supply and demand constraints to be simultaneously analyzed. The key roles of inventories, expectation adjustments, timing of the event, displacement, primary inputs and physical assets are addressed. Seasonality can be included by using *intra-year* IO tables that can be derived via the T-EURO method proposed in Chapter 1 or by the maximum entropy solution proposed in Chapter 2. Through a demo-economic extension, we include induced effects post-disaster, accounting for level and mix changes in labor force and household income/expenditure patterns. The GDIO is "general" in the sense that simpler models as the Leontief formulation, SIM and demo-economic models can be easily derived by using simplifying assumptions. The model also allows for the extraction of balanced IO tables at each time step, which might be advantageous in optimizing recovery efforts.

Despite these advances in modeling disaster events, the current version of the GDIO has several limitations. We are still restricted to assessing short-term effects, as in the long-term the underlying socio-economic structure might exhibit significant changes (e.g., New Orleans after

Hurricane Katrina (The Data Center, 2015)). The model also does not consider the impact of business cycles, when excess capacity might be extremely reduced (Hallegatte & Ghil, 2008), nor does it endogenize the recovery process according to local conditions in each period (the recovery schedule is exogenously imposed). Related to the latter, although we account for the impact of labor force availability in the region, this constraint needs to be modeled exogenously accounting for accessibility and housing stock. Moreover, additional mitigation strategies beyond inventories need to be implemented in future developments of the GDIO, as those suggested by Rose and Wei (2013).

A simple application showed the advantage of the GDIO in capturing the impact of uncertainty in the recovery process, through intertemporal expectation adjustments that are affected by heteroscedasticity in inventory levels and final demand (endogenous in our model). The new system offers a more natural recovery curve in which breaks in the recovery process are common. Further research will be needed, especially for an application of the model in a real natural disaster situation in a multi-region context with seasonal IO tables, and where comparison of the results with existing methodologies can be made.

CHAPTER 4: COMPARING THE ECONOMIC IMPACT OF NATURAL DISASTERS GENERATED BY DIFFERENT INPUT-OUTPUT MODELS: AN APPLICATION TO THE 2007 CHEHALIS RIVER FLOOD (WA)[57]

4.1. Introduction

Major disaster databases (Emergency Events Database (EM-DAT), Natural Hazards Assessment Network (NATHAN), Spatial Hazard Events, and Losses Database for the United States (SHELDUS)) tend to compile information only on *stock damages*, i.e. damages to physical or human capital, as these data are routinely collected and reported in the aftermath of a disaster (Gall, Borden, & Cutter, 2009). For example, in the US, the National Weather Service is required to provide monetary estimates of damages after flood events, paying special attention to property losses (National Oceanic and Atmospheric Administration, 2007). The amount of physical destruction and associated repair costs in the aftermath of a disaster are usually measured via engineering models (traditionally damage-depth functions for floods), and these estimated damages can then be validated through actual post-event assessments from public (local governments) and/or private insurance companies. Given their wide availability, *stock damages* are commonly used in hazard mitigation planning, especially in cost-benefit analyses, and are usually reported as the total impact of a disaster event. However, these values offer an incomplete picture of the underlying economic impact, since they do not account for the business interruptions induced either locally or in their trade partners.

Conversely, *flow losses* provide a more comprehensive economic view of the event by considering the direct loss in production arising from capital damages (first-order effects, according to Rose (2004)), the spillovers to non-affected industries and regions (higher-order effects), and the length of the recovery process. Flow losses capture ripple effects that can be significant if major industrial chains are disrupted or infrastructure is compromised. For instance, the 1993 Midwest flood halted freight in the Mississippi River, as well as highways and rail lines along the inundated areas, which led to $2 billion in losses. In Iowa, damaged crops from the flood caused $3.6 billion in losses to the state (Hewings & Mahidhara, 1996). More

[57] Part of this chapter is reprinted with permission from Avelino, A., & Dall'erba, S. (2018). Comparing the Economic Impact of Natural Disasters Generated by Different Input-Output Models. An Application to the 2007 Chehalis River Flood (WA). *Risk Analysis*. Advance online publication. DOI: 10.1111/risa.13006. Copyright 2018 by Wiley.

recently, physical damage from the 2012 Hurricane Sandy caused direct and indirect losses totaling $1.2 billion in New Jersey due to a plunge in tourism spending (U.S. Department of Commerce, 2013).

In the disaster literature, detailed data on *flow losses* are limited and usually incomplete, since their comprehensive assessment would entail tracking businesses inside and outside the affected area for an extensive time. Most available studies on business recovery are geographically constrained to the affected region(s) and qualitative in nature, and only a few provide a long-term assessment that extends beyond the reconstruction phase (exceptions are Tierney (1997) on the impact of the Northridge earthquake in the Greater Los Angeles area, and Green, Miles, Gulacsik, & Levy (2008) on the 2007 Chehalis flood in Lewis County, which is part of our study area).

Due to these pitfalls, several economic models have been proposed to estimate *flow losses*, most of which are rooted in the Input-Output (IO) framework that inherently captures linkages and feedbacks between the productive sectors of an economy. However, a lack of consensus on a preferred model has led to an increasing number of alternative specifications with varying results (Koks *et al.*, 2015). This Chapter explores the trade-offs of choosing between commonly used IO models in the disaster literature for single region analysis: the traditional Leontief model; a simplified version of Cochrane's rebalancing algorithm (Cochrane, 1997); the sequential interindustry model (Okuyama *et al.*, 2004); the dynamic inoperability IO model (Lian & Haimes, 2006); its inventory extension (Barker & Santos, 2010); and the inventory Adaptive Regional Input-Output model (Hallegatte, 2014). Additionally, we explore the use of the generalized dynamic input-output model (GDIO), a more comprehensive framework that combines the contributions of the previous models, while accounting for seasonality and demographic changes post-disaster (see Chapter 3). Taking a practitioner's view, we discuss the advantages, data requirements and underlying assumptions of each model, and highlight common theoretical misconceptions in their application when translating stock damages into flow impacts. Then, we compare each model's capacity to assess sectorial vulnerability and overall losses by using standard datasets and assumptions in evaluating the same benchmark event, the 2007 Chehalis flood in Washington State, which affected three counties with different economic structures and varying degrees of damages. Notwithstanding that every disaster is unique, the chosen benchmark event is typical of the US, where more than 60% of the floods with disaster declarations were issued in rural counties in the last six decades (Federal Emergency Management Agency [FEMA], 2017).

We conclude this Chapter by introducing the contributions of Chapters 1-3 in terms of datasets and methodologies to estimate the impact of the Chehalis flood. We use multisectoral quarterly data and explore the full capabilities of the GDIO model to show how demographics, seasonality and timing of the disruption can affect the estimation of flow losses. We contrast these results with the ones obtained using standard data and assumptions, which usually ignore such issues.

In the next Section we review the aforementioned models. Section 4.3 describes the roadmap to convert stock damages to flow losses and highlights the theoretical mistakes commonly made in the literature. Section 4.4 presents the benchmark event, and Section 4.5 discusses and compares the results of each model using standard datasets and assumptions. Section 4.6 re-work the flood assessment using the new data and methods proposed in this Chapters 1-3 and contrast with the results from Section 4.5. Section 4.7 concludes and offers some recommendations for future disaster analysis studies.

4.2. Methodology

In the disaster literature, econometric, computable general equilibrium (CGE) and IO models comprise the most used frameworks for flow loss estimation (Okuyama, 2007; Przyluski & Hallegatte, 2011). The strength of an econometric approach derives from estimations based on historical data. While they provide a statistical base for forecasting, time-series usually convey limited information on future disasters due to their infrequency and idiosyncrasy, and most specifications overlook interindustrial and interregional feedbacks. As a result, most models only represent partial equilibrium conditions, and estimated marginal effects obtained from this framework are not generalizable (Greenberg, Lahr, & Mantell, 2007). Conversely, CGE models provide a more comprehensive system-wide view of impacts, since they account for the complete flow of income across industries, factors and institutions within a region and between regions. They provide a greater degree of flexibility when modeling supply-demand co-movements, such as allowing non-linear specifications, substitution effects and behavioral responses (Okuyama & Santos, 2014). However, the practical applicability of CGE is limited by its large data requirements and the technical knowledge needed to build the models. Moreover, Greenberg *et al*. (2007) highlight that the source of many behavioral parameters is usually questionable: when the lack of regional data makes their estimation at the local level unfeasible, the missing data are regularly "borrowed" from national or international studies, which may lead to biased results. Oosterhaven (2017) also notes the challenge of separating short-run input substitution, which is fairly minimal, from long-run substitution effects, which are more flexible. In fact, due to these substitution effects and optimizing behavior assumptions, CGE models tend to present lower bound estimates (i.e., underestimate impacts) in disaster analyses (Meyer *et al.*, 2013; Przyluski & Hallegatte, 2011; Rose, 2004).

Even though the IO framework provides a more restricted focus on productive activities and rigidity in terms of inputs substitution and prices – that usually leads to upper bound estimates of losses and portrays a more short-run industrial behavior (Oosterhaven, 2017) – it offers several advantages over the other two frameworks: similarly to CGE, it models the economic linkages between industries and regions, which allows for the assessment of the spread of disruptions among different production chains; the relatively lower data requirements in comparison to CGE or survey analysis permit a faster and easier implementation to different regions and events; it has the benefit of portability, in that the same methodology can be applied to structurally different regions and the results can be compared; and the IO framework also permits an easy integration with external models (e.g. engineering models), and the incorporation of a diverse set of constraints. In practical terms, IO models have been commonly used in disaster assessments, particularly in the US, given the availability of IO data and standard models in off-the-shelf software like IMPLAN, which require minimal technical knowledge.

Among the various IO specifications applied in the literature, the traditional Leontief demand-driven model is one of the simplest and the most popular (see Miller & Blair (2009) for a detailed explanation). This model assumes linear production functions with perfectly complementary inputs that are portrayed in $\mathbf{A}^{\mathrm{P}}$, the pre-disaster direct input requirement table. Total output is a function of the interdependencies among industries presented in the Leontief inverse matrix $(\mathbf{I} - \mathbf{A}^{\mathrm{P}})^{-1}$ and the final demand to be supplied in the period $(\mathbf{f})$. Impact analysis is performed by calculating the Leontief inverse from an IO table, changing the demand vector to reflect post-disaster conditions ($\bar{\mathbf{f}}^*$) and pre-multiplying it by the original Leontief inverse to obtain the post-disaster output $\mathbf{x}^*$ (Equation 4.1).[58]

$$\mathbf{x}^*(t) = (\mathbf{I} - \mathbf{A}^{\mathrm{P}})^{-1}\bar{\mathbf{f}}^*(t) \tag{4.1}$$

Total flow losses per period are easily retrieved by subtracting the pre-disaster output from the post-disaster output. Hence, these flow losses define the amount of "inoperability" in the economy, i.e., the inability of the region to generate its intended production level (Haimes & Jiang, 2001).[59] This is the approach used by the Washington State Department of Transportation [WSDOT] (2008) in estimating the total economic impact of the I-5 and I-90 highways closures during the 2007 Chehalis flood.

The traditional Leontief model (LM) assumes that production is simultaneous and contained in each time period, i.e. all the output necessary to satisfy a given final demand is produced within the time interval without any lag, and that there are no trade constraints. The model is demand-driven and any supply constraint is therefore introduced indirectly through a reduction in final demand by, for example, applying the corresponding capacity constraint (γ_i) to $\mathbf{f}^{\mathrm{P}}$ (Equation 4.2).

$$\bar{f}_i^*(t) = \big(1 - \gamma_i(t)\big) f_i^P \quad \forall i, t \tag{4.2}$$

This simplified model has several limitations in modeling disruptive events. By assuming constant local input requirement coefficients ($\mathbf{A}^{\mathrm{P}}$) throughout the aftermath of the disaster, it cannot incorporate input substitution effects caused by local supply constraints. The static nature of the model combined with the assumption of production simultaneity, also limits the scope of the analysis because it restricts disruptive leakages within and between production chains as well as through time. The availability of inventories, that traditionally smooth volatile periods, are also not accounted for in this model. Therefore, the recovery process portrayed in the Leontief model underestimates losses since, despite demand changes, the local economic structure is constant from the pre-disaster scenario.

---

[58] The standard IO notation is used in this Chapter. Moreover, matrices are named in bold capital letters, vectors in bold lower-case letters (except inventories denoted by **I**) and scalars in italic lower-case letters. Finally, a hat sign over a vector indicates diagonalization and a prime sign transposition. Industries are indexed by i and time by t. The pre-disaster output vector is denoted $\mathbf{x}^{\mathrm{P}}$ and the pre-disaster final demand by $\mathbf{f}^{\mathrm{P}}$.

[59] Inoperability is defined as total output for the period divided by total output pre-disaster minus one.

In order to incorporate supply constraints explicitly in the demand-driven model, Cochrane (1997) and Oosterhaven and Bouwmeester (2016) propose a rebalancing of the post-disaster IO table. Oosterhaven and Bouwmeester rely on a nonlinear programming model that minimizes information gains subject to output and trade constraints, and recalculates the economic flows to support the post-disaster final demand. Such methodology can be implemented in both single and multi-regional environments, although it is primarily designed for the latter.[60] A simpler single-region rebalancing algorithm was introduced by Cochrane (1997): it is an iterative routine that checks for excess supply/demand and existing flexibility in inventories and trade to reallocate production accordingly (Figure 4.1). HAZUS (HAZard US), a standardized hazard risk assessment tool created by the Federal Emergency Management Agency that is widely used in mitigation planning and cost-benefit analysis, relies on a version of Cochrane's model in its Indirect Losses Module (Federal Emergency Management Agency [FEMA], 2015).

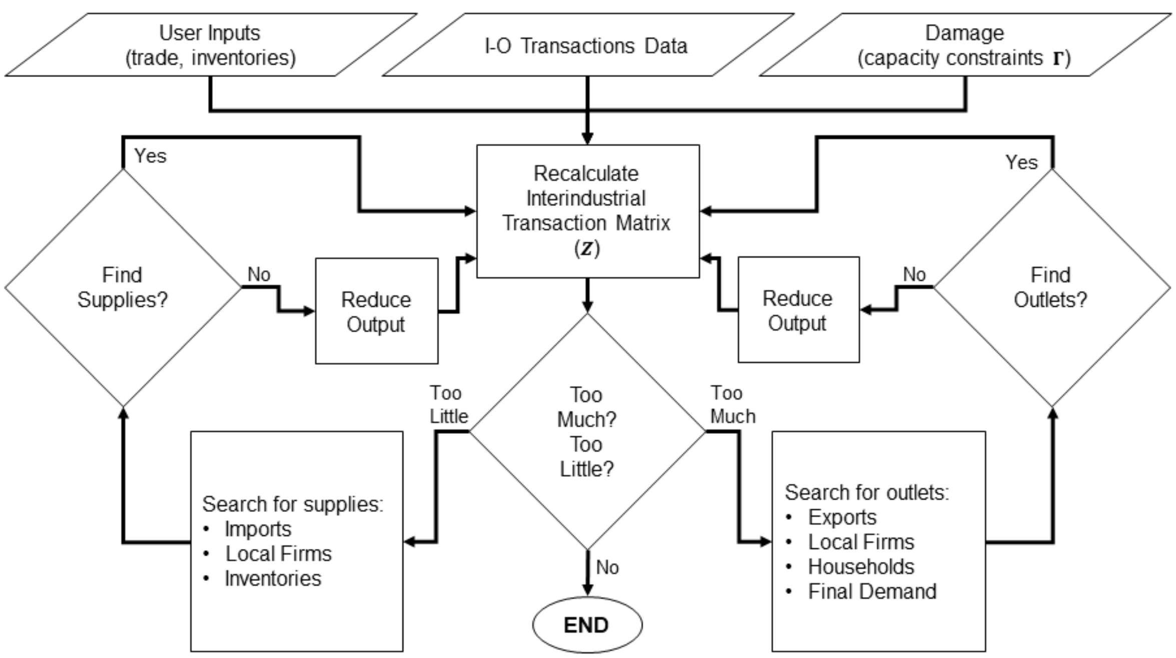


Figure 4.1: Cochrane's rebalancing scheme (Cochrane, 1997)

[60] In practice, interregional IO tables are usually not readily available to researchers, especially at small spatial units such as counties/municipalities. Hence, in this Chapter we focus only on single region applications.

The set of rebalanced IO tables reflect the new steady-state of the economy at each time period. If one assumes no trade constraints nor inventories, both models yield the same rebalanced matrix $\mathbf{A}^*(t)$**,** that can be directly calculated by pre-multiplying the pre-disaster input requirement table by a matrix of post-disaster remaining capacity $\mathbf{A}^*(t) = \big(\mathbf{I} - \mathbf{\Gamma}(t)\big)\mathbf{A}^{\mathrm{P}}$, where $\mathbf{\Gamma}(t)$ is a diagonal matrix with $\gamma_i(t)$ as the non-zero elements. This simplified version of the rebalancing model (RM) is shown in Equation 4.3.

$$\mathbf{x}^*(t) = \Big(\mathbf{I} - \big(\mathbf{I} - \mathbf{\Gamma}(t)\big)\mathbf{A}^{\mathrm{P}}\Big)^{-1}\bar{\mathbf{f}}^*(t) \tag{4.3}$$

Both rebalancing procedures overcome the supply-demand incompatibility of the Leontief model, relaxing the previous assumption of constant economic structure and mitigating its bias. However, additional assumptions on trade constraint are required. The models also expand the idea of the hypothetical extraction method (HEM) suggested by Dietzenbacher and Miller (2015) as another modeling option for disasters. They consider the impact of production constraints on both purchase and sales structures of the affected sectors, like the HEM, but also rebalance the rest of the economy to reach a new steady-state. Nonetheless, the static nature of these models implicitly assumes that the effects of the disruption are contained within the time interval, as if production was not a continuum. Hence, all constraints are exogenously imposed and intertemporal production restrictions cannot arise endogenously. The resulting bias in the estimates will depend on the length of the model's time interval, since shorter periods ignore larger intertemporal disruptive "leakages" on future production.

As highlighted by Cole (1989) and Romanoff and Levine (1977), the idea of an instantaneous production process is unrealistic because contractual obligations and production delays can linger in the economic system for several months, thus influencing output inter-temporally. A dynamic approach is, therefore, needed to more accurately assess the total impact of a disaster.

One of the first works attempting to incorporate dynamics in disruptive events is the time-lagged model applied to industrial plants closures proposed by Cole (1988, 1989). Its core assumption is that an income shock in the economy propagates with different levels of inertia (lags) at various points of the supply/demand chain that the traditional model ignores. However, Cole advocates for a full closure of the single-region model (i.e. endogenizing all components of final demand including trade), drawing a series of criticisms by Jackson, Madden and Bowman (1997), Jackson and Madden (1999) and Oosterhaven (2000) over the model's theoretically consistency and solvability.

An alternative dynamic formulation is the Sequential Interindustry Model (SIM). Proposed by Romanoff and Levine (1977) and based on the series expansion of the Leontief inverse, it introduces production timing in the IO framework. While developed before Cole's model, the SIM was applied to disaster contexts much later (Okuyama *et al.*, 2004). In the SIM, industries are classified according to three production schedules: anticipatory, just-in-time or responsive. Anticipatory industries are those sectors that produce before orders are placed – they anticipate the demand as their production process is lengthy and goods are standardized. Primary and manufacturing sectors fall in this category. Responsive sectors, such as construction, receive orders before they start production, while just-in-time sectors produce and deliver in the same period as orders are received due to shorter production times. In this model time is discretized, it is assumed constant, identical for all industries and synchronized across sectors. The Core SIM is derived from the supply-demand identity in the IO table as follows:

$$x_i(t) \equiv \sum_j z_{ij}(t) + f_i(t) \quad \forall i, t \tag{4.4}$$

Partitioning the traditional input requirement table ($\mathbf{A}$) between the different production types ($\mathbf{A_a}$: anticipatory; $\mathbf{A_j}$: just-in-time; and $\mathbf{A_r}$: responsive), we derive one equation for each "pure" production mode as if all industries followed the same schedule:

$$\mathbf{x}(t) = \mathbf{A_a}\mathbf{x}(t+1) + \mathbf{f}(t) \tag{4.5}$$

$$\mathbf{x}(t) = \mathbf{A_j}\mathbf{x}(t) + \mathbf{f}(t) \tag{4.6}$$

$$\mathbf{x}(t) = \mathbf{A_r}\mathbf{x}(t-1) + \mathbf{f}(t) \tag{4.7}$$

Since each sector follows one of these three modes, a mixed model for the whole economy is derived by combining the "pure" models in Equations 4.5-4.7:

$$\mathbf{x}^*(t) = \mathbf{A_a^P}\mathbf{x}^*(t+1) + \mathbf{A_j^P}\mathbf{x}^*(t) + \mathbf{A_r^P}\mathbf{x}^*(t-1) + \bar{\mathbf{f}}^*(t) \tag{4.8}$$

Notice that the traditional IO model is a special case of the SIM when all industries are just-in-time. Hence, the Core SIM reproduces the same accumulated total losses from the traditional Leontief model, but spreads them through time. However, it relies on a set of strong assumptions, such as perfect foresight of demand and perfect knowledge of interindustrial requirements (Mules, 1983), perfect knowledge of changes in the economic structure, and perfect sectoral adaptability to the disruption (no inventories). Romanoff and Levine (1986, 1990) have remedied some of these issues by including inventories, post-disaster technology changes and delivery delays, but their implementation is not straightforward (Okuyama *et al.*, 2004). Additionally, the system's inoperability in the SIM is inter-temporal only to the extent that intra-temporal impacts are carried over via production lags.

On the other hand, the Dynamic Inoperability Input-Output Model (DIIM) proposed by Lian and Haimes (2006) aims at introducing a framework that bridges intra-temporal and inter-temporal inoperability. The DIIM is the dynamic version of the Inoperability Input-Output Model (IIM) (Santos, 2003; Santos & Haimes, 2004) that we do not cover in this review because it offers no methodological advances compared to the traditional Leontief model (Dietzenbacher & Miller, 2015; Oosterhaven, 2017). The DIIM is based on the classic Dynamic Leontief model which assumes that current output accounts for both the production required to meet current demand and for any required capital to make possible production in the next period via the capital formation matrix $\mathbf{B}$ (Equation 4.9).

$$\mathbf{x}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{f}(t) + \mathbf{B}[\mathbf{x}(t+1) - \mathbf{x}(t)] \tag{4.9}$$

However, while the Dynamic Leontief model is a growth model through investment, the DIIM models a recovery process where the economy moves back to the pre-disaster condition. Hence, the capital formation matrix is replaced by a resilience matrix $\boldsymbol{K} = \hat{\boldsymbol{k}}$ that represents the speed at which the pre- vs. post-disaster production gap closes (Equation 4.10).

$$\begin{aligned} &\xRightarrow{\boldsymbol{B}=-\hat{\boldsymbol{k}}^{-1}} \mathbf{x}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{f}(t) - \mathbf{K}^{-1}[\mathbf{x}(t+1) - \mathbf{x}(t)] \\ &\Leftrightarrow \mathbf{x}(t+1) = \mathbf{x}(t) + \mathbf{K}\,[\mathbf{A}\mathbf{x}(t) + \mathbf{f}(t) - \mathbf{x}(t)] \end{aligned} \tag{4.10}$$

Note that besides the conceptual difference from the Dynamic Leontief model, the DIIM is not constrained by inversion issues (the capital formation matrix in the former may not be invertible) nor exhibits inconsistent output paths (the latter converges to the original equilibrium while the former does not usually converge to a steady-state growth path and can exhibit negative outputs after several interactions). The main contribution of the DIIM is its ability to model the recovery trajectory dynamically, and to account for how inoperability in one period impairs production in the following period. Also, instead of being treated exogenously, recovery is endogenously modeled as it depends on each sector's resilience and on the gap between supply and demand in each period (Baroud, Barker, Ramirez-Marquez, & Rocco, 2015; Pant, Barker, Grant, & Landers, 2011).

Taking $t = 0$ as the first period post-disaster and $t = T_i$ the time industry i takes to recover to a target (minimal) level of inoperability q_i, the interdependency recovery rate k_i is defined as:

$$k_i = \frac{\ln\left({q_i(0)} \big/ {q_i(T_i)} \right)}{T_i(1 - a_{ii}^{\mathrm{P}})} \tag{4.11}$$

Notice that Equation 4.11 defines an exponential recovery path. Moreover, the spread of inoperability among industries and its inertia in the system depends on the size of k_i. The larger the value of k_i, the faster is the recovery. In their original exposition, all matrices are normalized with the pre-disaster total output levels: $\mathbf{q}(t) = \left[\hat{\mathbf{x}}^{\mathrm{P}^{-1}}(\mathbf{x}^{\mathrm{P}} - \mathbf{x}^*(t))\right]$, $\mathbf{c}^*(t) = \left[\hat{\mathbf{x}}^{\mathrm{P}^{-1}}\left(\mathbf{f}^{\mathrm{P}} - \bar{\mathbf{f}}(t)\right)\right]$ and $\mathbf{A}^* = \left[\hat{\mathbf{x}}^{\mathrm{P}^{-1}}\mathbf{A}^{\mathrm{P}}\hat{\mathbf{x}}^{\mathrm{P}}\right]$, where $\hat{\mathbf{x}}^{\mathrm{P}}$ is the pre-disaster output vector diagonalized and $\bar{\mathbf{f}}$ is the post-disaster final demand. Barker and Santos (2010) describe such final demand vector as equivalent to the one used in the IIM, thus representing "a forced demand reduction from diminished supply and due to lingering consumer fear or doubt." (p. 133). This yields the model:

$$\mathbf{q}(t+1) = \mathbf{q}(t) + \mathbf{K}\left[\mathbf{A}^*\mathbf{q}(t) + \mathbf{c}^*(t) - \mathbf{q}(t)\right] \tag{4.12}$$

The connection between intra-temporal and inter-temporal inoperability is embedded in Equation 4.12, where an increase in current inoperability creates contemporaneous supply constraints that also influence the next period, hence accounting for both effects. The DIIM assumes that all industries operate in anticipatory mode using the previous period's demand-production imbalance as a measure of expected output. A key aspect of this model is the fact that the gap between actual production ($\mathbf{x}^*(t)$) and "potential final demand" ($\bar{\mathbf{f}}(t)$) determines the speed of recovery post-disaster, i.e. the model accounts for local conditions to drive its recovery pace that, as a result, can diverge from the exogenously imposed schedule from the previous models. Such feature, however, makes the model very sensitive to the definition of $\bar{\mathbf{f}}(t)$, as the latter can cause results to vary significantly (see Section 4.5). An *ad-hoc* proportional rationing rule is implicitly assumed to redistribute reduced output; there are no trade constraints and inventories are not available to mitigate inoperability. With regards to this latter issue, Barker and Santos (2010) extended the DIIM to include finished goods inventories (I_i^F) which magnitude defines a sector-specific inoperability p_i that is distinct from the overall inoperability q_i. The Inventory-DIIM introduces a sector-specific recovery rate (l_i) denoted "repair coefficient" that is similar to k_i in Equation 4.11, and that informs the speed of recovery from a physical inoperability (Equation 4.13).

$$l_i = \frac{\ln\left({p_i(0)} \middle/ {p_i(T_i)} \right)}{T_i} \tag{4.13}$$

Different functional forms could be applied to the recovery function, but Barker and Santos (2010) use the following:

$$p_i(t) = e^{-l_i t} p_i(0) \tag{4.14}$$

The initial overall inoperability conditions $q_i(0)$ are determined by the available finished goods inventory in the aftermath of the event ($\mathbf{I^F}(0)$), by the total anticipated output in the aftermath of the disaster ($x_i(0)$) and by the supply constraints (sector-specific inoperability post-disaster $p_i(0)$):

$$q_i(0) = \begin{cases} 0 & if\ I_i^{\mathrm{F}}(0) \geq p_i(0)x_i(0) \\ 1 - I_i^F(0)/p_i(0)x_i(0) & if\ 0 < I_i^{\mathrm{F}}(0) < p_i(0)x_i(0) \\ p_i(0) & if\ I_i^{\mathrm{F}}(0) = 0 \end{cases} \tag{4.15}$$

As a result, the evolution of each industry in the system depends on the remaining inventories in relation to output constraints (Equation 4.16). If the inventories are numerous enough to supplant the lost output, then a sector's inoperability will depend solely on its own previous inoperability and on the inoperability of the other sectors (condition 1). In case some inventory remains, but it is not enough to fully compensate the new production constraints, then the level of inoperability is mitigated proportionally (condition 2). If the inventories become depleted in the next period, but are still positive in the current period, an additional supply constraint appears in the system, which increases the overall inoperability (condition 3). Finally, if there are no contemporaneous inventories, we revert back to the traditional DIIM model (condition 4). Any remaining inventories ($I_i^{\mathrm{F}}(t)$), as well as the sector-specific inoperability ($p_i(t)$), are updated at the end of each time step.

$$q_i(t+1) = \begin{cases} q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] \; if \; I_i^{\mathrm{F}}(t+1) \geq p_i(t+1)x_i(t+1) \\ \max\begin{cases} p_i(t+1) - I_i^{\mathrm{F}}(t+1)/x_i(t+1) \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] \end{cases} if \; 0 < I_i^{\mathrm{F}}(t+1) < p_i(t+1)x_i(t+1) \\ \max\begin{cases} p_i(t+1) \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] \end{cases} if \; I_i^{\mathrm{F}}(t+1) = 0, \; I_i^{\mathrm{F}}(t) > 0 \\ q_i(t) + k_i\left[c_i^*(t) - q_i(t) + \sum_{j=1}^{n} a_{ij}^* q_j(t)\right] if \; I_i^{\mathrm{F}}(t+1) = 0, \; I_i^{\mathrm{F}}(t) = 0 \end{cases} \tag{4.16}$$

Although the approach above assesses the impact of pre-disaster inventories of *finished goods*, it does not explain their formation nor accounts for the presence of *materials and supplies* (M&S) inventories. Furthermore, the model lacks different production modes because it assumes all industries are anticipatory, and lacks trade constraints by assuming no import/export restrictions. The Inventory-DIIM still assumes that the external sectors can absorb local imbalances by providing more imports and purchasing excess production. As the latter is unlikely in real situations, overproduction can further decrease local production due to additions to inventories.

Building on these previous contributions, Hallegatte (2008, 2014) proposes a more comprehensive model that explicitly considers supply and demand restrictions as well as adaptive behavior post-disaster. In the Adaptive Regional Input-Output (ARIO) model, production bottlenecks arise when either industrial capacity or required intermediate inputs are binding constraints, and a rationing scheme prioritizes supply to other industries when total output in a particular sector is insufficient to attend total demand. Additionally, the ARIO model estimates price changes and the resulting impact on profits, although neither affects production, only local and external demand.[61]

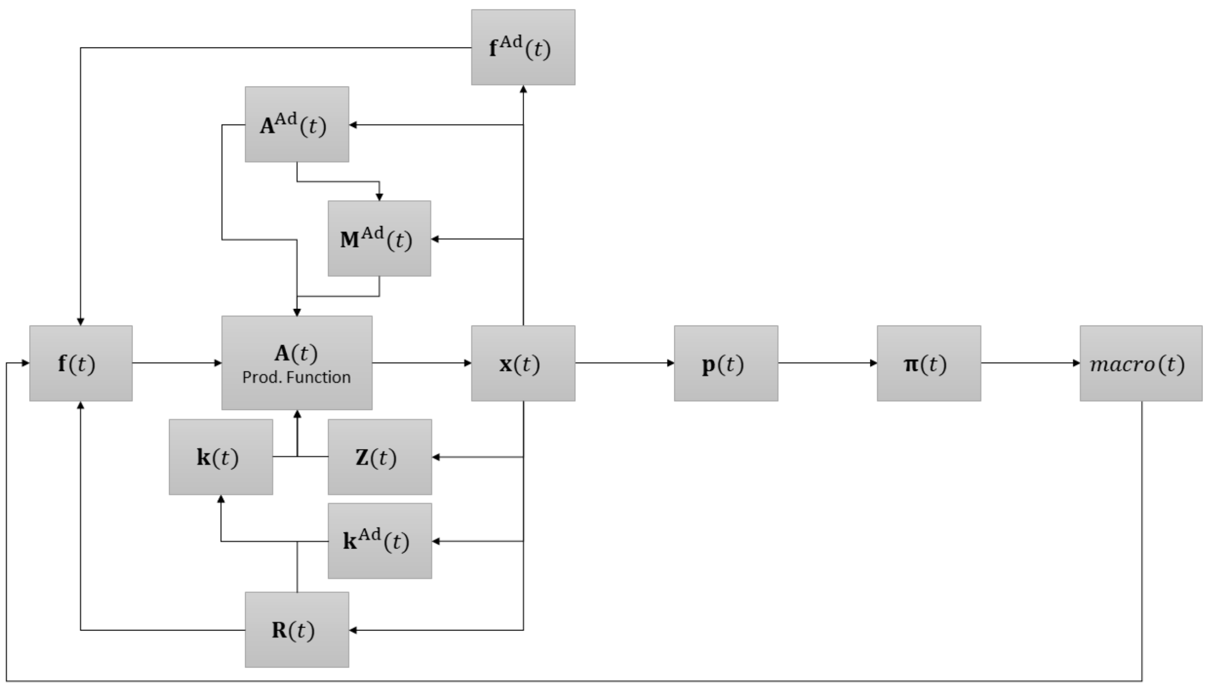


Figure 4.2: ARIO model schematics

The model is not intertemporal but iterates in each period until all flows converge (Figure 4.2, see full description of the model in Hallegatte (2008)). Starting from a first-guess demand level ($\mathbf{f}(t)$), the production capacity ($\mathbf{k}(t)$) and available intermediate inputs ($\mathbf{Z}(t)$) in each industry determine the total output ($\mathbf{x}(t)$) of the sector and whether rationing will occur. Available supply is then distributed to final demand (local and exports), intermediate consumption ($\mathbf{Z}(t)$) and reconstruction ($\mathbf{R}(t)$). Deviations in production from the pre-disaster levels determine new prices ($\mathbf{p}(t)$) that affect profits ($\boldsymbol{\pi}(t)$) and overall local macroeconomic

[61] Price changes are not entirely consistent with the IO framework, in which prices are constant to any level of production.

conditions ($macro(t)$). Final demand is adjusted via an adaptation process that considers the new prices, actual demand supplied and macroeconomic conditions ($\mathbf{f}^{\mathrm{Ad}}(t)$). Supply conditions also affect local input requirements ($\mathbf{A}^{\mathrm{Ad}}(t)$), imports ($\mathbf{M}^{\mathrm{Ad}}(t)$) and reconstruction ($\mathbf{R}(t)$), the latter also influencing capacity constraints ($\mathbf{k}^{\mathrm{Ad}}(t)$). These new levels of demand, available intermediate inputs and capacity constraints update the priors and are used to recalculate total output for the period. This iterative process proceeds until convergence is achieved in the period. The adaptation processes depend on the sensitivity of the demand to undersupply and the speed of recovery to pre-disaster levels, as well as a price-elasticity of substitution (local and external demands only).

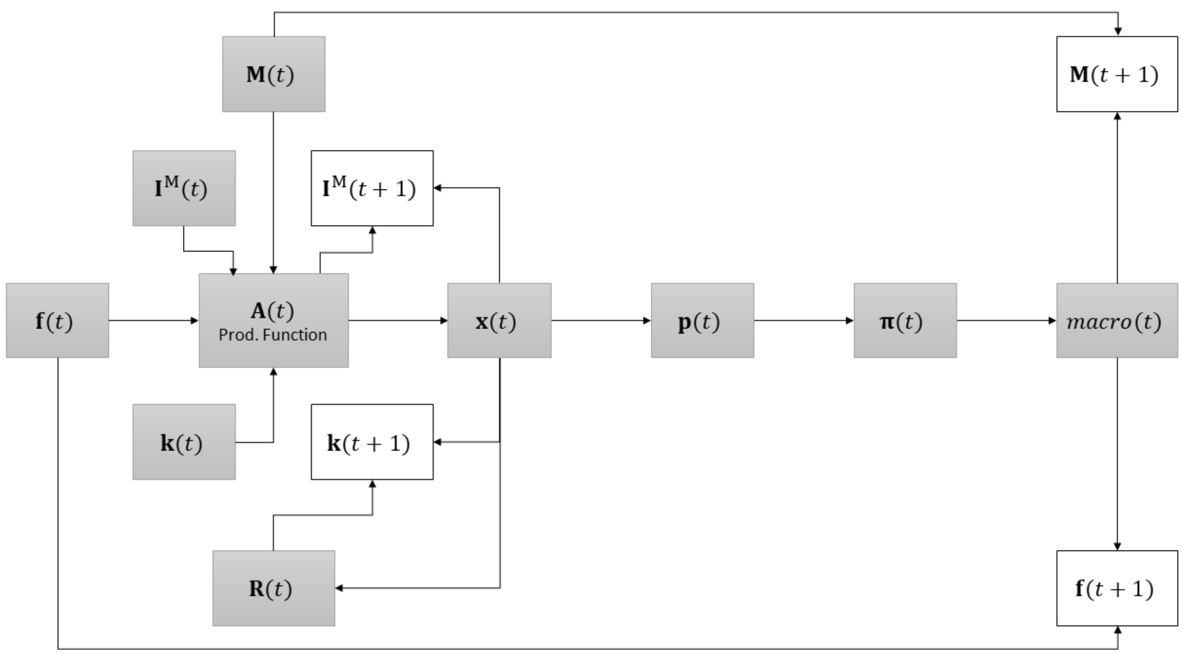


Figure 4.3: Inventory-ARIO model schematics

The ARIO model was later modified to include inventory dynamics (Hallegatte, 2014). In the Inventory-ARIO model, intertemporal dynamics is captured using materials and supplies inventories which hold enough intermediate inputs to sustain production for a given minimum number of days. Industries attempt to keep a *target inventory level* in each period, and this inventory dynamics substitutes the adaptation processes for final demand and direct input requirements from its previous version. The model schematics is presented in Figure 4.3 and a complete description is provided in Hallegatte (2014). As in the ARIO, production depends on capacity constraints ($\mathbf{k}(t)$) and intermediate inputs ($\mathbf{I}^{\mathrm{M}}(t)$), which are now drawn from inventories replenished in the previous period. Total supply for the period is then rationed between final demand, intermediate inputs (now inventories for the following period $\mathbf{I}^{\mathrm{M}}(t+1)$) and reconstruction. Macroeconomic conditions determine the new local and external final demand and imports for the next period. The remainder of the model is the same as the ARIO.

The Inventory-ARIO model allows for intertemporal inoperability, inventory formation and depletion, and modeling of backward and forward effects. Nonetheless, it does not distinguish between finished goods and intermediate goods inventories, nor includes labor constraints and induced effects (Hallegatte, 2014).

An important factor that is not considered in any of the previous models, neither by most of the literature on disasters, is the role of seasonality on estimated losses. Intra-year fluctuations in production capacity have a significant impact on the magnitude and distribution of impacts by affecting inventory levels and the sectoral adaptive response (see Chapters 1 and 2). Given the transient nature of natural disasters, "timing" plays a significant role in the amount of flow losses and affects both recovery paths and industrial interdependence. Also absent in most IO models is a proper representation of the effects of labor market changes and local consumption post-disaster, when displacement and loss of income might have a significant impact in the economy (Okuyama *et al*., 1999 and Li *et al*., 2013).

In an effort to integrate the methodological advances from the previous models and mitigate their limitations, Chapter 3 proposes the generalized dynamic input-output (GDIO) model. The GDIO models production as an intertemporal process (building on the scheduling scheme of the SIM framework) and supply-demand balance as an intratemporal process combining an extended demo-economic model to consider labor force changes. Expanding on the Inventory-ARIO model, it explicitly accounts for the formation/depletion of both M&S and finished goods inventories, inoperability from capital, and rationing procedures to handle supply restrictions. Seasonality is introduced by using intra-year IO tables. An overview of the model is presented in Figure 3.1. We direct readers to see the complete exposition of the GDIO in Chapter 3. In the next paragraph we provide a concise intuition for the model.

At the beginning of each period, producers determine the feasibility of their production schedules considering their current availability of M&S inventories (industrial inputs), capital and labor. Assuming non-substitutability between finished goods for intermediate and final consumptions, if the total scheduled production is not feasible, producers use a rationing rule to determine how much to offer in each market in excess of any inventories from the previous period. Therefore, final demand, influenced by reconstruction efforts, displacement, labor conditions and income, might be under- or over-supplied. Industries react to this supply-demand unbalance by adjusting their expectations for the next production cycle, and by attempting to purchase the necessary level of inputs. Since this interindustrial demand may also be under- or over-supplied, after markets clear, each sector determines a feasible production schedule for the upcoming period. The stock losses of a disaster occur between periods, diminishing inputs, capital and displacing population, thus affecting production feasibility and demand level/composition for the next period.

A summary of the main characteristics of each of the models and required data is available in Table E.1 in the Appendix. Notice that all models are demand-driven and measure the impacts of disasters mostly in terms of backward effects. Nonetheless, disasters also lead to important forward effects in the production chain that might be exacerbated if input substitution is limited, but the current literature still lacks comprehensive solutions to fully account for them: while the Gosh' supply-driven model relies on unrealistic core assumptions, CGE models present challenges in terms of data requirements and underlying assumptions, as noted earlier, and the rebalancing models presented above lack micro-economic foundations to explain the reallocation of production among industries and regions (Oosterhaven, 2017).

According to Oosterhaven (2017), disasters can have six different types of impacts: disruption in the supply of goods and services, which creates forward negative effects; disruption in the supply of non-replaceable inputs (such as labor), which also leads to negative forward effects; technical or spatial substitution effects (positive backward effects for the supplying industries); drops in demand levels due to income and supply constraints, which creates negative backward effects; change in demand composition, which can lead to positive/negative backward effects depending on the industry; and reconstruction demand (positive backward effects). The set of impacts that each model accounts for is shown in Table 4.1. Since each model captures a different subset of impacts, the results will necessarily vary between models, as will be discussed in Section 4.5.

Table 4.1: Types of impacts captured by model

	Supply goods/svcs.	Supply non-repl. inputs	Input substitution	Demand level drop	Demand composition change	Reconst. demand
LM				Yes	Yes	Yes
RM	Yes	Yes[1]	Yes	Yes	Yes	Yes
SIM				Yes	Yes	Yes
DIIM **Inv-DIIM**				Yes	Yes	Yes
Inv-ARIO	Yes	Yes[2]	Yes	Yes	Yes	Yes
GDIO	Yes	Yes	Yes	Yes[3]	Yes[3]	Yes

Notes: [1]Not in our simplified implementation of the model. See Oosterhaven and Bouwmeester (2016) for a more flexible implementation in a non-linear programming framework; [2]Only capital; [3]Endogenous via a demo-economic model.

4.3. From Stock Damages to Flow Losses

In order to calculate flow losses, we need to convert estimated or assessed stock damages into first-order flow losses for use in the IO model. When water-depth grids are available, the usual procedure involves two steps: first, the flood water-depth grids are run through an engineering model to estimate stock damages; second, the stock damages are used in an economic model to estimate flow losses. The relationship between all these components is shown in Figure 4.4.

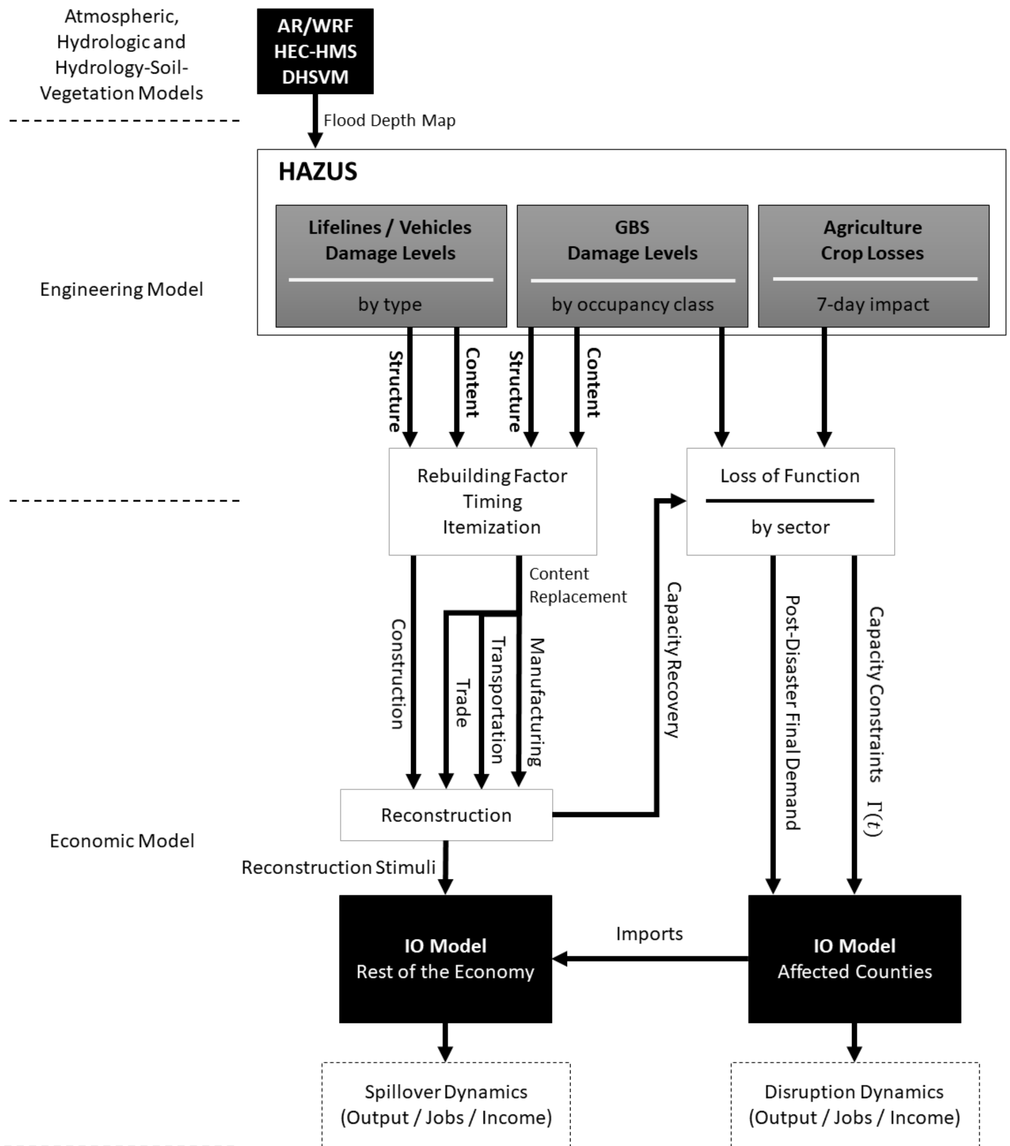


Figure 4.4: Modeling approach overview, stock damages to flow losses

HAZUS has been the most widely applied engineering model in the literature evaluating economic losses and performing cost-benefit analysis because it offers a balanced trade-off between modeling capability and required technical engineering knowledge (Banks, Camp, & Abkowitz, 2014). HAZUS uses water-depth grids to determine the percentage of damaged square footage by occupancy class at the census block level. These capital stock damages are measured in terms of repair costs, inventory, content, crop losses and vehicle replacement costs.

Damage to transportation infrastructure is only evaluated in terms of impacted bridges, so a comprehensive assessment of transportation disruptions is lacking. HAZUS provides estimates of first-order flow losses in business interruptions and rental income based on average sales data for the occupancy class, but in order to generate more accurate results we reestimate these first-order flow losses using the region's own IO table instead.

Table 4.2: Input-output table disaggregation and assumptions

NAICS	**Sector Description**	**Prod. Mode**	**Hold Inventories**	**HAZUS Occupancy Classes**
11	Ag., Forestry, Fishing & Hunting	A (90)	Yes	AGR1
21	Mining	A (30)	Yes	-
22	Utilities	JIT	No	-
23	Construction	JIT	Yes	IND6
31-33	Manufacturing	A (58)	Yes	IND1, IND2, IND3, IND4, IND5
42	Wholesale Trade	JIT	No	COM2
44-45	Retail Trade	JIT	No	COM1
48-49	Transportation & Warehousing	JIT	No	-
51-53	Information, Finance & Real Estate	JIT	No	COM5
54-56	Professional, Mgmt. & Adm.	JIT	No	COM4
61	Educational Services	JIT	No	EDU1, EDU2
62	Health & Social Services	JIT	No	RES6, COM6, COM7
71	Arts, Entertainment & Recreation	JIT	No	COM8, COM9
72	Accommodation & Food Services	JIT	No	RES4
81	Other Services	JIT	No	COM3, COM10, REL1
92	Government & non-NAICS	JIT	No	GOV1, GOV2

Notes: Production modes: A = anticipatory (number in parenthesis is the production lag in days), JIT = just-in-time, R = responsive.

Natural disasters generate both negative economic impacts (via capacity constraints and reduced final demand) and positive economic impacts (via reconstruction efforts), but not necessarily in the same region. Capacity constraints $\mathbf{\Gamma}(t)$ are determined by assuming both a homogeneous productivity per square foot for each industry in a specific county, and that industries operate at full capacity before the disaster. Using information on crop losses, on damaged squared footage from the General Building Stock (GBS), as well as information about the economic sectors these buildings belong to (HAZUS occupancy class classification is matched to NAICS classification, see Table 4.2), we set the capacity constraints based on the pre-disaster total output by industry (Figure 4.4). Besides capital damages, Agriculture production is reduced proportionally to the share of crop and livestock output in the county. Livestock losses are not considered independently as they are not reported by HAZUS.

The total square footage per industry before the disaster (s_i^{T}), the damaged square footage (s_i^{D}) and the timing of the disruption are used to determine the capacity constraints and the reduced local final demand in the economic model. We also assume that recovery is proportionally distributed through time according to the restoration timeframe provided by HAZUS. Details on these elements appear in tables 14.1, 14.5 and 14.12 of FEMA (2015). Based on this information, we define the level of inoperability of a particular industry i at time t as:

$$\gamma_i(t) = \frac{s_i^{\mathrm{D}}(t)}{s_i^{\mathrm{T}}} \tag{4.17}$$

As mentioned in Equation 4.3, the matrix $[\mathbf{I} - \mathbf{\Gamma}(t)]$, where $\mathbf{\Gamma}(t)$ is a matrix with $\gamma_i(t)$ in the main diagonal, represents the available production capacity for each industry at each time period in the post-disaster phase.

Due to labor restrictions and displacement, final demand is reduced from the pre-disaster level ($\mathbf{f}^{\mathrm{P}}$) to $\bar{\mathbf{f}}$. We assume that the expenditure structure remains fixed in the post-disaster period and that demand decreases proportionally to the plunge in income. Thus, in order to account for both capacity constraints and reduced household expenditure due to wage loss, we define the demand vector in the post-disaster period ($\bar{\mathbf{f}}^*$) for all models, except the Inventory-ARIO and GDIO[62], as:

$$\bar{f}_i^*(t) = \min\left(\left(1 - \gamma_i(t)\right) f_i^{\mathrm{P}}, \bar{f}_i(t)\right) \qquad \forall i, t \tag{4.18}$$

The reconstruction demand $\mathbf{R}(t)$ is determined by repair costs of the GBS and lifelines (construction stimuli), and replacement of building content and vehicles (manufacturing stimuli).

[62] The Inv-ARIO models demand changes endogenously. The GDIO endogenously determine income and consumption levels, so it only requires the inoperability level of each industry given by Equation 4.17.

Since IO models are based on producer prices and HAZUS provides repair costs in purchase prices[63], we assume that manufacturing orders include margins split 20/80% between transportation and trade (see Figure 4.4).

In addition to the intricacies noted so far, two important misconceptions that have recurrently appeared in the empirical literature need to be addressed: first, since the IO framework is defined in terms of flows, stocks should not enter the models directly, but should do so via a measure of a sector's reduced ability to provide goods/services at the same level as before. As explained above, we use the amount of substantially damaged physical space a sector occupies as a proxy for loss of productive capacity. Hallegatte (2008, 2014), however, allocates total housing stock and consumer durable goods damaged as direct productive capital losses to the FIRE sector to determine its inoperability. Because the production of this sector represents payment for services provided (e.g., for processing insurance claims), capital damages that do not directly affect this sector have no impact on its operations; second, transportation, retail and wholesale sectors are derived from margins (see Section 3.3.6 on Chapter 3), hence these sectors cannot hold finished goods inventories because they only provide services. However, Barker and Santos (2010) mistakenly allocate finished goods' inventories to retail and wholesale sectors using BEA's inventory-to-sales ratio, and similarly, Koks, Bočkarjova, de Moel and Aerts (2015) assume that inventories in trade sectors represent merchandise for sale. In sum, researchers willing to apply the IO framework appropriately should be aware of the methodology's nuances and avoid the above misconceptions.

4.4. Case Study: The 2007 Chehalis Flood

4.4.1. Region Overview

In order to compare the results of the IO methodologies listed before, we rely on the same benchmark event: the 2007 Chehalis Flood in Washington State. Over the period of December 1-4 2007, a system of storms formed by an atmospheric river hit the U.S. West Coast and led to a record-breaking 14 inches of precipitation at the Willapa Hills that feeds the main branches of both the Chehalis and the South Fork rivers. The surrounding areas experienced an additional 3-

[63] Purchase prices = producer prices + trade margin + transportation margin.

8 inches of rain. This event led to landslides, failed levees, overtopped dikes (Chehalis River Basin Flood Authority [CRBFA], 2010) and floods in western Washington and Oregon states. Traditionally, this region experiences an average precipitation of 7-13 inches for the entire October to March period (CRBFA, 2010). Most of the damage was concentrated alongside the Chehalis River Basin, southwest Washington. The flood extent is shown in Figure 4.5.

Figure 4.5: Flood-depth grid for the Chehalis Basin

The counties of Grays Harbor, Thurston and Lewis were the most affected and were declared major disaster areas on December 8, 2007. Around 75,000 customers lost power and several roads became impassable (Green *et al.*, 2008). The cities of Centralia and Chehalis, both in Lewis County, sustained the most damage with 25% and 33% of their respective areas inundated. The flood affected more than half of the commercial land-use and 32% of the industrial zones in the Centralia-Chehalis Urban Growth Area. Direct building damages in the county were assessed at $166 million and around 10,702 acres of the 22,919 acres of agricultural land in western Lewis County were flooded at an estimated replanting cost of $188-$490 million (Lewis County, 2009).

The tri-county region impacted by the 2007 Chehalis flood has contrasting characteristics: while Grays Harbor and Lewis counties are more primary-based economies with a significant commercial logging cluster[64], Thurston County is a service-based economy and is part of the Seattle-metro area. Economic data for 2008 indicates that, in terms of total output and employment, Thurston is the largest and the most diversified economy among the three (Figure 4.6). Lewis and Grays Harbor have similar sized economies with a combined output that is a third of Thurston's. The largest employers in Lewis County are the Government (17%), Retail (13%) and Manufacturing (13%) sectors. Grays Harbor has a somewhat similar economic structure (24%, 11% and 13%, respectively), whereas Government and Retail are the largest employers in Thurston County (34% and 11% of the jobs, respectively). On average 56-69% of all industrial inputs are imported in these counties, mostly by local Utilities, Construction and Manufacturing sectors, that mainly import manufacturing goods, professional, information and financial services.

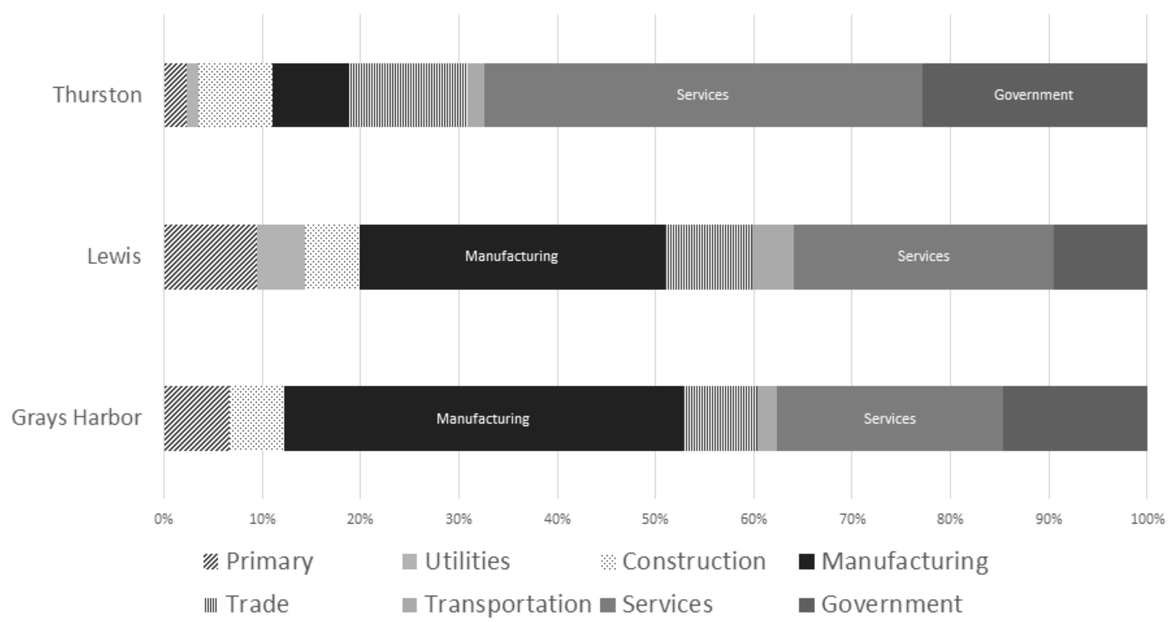


Figure 4.6: Annual share of output by sector, 2008

In terms of industrial linkages, agriculture in general and its commercial logging activity in particular, are the most intertwined sectors. Manufacturing sectors exhibit significant

[64] The commercial logging cluster comprises logging activities and wood related manufacturing (sawmills, paper manufacturing, etc.). Grays Harbor has also a large oil refinery sector (considered manufacturing in the IO table aggregation).

backward linkages in Grays Harbor (especially between "Commercial Logging" and "Sawmills and Wood Preservation" sectors), while service sectors are the most interconnected in Lewis and Thurston. As a result, any disruption affecting these key sectors will lead to additional inoperability in the rest of the local economy.

4.4.2. Data Sources

This Chapter relies on a fine scale estimate of floodplain and water-depth maps derived from the 2007 event. Observed data collected by the U.S. Army Corps of Engineers (USACE) from gauges along several river branches in the Chehalis basin were used in HEC-RAS to generate a water-depth map for the area (U.S. Army Corps of Engineers, 2010).

Direct losses were estimated in HAZUS-MH version 3.0 using the default dasymetric datasets and assuming a warning time of 48h (which implies a 35% loss reduction in building damage according to the embedded Day Curve). No reduction in vehicle damage is assumed since no reliable source of information is available. As the software informs both day and night losses for vehicles, we follow the flood timing reported by the National Weather Service (2008) and select day losses for Grays Harbor and Thurston, and night losses for Lewis County.

For the comparison between models in Section 4.5, we use the 2008 annual IO tables extracted from IMPLAN (2015) at a 16 sectors aggregation level (Table 4.2). We chose this level of aggregation to minimize incompatibilities when bridging HAZUS' occupancy class classification and the NAICS classification used by IMPLAN. For the full implementation of the GDIO model in Section 4.6 that requires intra-year data, we estimate the quarterly 2008 IO tables for the three counties following the methodology and databases presented in Chapter 2. The production modes and timing shown in Table 4.2 are *ad hoc*, except for manufacturing that was estimated using a variant of the methodology proposed by Thomas and Kandaswamy (2017) and based on data from the Manufacturers' Shipments, Inventories and Orders (M3) survey (Census Bureau, 2018b).[65]

[65] Flow time (FT_i) for an industry i is calculated from the not-seasonally adjusted series of value of shipments (v_i) and total inventories (t_i) between two dates, $d_0 < d_1$, and Little's Law (Thomas & Kandaswamy, 2017):

$$FT_i = (d_1 - d_0) \Big/ \left(\left(\sum_{t=d_0}^{d_1} v_i(t) \right) \Big/ \left(\left(\sum_{t=d_0}^{d_1} t_i(t) \right) \Big/ (d_1 - d_0) \right) \right)$$

We do not explicitly model interregional trade but assume that given the small size of the affected counties' economy relatively to Washington's (3.8% of the state's GDP), all imports are produced by the rest of the state and their production leads to negligible positive feedback to the affected counties. Moreover, all the reconstruction stimuli are allocated to the rest of Washington. Notice that the assumption of fixed prices holds here because of the small size of the affected region.

The inventory data for the DIIM are based on the December 2007 inventory-to-sales ratio for manufacturing reported by the Federal Reserve Bank of St. Louis (2016), as suggested in Barker and Santos (2010). This not-seasonally-adjusted ratio is 1.23 for the period under study, and we choose to apply it homogeneously to all counties. Data for wholesale and retail are not considered since these sectors' activities are recorded as margins, so they cannot hold finished goods inventories and, although they could hold "materials and supplies" and "work-in-progress" inventories, such data are not available. Besides Manufacturing (NAICS 31-33), resource activities (NAICS 11, 21) and Construction (NAICS 23) are the only sectors assumed to hold finished goods inventories (Table 4.1). Demographic information for the GDIO model (total population, employment and unemployment) was obtained from the Washington State Employment Security Department (2018).

All data were normalized to daily level since the models were estimated at a daily step. Annual data were distributed uniformly throughout the year, and quarterly data were distributed uniformly in each quarter. The results were aggregated to monthly level for presentation purposes. Finally, we assume total anticipated output for the Inv-DIIM is always equal to the pre-disaster output, i.e. $\mathbf{x}(t) = \mathbf{x}^{\mathrm{P}}\ \forall t$, and the parametrization for the Inv-ARIO is the same as in Hallegatte (2014) except for overproduction capacity which is set to zero for all industries.

4.4.3. Stock Damages Estimates via HAZUS

Using the water-depth grids in HAZUS, physical damages were estimated at \$678 million and, as expected, the largest impact occurred in Lewis County (a breakdown of damages is provided in Table 4.3). The only available counterfactual for direct losses is from Lewis County, where the total building losses (structure + inventory) were assessed at \$166.2 million (Lewis County, 2009), while our HAZUS-based estimates were \$150.5 million (\$142.5 million in buildings and \$8.1 million in inventories). This 9.4% difference can be explained, in part, by the fact that our model estimates the total number of buildings moderately damaged at 898, when 957 of them were actually reported (Lewis County, 2009). Also, five fire stations were affected during the flood, at a total repair cost of \$6 million (Lewis County, 2009), but these were not reported by HAZUS. Such discrepancies are due to the mismatch between the software's datasets and the event's year, its spatial scale (census block level), and the fact that the buildings' densities and locations are estimated. More accurate results would be obtained by using georeferenced building inventory data from local tax assessor offices (Ding, White, Ullman, & Fashokun, 2008; Tate, Muñoz, & Suchan, 2014), but since we only need a benchmark estimate of stock damages to compare the models, this step is out of the scope of this Chapter.

Table 4.3: Stock damages by county, in 2008 million dollars

	Grays Harbor	Lewis	Thurston
Agriculture			
Crops	-	-	-
Building Stock			
Capital Stock Damages			
Building Damage	\$ 71.3	\$ 142.5	\$ 22.2
Contents Damage	\$ 52.2	\$ 192.1	\$ 23.7
Inventory Damage	\$ 1.0	\$ 8.1	\$ 0.4
Vehicles			
	\$ 18.4	\$ 46.3	\$ 9.6
Infrastructure			
Transportation	-	-	-
Utilities	\$ 26.7	\$ 31.5	\$ 20.0
Essential Facilities			
Fire Station	-	-	-
Police Station	-	-	-
Hospitals	-	-	-
Schools	\$ 7.4	\$ 4.6	-
Total Stock Damage			
	\$ 176.9	**\$ 425.1**	**\$ 75.8**

When it comes to the estimated square footage damaged per industry, most of the affected area is concentrated in Lewis County, followed by Grays Harbor and then Thurston (see Figure 4.7). Agriculture, Construction and Healthcare are the main impacted industries, the latter being almost exclusively located in Lewis County. In Grays Harbor and Thurston, Agriculture is the main affected sector (Figure 4.8).

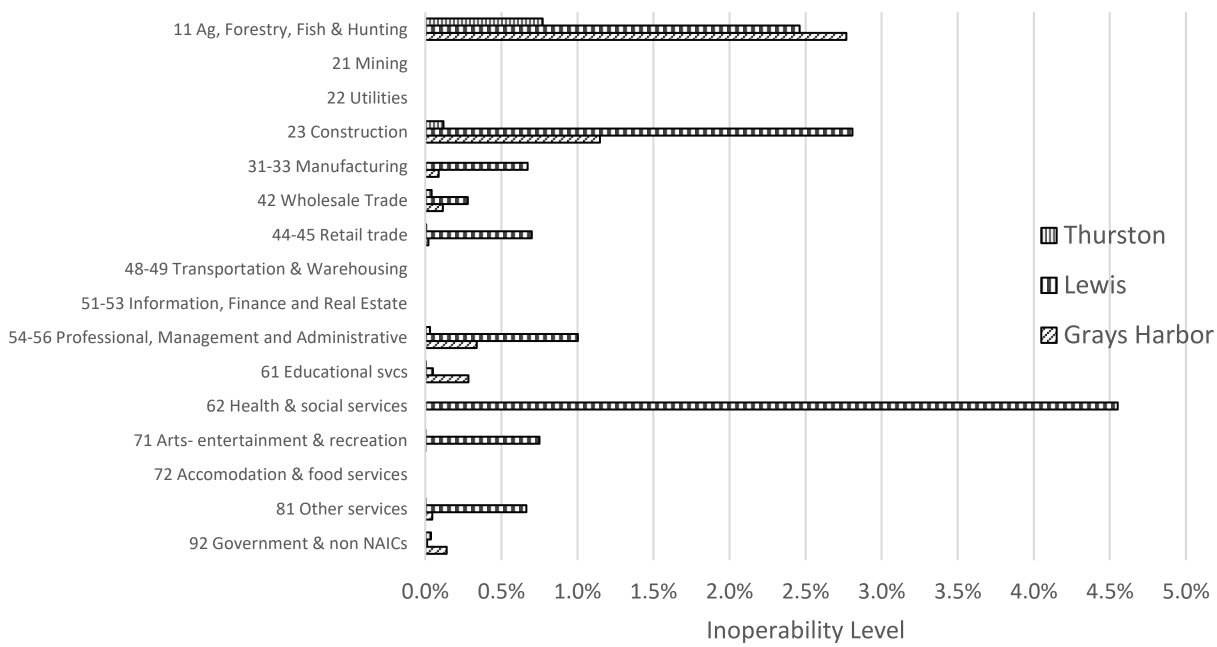
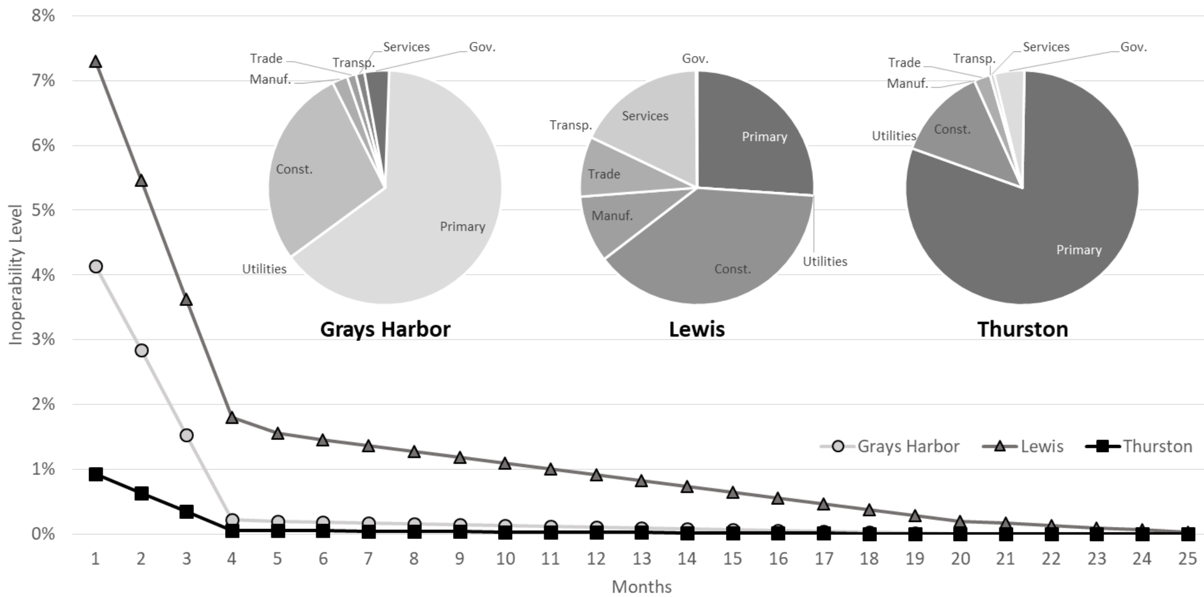


Figure 4.7: Initial inoperability by county



Notes: The damage restoration time is based on HAZUS (table 14.12 in FEMA, 2015) according to the average construction time by occupancy class and dominant restoration element. Inoperability, determined by the share of damage area by occupancy class and restoration time, is aggregated to NAICS classification according to Table 4.2.

Figure 4.8: Total inoperability by month (lines) and distribution by sector (pie charts)

4.5. Comparison Between Models

Considering the default recovery timing from HAZUS, we estimate a total direct output loss of $26.3 million over 25 months. First-order effects are the same across models and Healthcare, Agriculture and Manufacturing are the most affected sectors. Given the economic structure of the counties, Lewis has the most losses in service sectors, while Thurston experiences the most losses in government activities (Figure 4.7). Such loss of output translates into a $10.5 million decrease in direct labor income. Next, we use the models described in Section 4.2 to estimate higher-order effects. The full results by model, county and sector are presented in Tables 4.4-4.6.

Table 4.4: Estimated flow losses by sector and model, in 2008 million dollars, Grays Harbor

			Demand Reduced by Labor Income Losses and Supply Restrictions		Demand Reduced by Labor Income Losses			
Sector	**LM**	**RM**	**DIIM**	**Inv-DIIM**	**DIIM**	**Inv-DIIM**	**Inv-ARIO**	**GDIO**
11	-0.73	-1.98 (+170%)	-2.04 (+177%)	-2.01 (+174%)	-1.31 (+79%)	-1.29 (+76%)	-3.46 (+371%)	-1.38 (+88%)
21	-0.00	-0.00 (+13%)	-0.01 (+73%)	-0.01 (+69%)	-0.00 (-18%)	-0.00 (-22%)	-0.00 (-99%)	-0.00 (-23%)
22	-0.00	-0.00 (+13%)	-0.00 (+36%)	-0.00 (29%)	-0.00 (0%)	-0.00 (-8%)	-0.00 (-97%)	-0.00 (-62%)
23	-0.45	-0.51 (+13%)	-0.92 (+104%)	-0.92 (+104%)	-0.48 (+5%)	-0.48 (+5%)	-1.23 (+172%)	-0.49 (+8%)
31-33	-0.44	-0.52 (+20%)	-0.83 (+91%)	-0.54 (+22%)	-0.46 (+4%)	-0.16 (-64%)	-0.69 (+58%)	-0.37 (-15%)
42	-0.10	-0.18 (+92%)	-0.21 (+116%)	-0.20 (+109%)	-0.15 (+56%)	-0.14 (+49%)	-0.08 (-15%)	-0.13 (+37%)
44-45	-0.17	-0.17 (+4%)	-0.21 (+26%)	-0.21 (+26%)	-0.19 (+16%)	-0.19 (+15%)	-0.02 (-88%)	-0.07 (-59%)
48-49	-0.02	-0.03 (+45%)	-0.04 (+75%)	-0.04 (+64%)	-0.03 (+17%)	-0.03 (+6%)	-0.00 (-95%)	-0.02 (-26%)
51-53	-0.35	-0.39 (+13%)	-0.43 (+23%)	-0.43 (+22%)	-0.36 (+4%)	-0.36 (+3%)	-0.00 (-100%)	-0.10 (-70%)
54-56	-0.21	-0.49 (+129%)	-0.50 (+133%)	-0.50 (+131%)	-0.32 (+49%)	-0.31 (+47%)	-0.19 (-10%)	-0.39 (+83%)
61	-0.01	-0.01 (+12%)	-0.01 (+69%)	-0.01 (+69%)	-0.01 (+5%)	-0.01 (+5%)	-0.00 (-49%)	-0.01 (+2%)
62	-0.17	-0.17 (0%)	-0.17 (0%)	-0.17 (0%)	-0.17 (0%)	-0.17 (0%)	-0.00 (-100%)	-0.05 (-72%)
71	-0.03	-0.03 (+2%)	-0.03 (+4%)	-0.03 (+4%)	-0.03 (+3%)	-0.03 (+2%)	-0.00 (-98%)	-0.00 (-96%)
72	-0.07	-0.07 (+6%)	-0.08 (+11%)	-0.08 (+10%)	-0.07 (+2%)	-0.07 (+1%)	-0.00 (-100%)	-0.01 (-90%)
81	-0.08	-0.11 (+30%)	-0.14 (+67%)	-0.14 (+66%)	-0.11 (+31%)	-0.11 (+30%)	-0.03 (-68%)	-0.06 (-23%)
92	-0.78	-0.85 (+9%)	-1.29 (+66%)	-1.29 (+65%)	-0.58 (-26%)	-0.57 (-26%)	-0.40 (-48%)	-0.81 (+4%)
TOTAL	**-3.61**	**-5.54** (+53%)	**-6.91** (+91%)	**-6.56** (+82%)	**-4.26** (+18%)	**-3.92** (+8%)	**-6.11** (+69%)	**-3.90** (+8%)

Notes: The top 3 sectors with the highest losses by column are shaded (darker grays indicate higher losses). Percentage in parenthesis indicates the increase (positive) or decrease (negative) in flow losses in a given model with respect to the results from the Leontief model (LM).

Table 4.5: Estimated flow losses by sector and model, in 2008 million dollars, Lewis

			Demand Reduced by Labor Income Losses and Supply Restrictions		Demand Reduced by Labor Income Losses			
Sector	**LM**	**RM**	**DIIM**	**Inv-DIIM**	**DIIM**	**Inv-DIIM**	**Inv-ARIO**	**GDIO**
11	-0.84	-2.01 (+140%)	-2.17 (+159%)	-1.99 (+138%)	-1.37 (+63%)	-1.19 (+42%)	-4.09 (+387%)	-1.27 (+52%)
21	-0.01	-0.01 (+8%)	-0.02 (+54%)	-0.02 (+36%)	-0.01 (-8%)	-0.01 (-26%)	-0.00 (-99%)	-0.01 (-23%)
22	-0.39	-0.41 (+4%)	-0.48 (+22%)	-0.46 (+17%)	-0.36 (-9%)	-0.34 (-15%)	-0.00 (-100%)	-0.22 (-45%)
23	-1.05	-1.13 (+8%)	-2.06 (+97%)	-2.06 (+97%)	-1.05 (+1%)	-1.05 (0%)	-3.53 (+238%)	-1.10 (+5%)
31-33	-1.88	-1.96 (+4%)	-3.42 (+82%)	-1.92 (+2%)	-1.66 (-12%)	-0.16 (-92%)	-4.77 (+154%)	-1.84 (-2%)
42	-0.34	-0.47 (+37%)	-0.56 (+65%)	-0.53 (+55%)	-0.43 (+26%)	-0.39 (+15%)	-0.16 (-54%)	-0.28 (-19%)
44-45	-1.73	-1.82 (+6%)	-2.82 (+63%)	-2.81 (+63%)	-2.11 (+22%)	-2.11 (+22%)	-1.10 (-36%)	-1.71 (-1%)
48-49	-0.16	-0.17 (+10%)	-0.22 (+41%)	-0.20 (+28%)	-0.15 (-6%)	-0.13 (-19%)	-0.00 (-100%)	-0.10 (-38%)
51-53	-2.54	-2.63 (+3%)	-2.98 (+17%)	-2.96 (+16%)	-2.23 (-12%)	-2.21 (-13%)	-0.00 (-100%)	-1.44 (-43%)
54-56	-1.12	-1.86 (+67%)	-2.11 (+89%)	-2.08 (+86%)	-1.21 (+8%)	-1.18 (+6%)	-0.81 (-28%)	-1.30 (+16%)
61	-0.07	-0.07 (+1%)	-0.07 (+7%)	-0.07 (+7%)	-0.07 (+5%)	-0.07 (+5%)	-0.00 (-95%)	-0.01 (-92%)
62	-12.09	-12.24 (+1%)	-16.20 (+34%)	-16.20 (+34%)	-5.40 (-55%)	-5.40 (-55%)	-6.40 (-47%)	-12.09 (0%)
71	-0.18	-0.19 (+5%)	-0.29 (+61%)	-0.29 (+60%)	-0.25 (+38%)	-0.25 (+37%)	-0.11 (-38%)	-0.17 (-4%)
72	-0.42	-0.43 (+2%)	-0.46 (+10%)	-0.46 (+9%)	-0.39 (-7%)	-0.39 (-8%)	-0.00 (-100%)	-0.18 (-58%)
81	-0.84	-0.97 (+16%)	-1.40 (+67%)	-1.39 (+66%)	-0.90 (+7%)	-0.89 (+6%)	-0.52 (-38%)	-0.81 (-3%)
92	-0.35	-0.36 (+3%)	-0.43 (+21%)	-0.42 (+19%)	-0.35 (-2%)	-0.34 (-4%)	-0.02 (-93%)	-0.11 (-69%)
TOTAL	**-24.01**	**-26.75** (+11%)	**-35.71** (+49%)	**-33.86** (+41%)	**-17.94** (-25%)	**-16.10** (-33%)	**-21.52** (-10%)	**-22.64** (-6%)

Notes: The top 3 sectors with the highest losses by column are shaded (darker grays indicate higher losses). Percentage in parenthesis indicates the increase (positive) or decrease (negative) in flow losses in a given model with respect to the results from the Leontief model (LM).

Table 4.6: Estimated flow losses by sector and model, in 2008 million dollars, Thurston

			Demand Reduced by Labor Income Losses and Supply Restrictions		Demand Reduced by Labor Income Losses			
Sector	**LM**	**RM**	**DIIM**	**Inv-DIIM**	**DIIM**	**Inv-DIIM**	**Inv-ARIO**	**GDIO**
11	-0.36	-0.49 (+37%)	-0.72 (+101%)	-0.72 (+101%)	-0.36 (+2%)	-0.36 (+2%)	-0.95 (+166%)	-0.39 (+9%)
21	-0.00	-0.00 (+7%)	-0.00 (+64%)	-0.00 (+64%)	-0.00 (-14%)	-0.00 (-14%)	-0.00 (-35%)	-0.00 (-27%)
22	-0.01	-0.01 (+5%)	-0.02 (+16%)	-0.02 (+16%)	-0.01 (+1%)	-0.01 (+1%)	-0.00 (-100%)	-0.00 (-90%)
23	-0.20	-0.20 (+4%)	-0.38 (+96%)	-0.38 (+96%)	-0.19 (-2%)	-0.19 (-2%)	-0.49 (+150%)	-0.20 (+1%)
31-33	-0.03	-0.03 (+4%)	-0.04 (+26%)	-0.04 (+26%)	-0.03 (0%)	-0.03 (0%)	-0.00 (-100%)	-0.02 (-47%)
42	-0.20	-0.27 (+31%)	-0.36 (+78%)	-0.36 (+78%)	-0.22 (+8%)	-0.22 (+8%)	-0.11 (-45%)	-0.23 (+13%)
44-45	-0.15	-0.15 (+2%)	-0.19 (+28%)	-0.19 (+28%)	-0.18 (+23%)	-0.18 (+23%)	-0.03 (-82%)	-0.07 (-54%)
48-49	-0.02	-0.02 (+14%)	-0.02 (+39%)	-0.02 (+39%)	-0.02 (+4%)	-0.02 (+4%)	-0.00 (-90%)	-0.00 (-76%)
51-53	-0.39	-0.42 (+6%)	-0.44 (+12%)	-0.44 (+12%)	-0.40 (+2%)	-0.40 (+2%)	-0.00 (-100%)	-0.06 (-86%)
54-56	-0.22	-0.38 (+77%)	-0.41 (+91%)	-0.41 (+91%)	-0.26 (+22%)	-0.26 (+22%)	-0.13 (-41%)	-0.27 (+24%)
61	-0.02	-0.02 (+2%)	-0.02 (+14%)	-0.02 (+14%)	-0.02 (+11%)	-0.02 (+11%)	-0.00 (-91%)	-0.00 (-82%)
62	-0.19	-0.19 (0%)	-0.19 (0%)	-0.19 (0%)	-0.19 (0%)	-0.19 (0%)	-0.00 (-100%)	-0.04 (-80%)
71	-0.02	-0.02 (+2%)	-0.02 (+8%)	-0.02 (+8%)	-0.02 (+5%)	-0.02 (+5%)	-0.00 (-96%)	-0.00 (-92%)
72	-0.06	-0.06 (+4%)	-0.06 (+6%)	-0.06 (+6%)	-0.06 (+1%)	-0.06 (+1%)	-0.00 (-100%)	-0.00 (-97%)
81	-0.06	-0.06 (+7%)	-0.07 (+19%)	-0.07 (+19%)	-0.06 (+5%)	-0.06 (+5%)	-0.00 (-95%)	-0.01 (-84%)
92	-0.97	-1.01 (+4%)	-1.59 (+63%)	-1.59 (+63%)	-0.67 (-31%)	-0.67 (-31%)	-0.48 (-51%)	-0.99 (+2%)
TOTAL	**-2.89**	**-3.34** (+15%)	**-4.53** (+57%)	**-4.53** (+57%)	**-2.70** (-7%)	**-2.70** (-7%)	**-2.19** (-24%)	**-2.28** (-21%)

Notes: The top 3 sectors with the highest losses by column are shaded (darker grays indicate higher losses). Percentage in parenthesis indicates the increase (positive) or decrease (negative) in flow losses in a given model with respect to the results from the Leontief model (LM).

First, notice that the distribution of losses by sectors is somewhat homogenous across models in each county. This result makes sense since the economic structure does not vary considerably; however, it might not hold in an event that generates large capacity constraints because the rebalancing model may significantly alter local linkages.

The size of the difference in total flow losses between the Leontief model (LM) and the rebalancing model (RM) reflects the forward effects of the disruption in supply of goods and services, an impact that is not captured in LM (see Table 4.1). The increase in losses in RM is driven by the amount of inoperability in industries with high "fields of influence", i.e. industries in which small changes in the $\mathbf{A}^{P}$ matrix (Equation 4.3) affect the coefficients in the Leontief Inverse the most (Figure E.1 in the Appendix). This is the case in Grays Harbor where agriculture is both the most impacted sector and the one with the largest effect on the Leontief Inverse, leading to a 53% difference with LM results. The same sector has also high fields of influence in Thurston but since its inoperability is small, the difference in losses is significantly lower (15%). In the case of Lewis, the most inoperable sectors have small effects on the overall linkages in the economy, leading to reduced forward effects and the least difference between the regions (11%).

When it comes to monthly losses by county (Figures 4.9, 4.10 and 4.11), the RM shows the highest production plunges in the initial post-disaster periods, when the economic structure is the most impaired. This highlights the importance of accounting for both capacity constraints and local interdependence, i.e. backwards and forwards effects, because if highly interdependent sectors are affected and the economic structure is kept fixed, the bias is exacerbated. As the economy rebounds and returns to its original steady state, RM approaches the traditional LM model estimates.

Moreover, because the Leontief and rebalancing models are static, the initial inoperability does not spread inter-temporally, so the large loss in the first post-disaster months fades quickly. Although not shown, the SIM distributes losses in time due to perfect foresight, so the efficient output path begins pre-disaster and involves lower reductions in output in each period. While we are aware that an event like the one studied here cannot be expected, it is important to recall that the SIM is originally designed for positive shocks. Total losses in the SIM are the same as in the RM, since the latter only spreads the inoperability through time (they both capture the same set of impacts). The shape of the recovery process will vary with the assumed production timing of each sector.

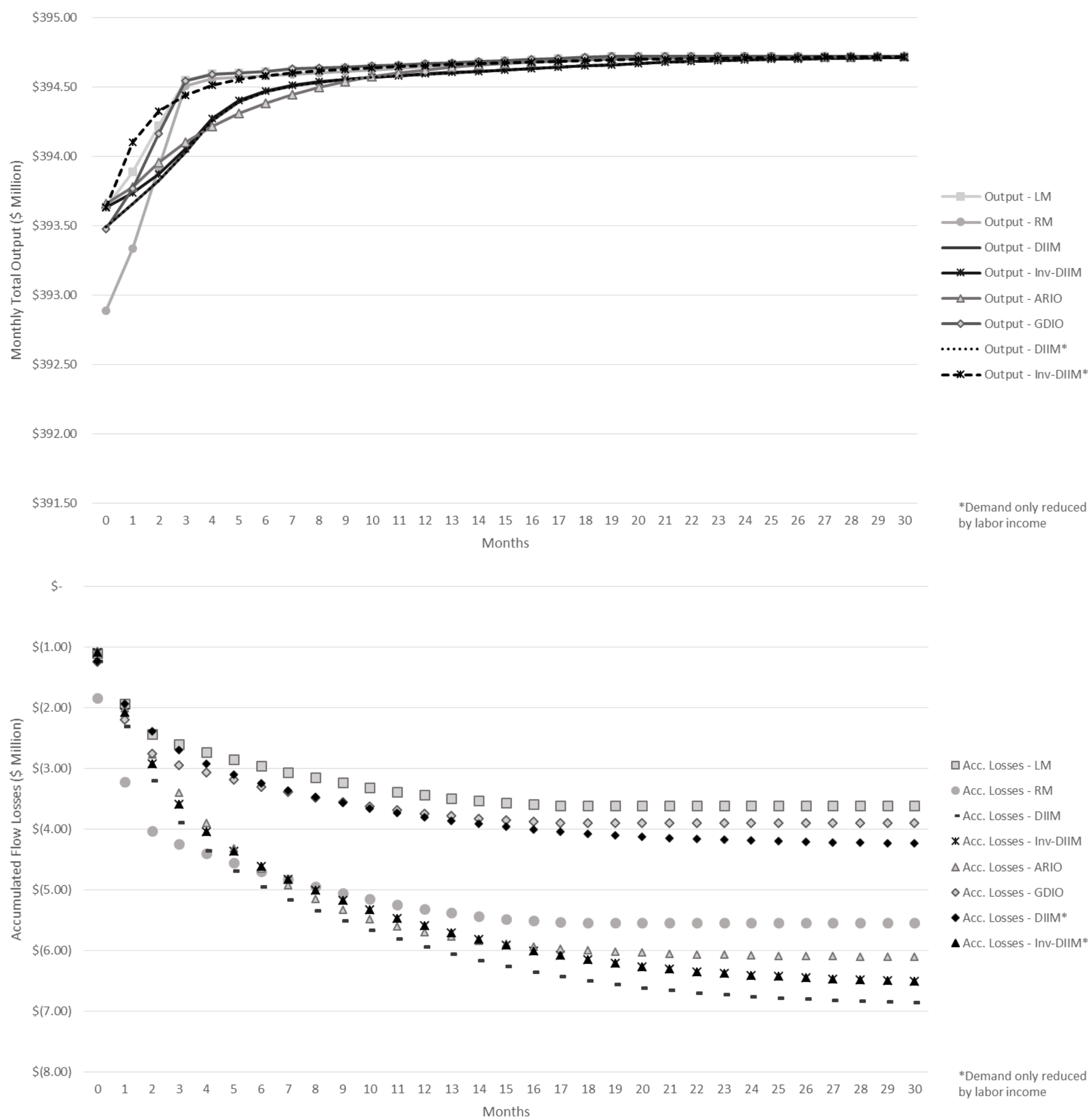


Figure 4.9: Monthly output (top) and accumulated flow losses (bottom) by model, Grays Harbor

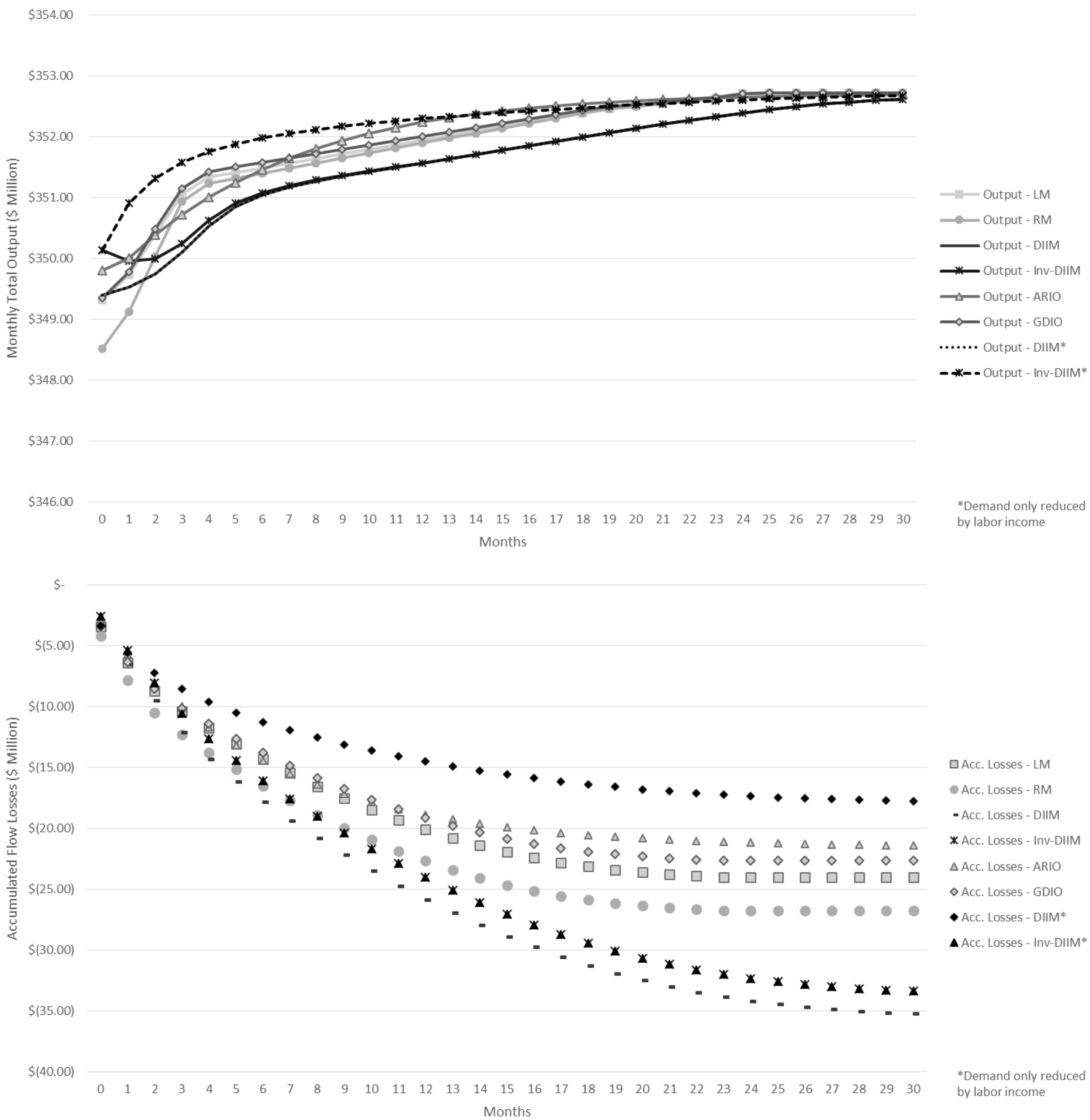


Figure 4.10: Monthly output (top) and accumulated flow losses (bottom) by model, Lewis

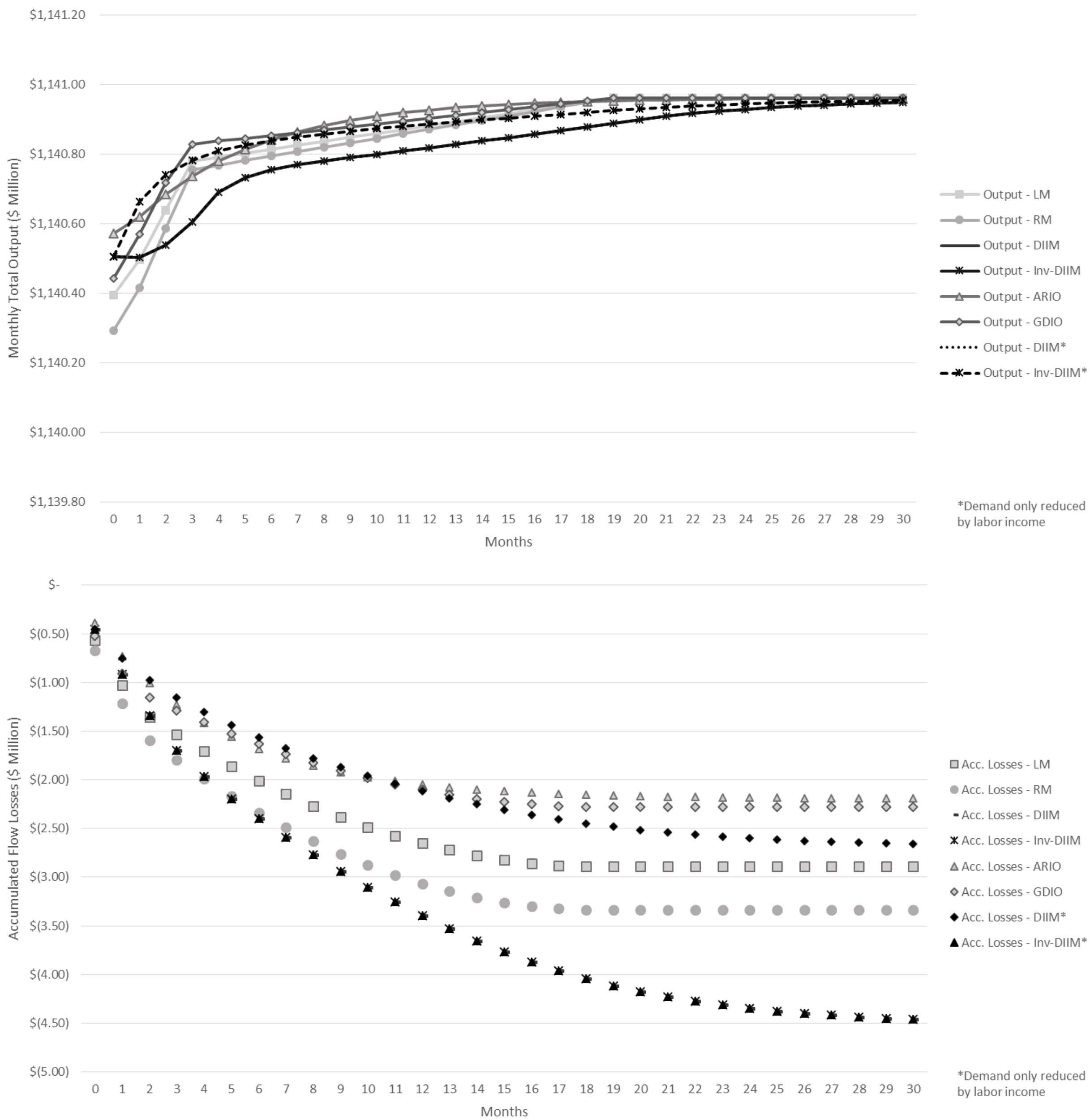


Figure 4.11: Monthly output (top) and accumulated flow losses (bottom) by model, Thurston

With the current assumptions that final demand is reduced by income loss and by the sectoral inoperability (Equation 4.18), both DIIM and Inv-DIIM provide the upper-bound estimate of the total losses. Based on our case study, they are 41-91% higher than the LM estimates. Although these models are only able to capture the same set of impacts as the simple Leontief model (Table 4.1), the large discrepancy is generated by the speed of the endogenous recovery process that is slower than the exogenously imposed schedule (see Figures 4.9-4.11), since the imbalance between supply and demand in each period is not large. Now, using the same resilience and repair coefficients, we re-estimated the models assuming that the post-disaster demand is only reduced by labor income losses (Tables 4.4-4.6 columns 5-6). The results indicate that the total losses vary significantly from the previous assumptions, with the Inventory-DIIM going from the upper-bound to the lower-bound of total losses in Lewis County. This result highlights that defining the components of the final demand vector requires some care in the DIIM framework. On the other hand, the definition of the demand vector in the LM and RM models is straightforward: in the former, both inoperability and demand perturbation need to be included in order to account for demand/supply constraints, while in the latter, the demand vector is entirely determined by the rebalancing algorithm.

The difference between the DIIM and its inventory version depends on the composition of demand and on the importance and intersectoral linkages of the sectors that have finished goods inventories. These sectors are usually primary and secondary industries, but in our case it is simply the manufacturing sector due to data restrictions. Both models yield very close results in Thurston due to the low presence of local manufacturing in its economy (94% of manufacturing inputs are imported and this sector represents only 9% of final demand). Conversely, manufacturing represents a significant share of final demand (mostly through exports) in Grays Harbor (44%) and Lewis (34%) due to their commercial logging cluster. Therefore, inventories directly mitigate the disruption in that sector, and indirectly reduce the inoperability in the rest of the economy through the agricultural sector which has the largest backward linkages.

The Inventory-ARIO model (and the GDIO) captures most of the disaster impacts described in Oosterhaven (2017). The net effect of positive and negative impacts will vary between regions, which partially explains the higher losses in Grays Harbor and lower losses in Lewis and Thurston when compared to the Leontief Model (Tables 4.4-4.6). The Inventory-

ARIO also concentrates flow losses on the sectors directly affected by the initial inoperability, as its target inventory approach (90-day inventories) restricts the spread of the disruption to downstream sectors (i.e. forward effects). Total flow losses are close to the ones from the GDIO model, except for Grays Harbor, where losses in Agriculture are the largest from all models, since the sector itself consumes 31% of its own production.

Except for the GDIO (and Inv-ARIO), all previous models account for changes in post-disaster household consumption exogenously by reducing the final demand of a given period by the amount of labor income lost due to the inoperability of the sectors (Equation 4.18). It is also common practice in the literature to consider induced effects by endogenizing households in the model as an additional "sector" in the economy. A major drawback of such solutions is the implicit assumption that if an individual becomes unemployed he/she stops consuming locally as his/her wage income ceases (Batey and Weeks, 1989; Batey *et al*., 2001). In the context of negative shocks in a demand-driven model, the flow losses are overestimated since the expenditures of non-working households are ignored (Batey, 2018). The GDIO is the only framework that models induced effects endogenously using a demo-economic approach that considers changes in income and consumption of all residents (Figure 3.2), thus capturing demand composition change impacts. This explains the relatively low estimates of the GDIO in comparison to the other models, even though its results reflect direct, indirect and induced effects. Also contributing to these results is the dynamic behavioral response of industries in the GDIO – through formation of inventories of both raw materials and finished goods, and adjustment time (most industries are just-in-time) – that reduces the inertial effect of the disruption.

4.6. Timing of the Event: The Role of Seasonality in Disaster Analysis

As shown in Chapters 1 and 2, the economic structure of a region can vary substantially within the year, especially if it is primarily dependent on seasonal industries such as agriculture and tourism. Hence, the timing of a disaster will affect the scale and scope of its impacts depending on how production is organized at that moment. Consideration of such structural changes in the economy has been lacking in most of the disaster literature, particularly in modeling flow losses. Disaster assessments are usually based on annual IO tables, and implicitly assume a homogenous economic structure throughout the year, as presented in the previous Section. In order to show the importance of intra-year production fluctuations to calculate losses, we reestimated the Chehalis flood event using quarterly data in the GDIO model.

We follow the same specifications as before but use the quarterly IO tables for each county instead of the annual tables. Total losses were calculated as the difference between the baseline simulation (no disruption) and the disaster simulation. We use the GDIO model since it was designed to handle intra-year tables in a dynamic fashion, besides endogenously accounting for demographic changes within the year (see Chapter 3).

The quarterly GDP by county is presented in Table 4.7. For all regions, Q3 generates the highest regional income in the year, while Q1 generates the lowest in Lewis and Thurston, and Q2 in Grays Harbor. Thurston has the largest intra-year production variability of all counties, especially in Construction, Wholesale Trade and Public Administration. In Lewis County, Agriculture, Construction, Healthcare and Manufacturing show high fluctuation within the year. The former three sectors are directly impacted by the flood, so we should expect different results when using quarterly data instead of annual. Grays Harbor exhibits larger Q1 multipliers overall, in clear contrast with Lewis and Thurston, where Q1 has overall lower linkages in relation to the rest of the year.

Table 4.7: Evolution of total GDP per quarter, 2008 million dollars

	Q1	**Q2**	**Q3**	**Q4**	**Annual**
Grays Harbor	483	479	499	482	1,942
Lewis	504	513	526	511	2,054
Thurston	2,155	2,187	2,264	2,248	8,855

The use of intra-year data reduces the total flow losses in both Lewis and Thurston counties (Table 4.8), since the initial months post-disaster (when inoperability is the highest) coincide with the quarter in which production is the lowest in the year (Q1). As expected, the largest decline is observed in Thurston (-1.3%), the county with the highest variability between quarters. Thurston's estimates reduce due to weaker first and second quarters when compared to the rest of the year, especially driven by Wholesale Trade and Professional Services, which are very seasonal and represent a significant portion of the losses. Lewis has a somewhat uniform reduction in losses across all sectors, caused primarily by weaker linkages in Q1. Notice that Grays Harbor shows a small, but positive change from the annual data estimates (+0.1%), as Q1 and Q4 have a similar level of interindustrial connectivity.

Table 4.8: Comparison of results using annual vs quarterly data

	Grays Harbor		**Lewis**		**Thurston**	
Sector	**Annual**	**Quarterly**	**Annual**	**Quarterly**	**Annual**	**Quarterly**
11 Ag., Fore., Fish & Hun.	-1.38	-1.36	-1.27	-1.26	-0.39	-0.39
21 Mining	-0.00	-0.00	-0.01	-0.01	-0.00	-0.00
22 Utilities	-0.00	-0.00	-0.22	-0.22	-0.00	-0.00
23 Construction	-0.49	-0.49	-1.10	-1.07	-0.20	-0.20
31-33 Manufacturing	-0.37	-0.37	-1.84	-1.83	-0.02	-0.02
42 Wholesale Trade	-0.13	-0.13	-0.28	-0.28	-0.23	-0.16
44-45 Retail Trade	-0.07	-0.07	-1.71	-1.71	-0.07	-0.06
48-49 Transp. & Ware.	-0.02	-0.02	-0.10	-0.10	-0.00	-0.00
51-53 Inf. & FIRE	-0.10	-0.11	-1.44	-1.44	-0.06	-0.11
54-56 Prof., Mgmt. & Adm.	-0.39	-0.40	-1.30	-1.30	-0.27	-0.23
61 Educational Svcs.	-0.01	-0.01	-0.01	-0.01	-0.00	-0.00
62 Health & Social Svcs.	-0.05	-0.05	-12.09	-12.05	-0.04	-0.06
71 Arts, Ent. & Rec.	-0.00	-0.00	-0.17	-0.17	-0.00	-0.00
72 Accom. & Food Svcs.	-0.01	-0.01	-0.18	-0.17	-0.00	-0.01
81 Other Svcs.	-0.06	-0.06	-0.81	-0.81	-0.01	-0.02
92 Gov. & non-NAICS	-0.81	-0.81	-0.11	-0.11	-0.99	-0.99
TOTAL	**-3.90**	**-3.90**	**-22.64**	**-22.53**	**-2.28**	**-2.25**
	+0.1%		**-0.5%**		**-1.3%**	

Next, we analyze how the timing of the event affects the estimated losses. The date in which the disruption occurs is irrelevant when the models are based on annual data, since the underlying economic structure does not change within the year. Nonetheless, using sub-annual data, the time dimension becomes significant because the direct and indirect linkages between industries are varying. To understand its implications, we simulate the Chehalis flood with the same parametrization as before, but we start the event at different months in 2007.

Figure 4.12 shows the differences in total losses between the simulations and the actual event. Grays Harbor and Lewis County have the lowest variation within the year and Thurston the largest, as expected from the previous discussion. The estimated total impact of the flood in Grays Harbor is larger than the yearly-based estimates if the disruption occurred in the first and third quarters, driven mainly by increased losses in Retail and FIRE activities (Figure 4.13).

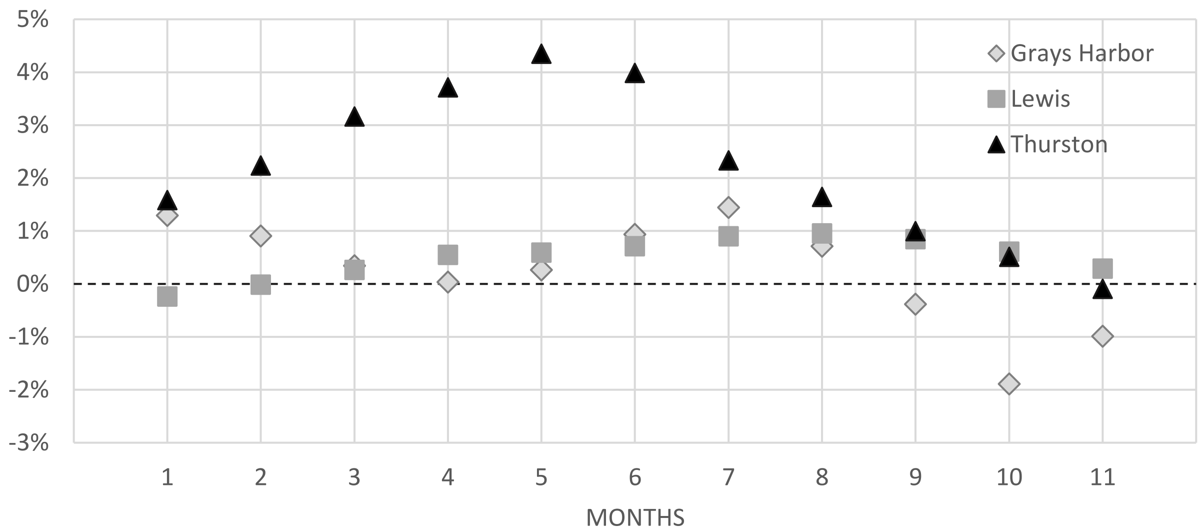
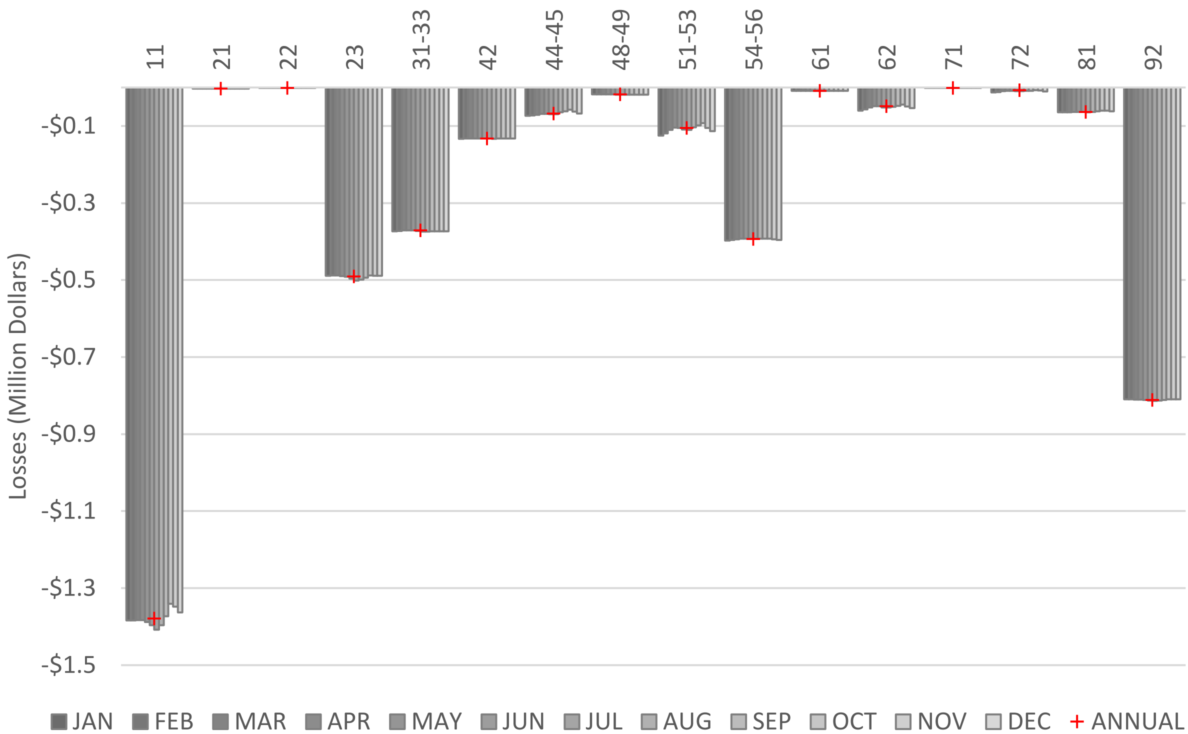


Figure 4.12: Change in total losses from December due to different event dates

The distribution of sectoral losses in Lewis County are quite stable irrespectively of the timing of the disruption (Figure 4.14), and are very close to the yearly-based distribution. Healthcare, the most impacted sector in the flood, shows only a 1% difference when varying the timing of the disruption. Construction fluctuates the most (8%), with larger total losses in Q3 when it is more active in the region. In this case, the use of the annual IO table does not bias the scope of the losses (although it affects the scale, see Table 4.8).

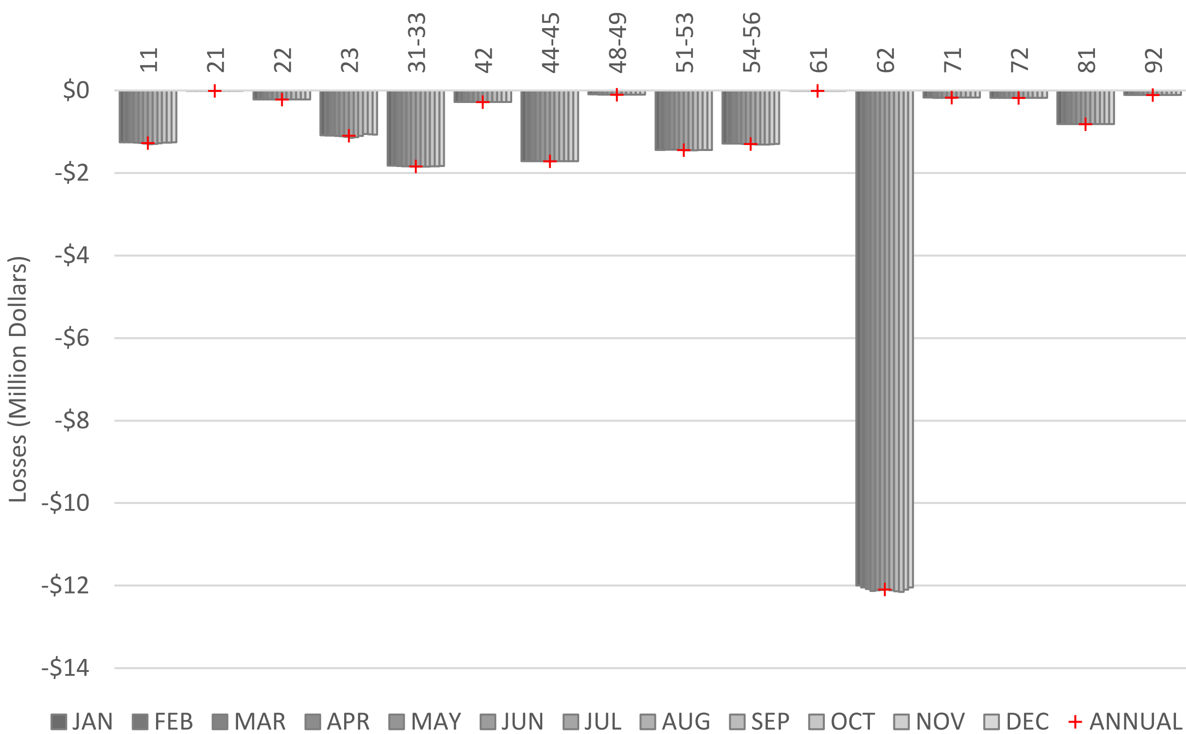


Notes: (11) Ag., Fore., Fish & Hun.; (21) Mining; (22) Utilities; (23) Construction; (31-33) Manufacturing; (42) Wholesale Trade; (44-45) Retail Trade; (48-49) Transp. & Ware.; (51-53) Inf. & FIRE; (54-56) Prof., Mgmt. & Adm.; (61) Educational Svcs.; (62) Health & Social Svcs.; (71) Arts, Ent. & Rec.; (72) Accom. & Food Svcs.; (81) Other Svcs.; (92) Gov. & non-NAICS.

Figure 4.13: Changes in losses by industry due to different event dates, Grays Harbor

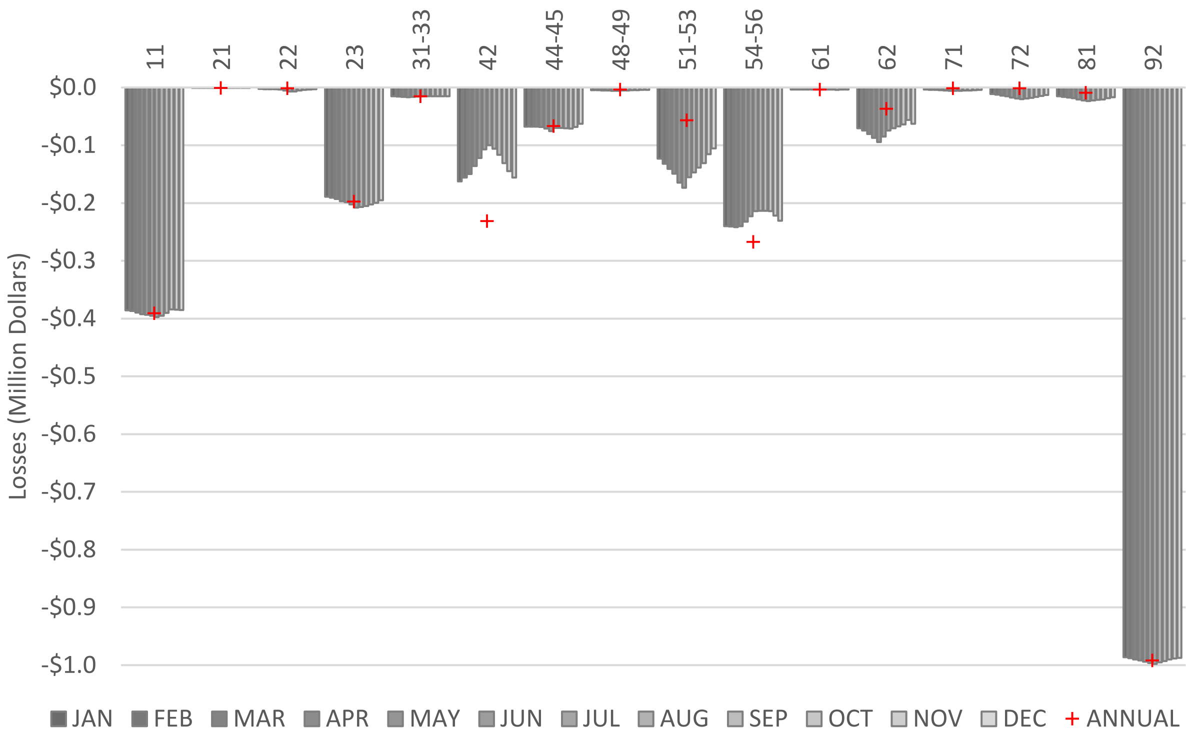
Thurston' simulations show a more pronounced variation in scale and scope of the losses especially in Construction, Trade, Services and Public Administration (Figure 4.15). Except for Wholesale Trade, these sectors would have their largest losses if the flood had occurred in the middle of the year, when their output and linkages to the rest of the economy are the strongest. Hence, for this particular county, the timing of the flood is a significant factor in determining its impact and the distribution of effects. Although these variations at first seem small, recall that Thurston had the least amount of inoperability among all counties (less than 1%), so we expect these differences to become more significant in a larger disruption.

In sum, these results allude to how regional idiosyncrasies can have diametrical effects when the timing of the event and the seasonality in the economic structure are ignored. Since we cannot generalize these observations to other counties or disasters, practitioners need to be aware of the bias that they might incur from the common practice of using annual data to assess transient phenomena.



Notes: (11) Ag., Fore., Fish & Hun.; (21) Mining; (22) Utilities; (23) Construction; (31-33) Manufacturing; (42) Wholesale Trade; (44-45) Retail Trade; (48-49) Transp. & Ware.; (51-53) Inf. & FIRE; (54-56) Prof., Mgmt. & Adm.; (61) Educational Svcs.; (62) Health & Social Svcs.; (71) Arts, Ent. & Rec.; (72) Accom. & Food Svcs.; (81) Other Svcs.; (92) Gov. & non-NAICS.

Figure 4.14: Changes in losses by industry due to different event dates, Lewis



Notes: (11) Ag., Fore., Fish & Hun.; (21) Mining; (22) Utilities; (23) Construction; (31-33) Manufacturing; (42) Wholesale Trade; (44-45) Retail Trade; (48-49) Transp. & Ware.; (51-53) Inf. & FIRE; (54-56) Prof., Mgmt. & Adm.; (61) Educational Svcs.; (62) Health & Social Svcs.; (71) Arts, Ent. & Rec.; (72) Accom. & Food Svcs.; (81) Other Svcs.; (92) Gov. & non-NAICS.

Figure 4.15: Changes in losses by industry due to different event dates, Thurston

The estimated flow losses have so far assumed absence of trade restrictions during the post-disaster period. However, according to WSDOT (2008) the Chehalis flood also led to a 4-day closure of interstate I-5 (Dec-3 to Dec-6), during which accessibility to the region was compromised, especially in Lewis County. Since we are able to more properly capture local economic conditions at the time of the disaster using the quarterly data, and accessibility constraints can be easily implement in the GDIO model, we simulated this highway closure by reducing the trade volume in the counties in 50% during these four days.

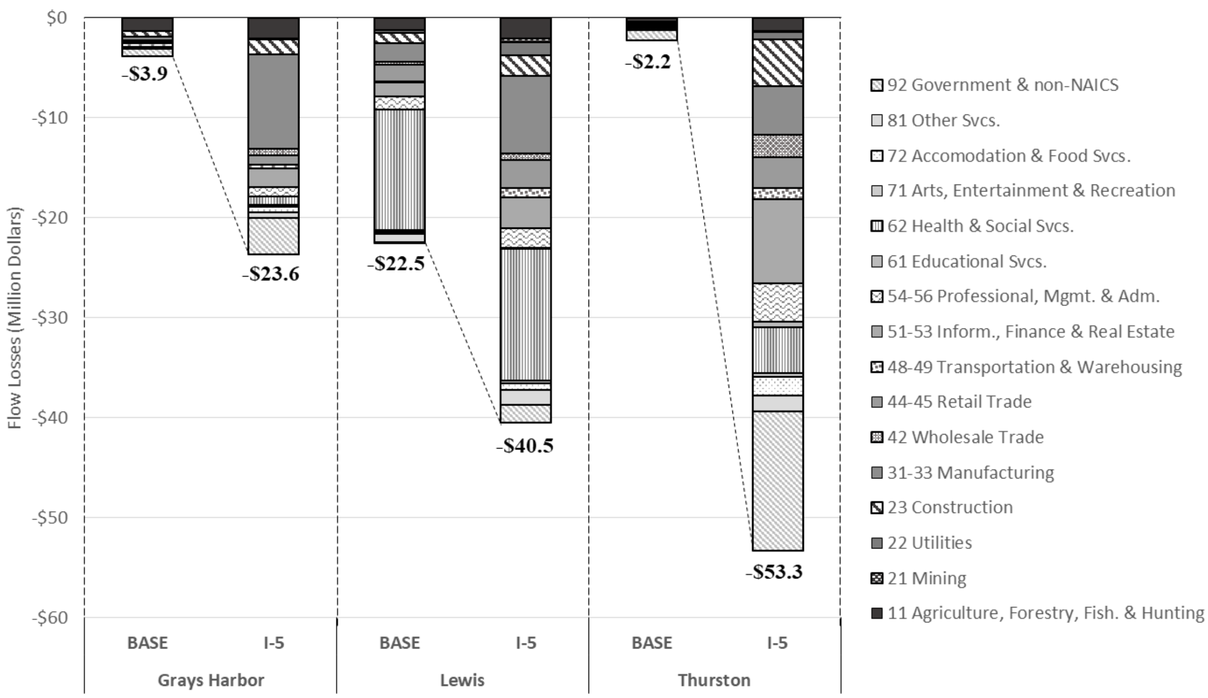


Figure 4.16: Differences in flow losses between annual and quarterly IO tables

The results indicate a significant increase in impacts in all counties, particularly in Thurston, where public administration, FIRE, construction and manufacturing sectors are the most impacted (Figure 4.16). Lewis County has the lowest increase, due to the higher inoperability in its economy during the closure period that led to a forced reduction in local import requirements. Grays Harbor shows a significant increase in losses from manufacturing because of its high multiplier in the quarter and high dependence on external markets.[66]

4.7. Conclusions

Although stock damages are well understood, flow impacts taking place in the post-disaster period tend to be overlooked (Koks *et al.*, 2015; Meyer *et al.*, 2013). As a result, mitigation strategies for future events are myopically applied to the affected economies, as if

[66] WSDOT (2008) provides an estimate of the flow losses impacts of this disruption based on a Leontief model using annual data from IMPLAN. Our results are not comparable to WSDOT's since we are considering the cumulative effect of the local inoperability in the region compounded with the highways closure, while WSDOT accounts only for the impact of the trucking industry on the other sectors in the state.

they had no spatial and temporal linkages. This partial account of impacts ignores the interconnectivity of modern production chains and may lead to significant negative effects to non-affected regions.

The disaster literature has several models to assess flow losses and most of them are rooted in the IO framework. However, there is no consensus on a preferred methodology. Therefore, researchers are often faced with a model selection issue based on the characteristics of the disaster, of the affected region(s), and on their assumptions on the mechanics of the local economy.

Until the criticism of Dietzenbacher and Miller (2015) and Oosterhaven (2017), several disaster applications were based on the static IIM. Besides this model, Cochrane's rebalancing algorithm has also been widely used because of its practicality, minimum data requirement and, more especially, availability in HAZUS's Indirect Economic Model. As this feature has been deactivated in the most recent versions of the software, we anticipate that future analyses will rely even more on the traditional Leontief Model, that is quite popular due to software solutions like IMPLAN, which require no specialized knowledge. However, our results indicate that the benefits of such practicality come at the expense of a loss of accuracy due to problematic assumptions of the traditional Leontief model when used in disaster situations. While for small regions with minimal damages and low seasonality the trade-off between practicality and accuracy might be small, these errors tend to increase with the size of the stock damages, complexity of economic linkages and whether locally important industries are impacted.

In this Chapter, we use fine-scale characteristics of a single event, the 2007 Chehalis flood (WA), to calculate the flow losses that are generated by seven models in the disaster literature. The results highlight their bias under different economic structures, level of industrial interdependency in affected sectors and amount of inoperability. We also show that the common practice of ignoring intra-year fluctuations in the economic structure can have significant impacts in the results depending on the characteristics of the local economy.

Since every disaster event and affected region is unique, the more often practitioners and stakeholders use their knowledge of the local economy to calibrate these models, the more accessible they appear to future users. For instance, the impact on regions dependent on non-seasonal industries might be fairly well estimated using annual datasets. However, in cases where data is very limited to perform an analysis, we recommend using at least a rebalancing method such as Cochrane's, instead of the traditional Leontief model. Compared to the latter, capacity constraints in the former are better captured, and the effects of forward impacts are partially introduced at no additional data cost to the user. At optimum, a model as the GDIO would be preferred, since its theoretical foundations more closely capture the local economic dynamic post-disaster.

This Chapter also highlighted the importance of spatio-temporal aspects of disasters, showing how different regional structures and timing of the event can significantly alter the extent and scope of impacts. Since local sectoral linkages and external trade patterns change throughout the year, they also affect input substitution availability, inventories and capacity constraints which create different feasible recovery options. Hence, including these data when estimating flow losses is paramount.

Due to its flexibility, easy implementation and interpretation, the IO framework should be in the toolbox of practitioners in the disaster field, who should also be aware of the assumptions and limitations of the different models. As shown in this Chapter, to provide a more comprehensive solution to practitioners, it is feasible to develop an integrated framework linking HAZUS and the GDIO model with quarterly data of different counties in the US, which would account for time and spatial characteristics of the region and the disruptive event. While the additional complexity of such extensions seems to conflict with the short timeframe emergency and disaster relief efforts operate under, the more accurate and detailed analysis they generate, the better such analysis can informs us of the current vulnerability of our economic system, and allow us to adapt more suitably to future events (Okuyama, 2007).

REFERENCES

Abowd, J., Stephens, B., Vilhuber, L., Andersson, F., McKinney, K., Roemer, M., & Woodcock, S. (2005). *The LEHD Infrastructure Files and the Creation of the Quarterly Workforce Indicators*. U.S. Census Bureau, Technical Paper No. TP-2006-01. Available from https://lehd.ces.census.gov/doc/technical_paper/tp-2006-01.pdf

Albertson, K., & Aylen, J. (1996). Modelling the Great Lakes Freeze: Forecasting and Seasonality in the Market for Ferrous Scrap. *International Journal of Forecasting*, 12(3), 345-359.

Aulin-Ahmavaara, P. (1990). Dynamic Input-Output and Time. *Economic Systems Research*, 2(4), 329-344.

Bacharach, M. (1970). *Biproportional Matrices and Input-Output Change*. Cambridge: Cambridge University Press.

Banks, J., Camp, J., & Abkowitz, M. (2014). Adaptation Planning for Floods: a Review of Available Tools. *Natural Hazards*, 70(2), 1327-1337.

Barker, K., & Santos, J. (2010). Measuring the Efficacy of Inventory with a Dynamic Input-Output Model. *International Journal of Production Economics*, 126, 130-143.

Baroud, H., Barker, K., Ramirez-Marquez, J., & Rocco, C. (2015). Inherent Costs and Interdependent Impacts of Infrastructure Network Resilience. *Risk Analysis*, 35(4), 642-662.

Batey, P. (2018). What Can Demographic-Economic Modeling Tell Us About the Consequences of Regional Decline? *International Regional Science Review*, 41(2), 256-281.

Batey, P., & Weeks, M. (1989). The Effects of Household Disaggregation in Extended Input-Output Models. In R. Miller, K. Polenske and A. Rose (Eds.), *Frontiers of Input-Output Analysis* (pp. 119-133). New York: Oxford University Press.

Batey, P., Bazzazan, F., & Madden, M. (2001). Dynamic Extended Input-Output Models: Some Initial Thoughts. In D. Felsentein, R. Mcquaid, P. McCann and D. Shefer (Eds.), *Public Investment and Regional Development* (pp. 26-39). Northampton: Edward Elgar.

Batten, B. (1981). *Entropy, Information Theory and Spatial Input-Output Analysis* (Doctoral dissertation). Retrieved from Umeå University Library. (URN No. urn:nbn:se:umu:diva-73612)

Bénassy, J. (2002). *The Macroeconomics of Imperfect Competition and Nonclearing Markets*. Cambridge: MIT Press.

Bernadini, R. (2008). A Composite Generalized Cross-Entropy Formulation in Small Samples Estimation. *Econometric Reviews*, 27(4-6), 596-609.

Beutel, J. (2002). *The Economic Impact of Objective 1 Interventions for the Period 2000-2006, Report to the Directorate-General for Regional Policies, Konstanz*. Retrieved from http://ec.europa.eu/regional_policy/sources/docgener/studies/pdf/objective1/final_report.pdf

Beyers, W. (1978). *Estimating Constraint Values for the Bi-proportional Method of Constructing Regional Input-Output Tables*. Mimeographed paper, University of Washington, Seattle.

Bočkarjova, M. (2007). *Major Disasters in Modern Economies: An Input-Output Based Approach at Modelling Imbalances and Disproportions* (Unpublished doctoral dissertation). University of Twente, Enschede, Netherlands.

Bureau of Labor Statistics. (2018a). Handbook of Methods – Quarterly Census of Employment and Wages. Available from https://www.bls.gov/opub/hom/cew/home.htm

Bureau of Labor Statistics. (2018b). *Quarterly Census of Employment and Wages* [Data file]. Available from https://www.bls.gov/cew/datatoc.htm

Bureau of Economic Analysis. (2017). *Concepts and Methods of the U.S. National Income and Product Accounts*. Retrieved from https://www.bea.gov/methodologies/index.htm#national_meth

Bureau of Economic Analysis. (2018a). *Input-Output Accounts Data* [Data file]. Available from https://www.bea.gov/industry/io_annual.htm

Bureau of Economic Analysis. (2018b). *International Economic Accounts* [Data file]. Available from https://www.bea.gov/international/index.htm

Bureau of Economic Analysis. (2018c). *National Economic Accounts* [Data file]. Available from https://www.bea.gov/national/index.htm

Butterfield, M., & Mules, T. (1980). A Testing Routine for Evaluating Cell-by-Cell Accuracy in Short-cut Regional Input-Output Tables. *Journal of Regional Science*, 20, 293-310.

Carter, A. (1970). *Structural Change in the American Economy*. Cambridge: Harvard University Press.

Census Bureau. (2018a). *Construction Spending Survey* [Data file]. Available from https://www.census.gov/construction/c30/c30index.html

Census Bureau. (2018b). *Manufacturers' Shipments, Inventories, & Orders* [Data file]. Available from https://www.census.gov/manufacturing/m3/historical_data/index.html

Census Bureau. (2018c). *Manufacturing & Trade Inventories & Sales* [Data file]. Available from https://www.census.gov/mtis/historic_releases.html

Census Bureau. (2018d). *Quarterly Workforce Indicators* [Data file]. Available from https://ledextract.ces.census.gov/static/data.html

Chehalis River Basin Flood Authority. (2010). Chehalis River Basin Comprehensive Flood Hazard Management Plan. Retrieved from http://lewiscountywa.gov/attachment/3009/JuneFloodPlan 6.10.pdf

Cochrane, H. (1997). Forecasting the Economic Impact of a Midwest Earthquake. In B. Jones (Ed.), *Economic Consequences of Earthquakes: Preparing for the Unexpected* (pp. 223-247). Buffalo: NCEER.

Cole, S. (1988). The Delayed Impacts of Plant Closures in a Reformulated Leontief Model. *Papers of the Regional Science Association*, 65, 135-149.

Cole, S. (1989). Expenditure Lags in Impact Analysis. *Regional Studies*, 23(2), 105-116.

Crosson, P. (1960). Further Comment on Economic Base Theory. *Land Economics*, 36(2), 197-201.

The Data Center. (2015). *Facts for Features: Katrina Recovery*. Retrieved from https://www.datacenterresearch.org/data-resources/katrina/facts-for-features-katrina-recovery/

Debreu, G. (1959). *Theory of Value*. New Haven: Yale University Press.

Dietzenbacher, E., & Miller, R. (2009). RAS-ing the Transactions or the Coefficients: It Makes no Difference. *Journal of Regional Science*, 49, 555-566.

Dietzenbacher, E., & Miller, R. (2015). Reflections on the Inoperability Input-Output Model. *Economic Systems Research*, 27(4), 478-486.

Ding, A., White, J., Ullman, P., & Fashokun, A. (2008). Evaluation of HAZUS-MH Flood Model with Local Data and Other Program. *Natural Hazards Review*, 9(1), 20-28.

Donaghy, K., Balta-Ozkan, N., & Hewings, G. (2007). Modeling Unexpected Events in Temporally Disaggregated Econometric Input-Output Models of Regional Economies. *Economic Systems Research*, 19, 125-145.

Duchin, F., & Levine, S. (2011). Sectors May Use Multiple Technologies Simultaneously: The Rectangular Choice-of-Technology Model with Binding Factor Constraints. *Economic Systems Research*, 23(3), 281-302.

Eurostat. (2008). *Eurostat Manual of Supply, Use and Input-Output Tables*. Luxembourg: Office for Official Publications of the European Communities.

Federal Reserve Bank of St. Louis. (2016). *Manufacturers: Inventories to Sales Ratio* [Data file]. Available from https://research.stlouisfed.org/fred2

Federal Emergency Management Agency. (2015). *Multi-Hazard Loss Estimation Methodology, Flood Model, HAZUS-MH Technical Manual*. Department of Homeland Security, Emergency Preparedness and Response Directorate, FEMA, Mitigation Division, Washington, D.C.

Federal Emergency Management Agency. (2017). *FEMA Disaster Declarations Dataset* [Data file]. Available from https://www.fema.gov/media-library/assets/documents/28318

Fernández-Vázquez, E. (2010). Recovering Matrices of Economic Flows from Incomplete Data and a Composite Prior. *Entropy*, 12, 516-527.

Fernández-Vázquez, E. (2015). Empirical Estimation of Non-Linear Input-Output Models: An Entropy Econometrics Approach. *Economic Systems Research*, 27(4), 508-524.

Fernández-Vázquez, E., Hewings, G., & Ramos, C. (2015). Adjustment of Input-Output Tables from Two Initial Matrices. *Economic Systems Research*, 27(3), 345-361.

Gall, M., Borden, K., & Cutter, S. (2009). When do Losses Count? *Bulletin of the American Meteorological Society*, 90(6), 799-809.

Gilchrist, D., & St. Louis, L. (1999). Completing Input-Output Tables using Partial Information, with an Application to Canadian Data. *Economic Systems Research*, 11, 185-194.

Golan, A. (2001). A Simultaneous Estimation and Variable Selection Rule. *Journal of Econometrics*, 101, 165-193.

Golan, A., Judge, G., & Miller, D. (1996). *Maximum Entropy Econometrics: Robust Estimation with Limited Data*. New York: Wiley.

Golan, A., Judge, G., & Robinson, S. (1994). Recovering Information from Incomplete or Partial Multisectoral Economic Data. *Review of Economics and Statistics*, 76(3), 541-549.

Green, R., Miles, S., Gulacsik, G., & Levy, J. (2008). Business Recovery Related to High-Frequency Natural Hazard Events. *Quick Response Report*, 197. Retrieved from http://hermes.cde.state.co.us/drupal/islandora/object/co%3A9432/datastream/OBJ/view

Greenberg, M., Lahr, M., & Mantell, N. (2007). Understanding the Economic Costs and Benefits of Catastrophes and their Aftermath: a Review and Suggestions for the U.S. Federal Government. *Risk Analysis*, 27(1), 83-96.

Guilhoto, J., & Sesso Filho, U. (2005). Estimação da Matriz Insumo-Produto a Partir de Dados Preliminares das Contas Nacionais. *Economia Aplicada*, 9, 277-299.

Haimes, Y., & Jiang, P. (2001). Leontief-Based Model of Risk in Complex Interconnected Infrastructures. *Journal of Infrastructure Systems*, 7(1), 1-12.

Hallegatte, S. (2008). An Adaptive Regional Input-Output Model and its Application to the Assessment of the Economic Cost of Katrina. *Risk Analysis*, 28(3), 779-799.

Hallegatte, S. (2014). Modeling the Role of Inventories and Heterogeneity in the Assessment of the Economic Costs of Natural Disasters. *Risk Analysis*, 34(1), 152-167.

Hallegatte, S., & Ghil, M. (2008). Natural Disasters Impacting a Macroeconomic Model with Endogenous Dynamics. *Ecological Economics*, 68, 582-592.

Hendricks, K., & Singhal, V. (2005). An Empirical Analysis of the Effect of Supply Chain Disruptions on Long-Run Stock Price Performance and Equity Risk of the Firm. *Production and Operations Management*, 14(1), 35-52.

Hewings, G. (1977). Evaluating the Possibilities for Exchanging Regional Input-Output Coefficients. *Environment and Planning A*, 9, 927-944.

Hewings, G., Changnon, S., & Dridi, C. (2000). Testing for the Significance of Extreme Weather and Climate Events on State Economies. *REAL Discussion Papers*, 00-T-06. Retrieved from http://www.real.illinois.edu/d-paper/00/00-t-6.pdf

Hewings, G., & Mahidhara, R. (1996). Economic Impacts: Lost Income, Ripple Effects, and Recovery. In S. Changnon (Ed.), *The Great Flood of 1993: Causes, Impacts, and Responses* (pp. 205-217). Boulder: Westview Press.

IMPLAN. (2015). *2008 Washington State Input-Output Tables* [Data file]. Available from http://www.implan.com/data/

IMPLAN. (2018). *2015 Illinois State Input-Output Tables* [Data file]. Available from http://www.implan.com/data/

Instituto Brasileiro de Geografia e Estatística. (2014). *Sistema de Contas Nacionais - Brasil 2005-2009* [Data file]. Available from https://ww2.ibge.gov.br/home/estatistica/economia/contasnacionais/2009/default.shtm

Isard, W. (1951). Interregional and Regional Input-Output Analysis: A Model of a Space Economy. *Review of Economics and Statistics*, 33, 318-328.

Israilevich, P., Hewings, G., Sonis, M., & Schindler, G. (1997). Forecasting Structural Change with a Regional Econometric Input-Output Model. *Journal of Regional Science*, 37, 565-590.

Isserman, A. (1977). The Location Quotient Approach to Estimating Regional Economic Impacts. *Journal of the American Institute of Planners*, 43, 33-41.

Jackson, R., Madden, M., & Bowman, H. (1997). Closure in Cole's Reformulated Leontief Model. *Papers in Regional Science*, 76(1), 21-28.

Jackson, R., & Madden, M. (1999). Closing the Case on Closure in Cole's Model. *Papers in Regional Science*, 78(4), 423-427.

Jackson, R., & Murray, A. (2004). Alternative Input-Output Matrix Updating Formulations. *Economic Systems Research*, 16, 135-148.

Jalili, A. (2000). Evaluating Relative Performances of Four non-Survey Techniques of Updating Input-Output Coefficients. *Economics of Planning*, 33, 221-237.

Jaynes, E. (1957). Information Theory and Statistical Mechanics. *Physics Review*, 106, 620-630.

Junius, T., & Oosterhaven, J. (2003). The Solution of Updating or Regionalizing a Matrix with both Positive and Negative Entries. *Economic Systems Research*, 15, 87-96.

Kim, K., Kratena, K., & Hewings, G. (2014). The Extended Econometric Input-Output Model with Heterogeneous Household Demand System. *Economic Systems Research*, 27(2), 257-285.

Kim, K., & Hewings, G. (2018). Bayesian Estimation of Labor Demand by Age: Theoretical Consistency and an Application to an Input-Output Model. *Economic Systems Research*. Advance online publication.

Knudsen, D., & Fotheringham, A. (1986). Matrix Comparison, Goodness-of-fit and Spatial Interaction Modeling. *International Regional Science Review,* 10, 127-147.

Koks, E., Bočkarjova, M., de Moel, H., & Aerts, J. (2015). Integrated Direct and Indirect Flood Risk Modeling: Development and Sensitivity Analysis. *Risk Analysis,* 35(5), 882-900.

Koks, E., & Thissen, M. (2016). A Multiregional Impact Assessment Model for Disaster Analysis. *Economic Systems Research*, 29(4), 429-449.

Kratena, K., Streicher, G., Temurshoev, U., Amores, A., Arto, I., Mongelli, I., … Andreoni, V. (2013). *FIDELIO 1: Fully Interregional Dynamic Econometric Long-term Input-Output Model for the EU27*. Luxembourg: Publications Office of the European Union.

Kronenberg, T. (2009). Construction of Regional Input-Output Tables Using Nonsurvey Methods: The Role of Cross-Hauling. *International Regional Science Review*, 32, 40-64.

Kullback, S., & Leibler, R. (1951). On Information and Sufficiency. *Annals of Mathematical Statistics*, 4, 99-111.

Lahr, M. (2001). A Strategy for Producing Hybrid Regional Input-Output Tables. In M. Lahr & E. Dietzenbacher (Eds.), *Input-Output Analysis: Frontiers and Extensions* (pp. 211-242). New York: Palgrave.

Lemelin, A. (2009). A GRAS Variant Solving for Minimum Information Loss. *Economic Systems Research*, 21(4), 399-408.

Lenzen, M., Moura, C., Geschke, A., Kanemoto, K., & Moran, D. (2012). A Cycling Method for Constructing Input-Output Table Time Series from Incomplete Data. *Economic Systems Research*, 24, 413-432.

Lenzen, M., Gallego, B., & Wood, R. (2009). Matrix Balancing under Conflicting Information. *Economic Systems Research*, 21, 23-44.

Lenzen, M., Moran, D., Geschke, A., & Kanemoto, K. (2014). A Non-Sign-Preserving RAS Variant. *Economic Systems Research*, 26, 197-208.

Lenzen, M., Wood, R., & Gallego, B. (2007). Some Comments on the GRAS Method. *Economic Systems Research*, 19(4), 461-465.

Leontief, W. (1970). The Dynamic Inverse. In A. Carter and A. Bródy (Eds.), *Contributions to Input-Output Analysis I* (pp. 17-46). London, UK: North-Holland.

Lewis County. (2009). *Lewis County 2007 Flood Disaster Recovery Strategy*. Retrieved from https://www.ezview.wa.gov/Portals/_1492/images/default/April%202009%20Lewis%20Co%20Recovery%20Strategy.pdf

Li, J., Crawford-Brown, D., Syddall, M., & Guan, D. (2013). Modeling Imbalanced Economic Recovery Following a Natural Disaster Using Input-Output Analysis. *Risk Analysis*, 33(10), 1908-1923.

Lian, C., & Haimes, Y. (2006). Managing the Risk of Terrorism to Interdependent Infrastructure Systems through the Dynamic Inoperability Input-Output Model. *Systems Engineering*, 9(3), 241-258.

López, X., & Cantuche, J. (2013) *Métodos de Actualización Global de Tablas Input-Output con Información Limitada: su Importancia para el Análisis Regional*. Retrieved from https://old.reunionesdeestudiosregionales.org/Oviedo2013/htdocs/pdf/p728.pdf

Lunsford, K. (2017). Lingering Residual Seasonality in GDP Growth. *Federal Reserve Bank of Cleveland*, Economic Commentary, March 2017.

Madden, M. (1993). Welfare Payments and Migration in a Nonlinear, Extended Input-Output Model with an Application to Scotland. *Papers in Regional Science*, 72(2), 177-199.

Matuszewski, T., Pitts, P., & Sawyer, J. (1964). Linear programming estimates of changes in input-output coefficients. *Canadian Journal of Economics and Political Science*, 30, 203-211.

Meyer, V., Becker, N., Markantonis, V., Schwarze, R., van Den Bergh, J., Bouwer, L., … Viavattene, C. (2013). Review article: Assessing the costs of natural hazards-state of the art and knowledge gaps. *Natural Hazards and Earth System Science*, 13(5), 1351-1373.

Miller, R., & Blair, P. (2009) *Input-Output Analysis: Foundations and Extensions*. New York: Cambridge University Press.

Mínguez, R., Oosterhaven, J., & Escobedo, F. (2009). Cell-Corrected RAS Method (CRAS) for Updating or Regionalizing an Input-Output Matrix. *Journal of Regional Science*, 49, 329-348.

Mules, T. (1983). Some Simulations with a Sequential Input-Output Model. *Papers of the Regional Science Association*, 51, 197-204.

National Oceanic and Atmospheric Administration. (2007). *Storm Data Preparation. National Weather Service Instruction 10-1605, 97*. Retrieved from http://www.nws.noaa.gov/directives/sym/pd01016005curr.pdf

National Weather Service. (2008). *Pacific Northwest Storms of December 1-3, 2007*. Retrieved from https://www.weather.gov/media/publications/assessments/pac_nw08.pdf.

Norcliffe, G. (1983). Using Location Quotients to Estimate the Economic Base and Trade Flows. *Regional Studies*, 17, 161-168.

Okuyama, Y. (2007). Economic Modeling for Disaster Impact Analysis: Past, Present, and Future. *Economic Systems Research*, 19(2), 115-124.

Okuyama, Y. (2009). *Critical Review of Methodologies on Disaster Impact Estimation*. Available at https://www.gfdrr.org/sites/gfdrr/files/Okuyama_Critical_Review.pdf

Okuyama, Y., Hewings, G., Kim, T., Boyce, D., Ham, H., & Sohn, J. (1999). Economic Impacts of an Earthquake in the New Madrid Seismic Zone: A Multiregional Analysis. In W. Elliot and P. McDonough (Eds.), *Optimizing Post-Earthquake Lifeline System Reliability: Proceedings of the 5th U.S. Conference on Lifeline Earthquake Engineering August 12-14, 1999* (pp. 592-601). Reston: American Society of Civil Engineers.

Okuyama, Y., Hewings, G., & Sonis, M. (2002) Economic Impacts of Unscheduled Events: Sequential Interindustry Model (SIM) Approach. *REAL Discussion Papers*, 02-T-11. (Unpublished).

Okuyama, Y., Hewings, G., & Sonis, M. (2004). Measuring Economic Impacts of Disasters: Interregional Input-Output Analysis Using Sequential Interindustry Model. In Y. Okuyama and S. Chang (Eds.), *Modeling Spatial and Economic Impacts of Disasters* (pp. 77-102). Berlin, Germany: Springer.

Okuyama, Y., & Lim, H. (2002). Linking Economic Model and Engineering Model: Application of Sequential Interindustry Model (SIM). *REAL Discussion Papers*, 02-T-12. (Unpublished).

Okuyama, Y., & Santos, J. (2014). Disaster Impact and Input-Output Analysis. *Economic Systems Research*, 26(1), 1-12.

Olshansky, R., Hopkins, L., & Johnson, L. (2012). Disaster and Recovery: Processes Compressed in Time. *Natural Hazards Review*, 13, 173-178.

Oosterhaven, J. (2000). Lessons from the Debate on Cole’s Model Closure. *Papers in Regional Science*, 79(2), 233-242.

Oosterhaven, J. (2017). On the Limited Usability of the Inoperability IO Model. *Economic Systems Research*, 29(3), 452-461.

Oosterhaven, J., & Bouwmeester, M. (2016). A New Approach to Modelling the Impacts of Disruptive Events. *Journal of Regional Science*, 56(4), 583-595.

Oosterhaven, J., & Többen, J. (2017). Wider Economic Impacts of Heavy Flooding in Germany: a Non-linear Programming Approach. *Spatial Economic Analysis*, 12(4), 404-428.

Pan, Q., & Richardson, H. (2015). Theory and Methodologies: Input-Output, SCPM and CGE. In H. Richardson, Q. Pan, J. Park and J. Moore II (Eds.), *Regional Economic Impacts of Terrorist Attacks, Natural Disasters and Metropolitan Policies* (pp. 21-45). New York: Springer.

Pant, R., Barker, K., Grant, F., & Landers, T. (2011). Interdependent Impacts of Inoperability at Multi-modal Transportation Container Terminals. *Transportation Research Part E: Logistics and Transportation Review*, 47(5), 722-737.

Park, J., & Richardson, H. (2014). National Interstate Economic Model (NIEMO). In H. Richardson, J. Park, J. Moore II, and Q. Pan (Eds.), *National Economic Impact Analysis of Terrorist Attacks and Natural Disasters* (pp. 4-23). Cheltenham: Edward Elgar.

Przyluski, V., & Hallegatte, S. (2011). *Indirect Costs of Natural Hazards* (No. WP2 Final Report). SMASH-CIRED. Retrieved from https://www.ufz.de/export/data/2/122162_CONHAZ%20REPORT%20WP02_2.pdf

Ptak, C., & Smith, C. (2011). *Orlicky's Material Requirements Planning*, Third Edition. New York: McGraw-Hill.

Richardson, H. (1985). Input-Output and Economic Base Multipliers: Looking Backward and Forward. *Journal of Regional Science,* 25, 607-661.

Robinson, S., Cattaneo, A., & El-Said, M. (2001). Updating and Estimating a Social Accounting Matrix Using Cross Entropy Methods. *Economic Systems Research*, 13(1), 47-64.

Romanoff, E., & Levine, S. (1977). Interregional Sequential Interindustry Model: A Preliminary Analysis of Regional Growth and Decline in a Two Region Case. *Northeast Regional Science Review*, 7, 87-101.

Romanoff, E., & Levine, S. (1981). Anticipatory and Responsive Sequential Interindustry Models. *IEE Transactions on Systems, Man, and Cybernetics*, 11(3), 181-186.

Romanoff, E., & Levine, S. (1986). Capacity Limitations, Inventory and Time-Phased Production in the Sequential Interindustry Model. *Papers of the Regional Science Association*, 59, 73-91.

Romanoff, E., & Levine, S. (1990). Technical Change in Production Processes of the Sequential Interindustry Model. *Metroeconomica*, 41(1), 1-18.

Rose, A. (2004). Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation. In Y. Okuyama and S. Chang (Eds.), *Modeling Spatial and Economic Impacts of Disasters* (pp. 13-36). Berlin, Germany: Springer.

Rose, A., & Benavides, J. (1998). Regional Economic Impacts. In M. Shinozuka, A. Rose and R. Eguchi (Eds.), *Engineering and Socioeconomic Impacts of Earthquakes: An Analysis of Electricity Lifeline Disruptions in the New Madrid Area* (pp. 95-124). Buffalo: MCEER.

Rose, A., & Wei, D. (2013). Estimating the Economic Consequences of a Port Shutdown: The Special Role of Resilience. *Economic Systems Research*, 25(2), 212-232.

Rudebusch, G., Wilson, D., & Mahedy T. (2015). The Puzzle of Weak First-Quarter GDP Growth. *Federal Reserve Bank of San Francisco*, Economic Letter, 2015-16.

Ryaboshlyk, V. (2006). A Dynamic Input-Output Model with Explicit New and Old Technologies: an Application to the UK. *Economic Systems Research*, 18, 183-203.

Santos, J. (2003). *Interdependency Analysis: extensions to demand reduction inoperability input-output modeling and portfolio selection* (Unpublished doctoral dissertation). University of Virginia, Charlottesville, Virginia.

Santos, J., & Haimes, Y. (2004). Modeling the Demand Reduction Input-Output (I-O) Inoperability Due to Terrorism of Interconnected Infrastructures. *Risk Analysis*, 24(6), 1437-1451.

Sargento, A. (2009). Introducing Input-Output Analysis at the Regional Level: Basic Notions and Specific Issues. *REAL Discussion Papers*, 09-T-4. Retrieved from http://www.real.illinois.edu/d-paper/09/09-T-4.pdf

Schnitkey, G., & Coppess, J. (2018). *Pre-Harvest Hedging and Revenue Protection*. farmdoc daily (8):88, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign. Retrieved from http://farmdocdaily.illinois.edu/2018/05/pre-harvest-hedging-revenue-protection.html

Sevaldson, P. (1970). The Stability of Input-Output Coefficients. In A. Carter & A. Bródy (Eds.), *Applications of Input-Output Analysis Vol. 2* (pp. 207-237). Amsterdam, Netherlands: North-Holland.

Shannon, C. (1948). A Mathematical Theory of Communication. *The Bell System Technical Journal*, 27, 379-423.

Snower, D. (1990). New Methods of Updating Input-Output Matrices. *Economic Systems Research*, 2, 27-37.

Sohn, J., Hewings, G., Kim, T., Lee, J., & Jang, S. (2004). Analysis of Economic Impacts of an Earthquake on Transportation Network. In Y. Okuyama and S. Chang (Eds.), *Modeling Spatial and Economic Impacts of Disasters* (pp. 233-256). Berlin, Germany: Springer.

Sonis, M., & Hewings, G. (1989). Error and Sensitivity Input-Output Analysis: a New Approach. In R. Miller, K. Polenske, and A. Rose (Eds.), *Frontiers of Input-Output Analysis* (pp. 232-244). New York: Oxford University Press.

Sonis, M., & Hewings, G. (1999). Economic Landscapes: Multiplier Product Matrix Analysis for Multiregional Input-Output Systems. *Hitotsubashi Journal of Economics*, 40, 59-74.

Stark, T. (2015). First Quarters in the National Income and Product Accounts. *Federal Reserve Bank of Philadelphia*, Research Rap Special Report, May 14.

Stone, R., & Brown, A. (1962). *A Computable Model of Economic Growth*. London, UK: Chapman and Hall.

Tarancón, M., & Río, P. (2005). Projection of Input-Output Tables by Means of Mathematical Programming Based on the Hypothesis of Stable Structural Evolution. *Economic Systems Research*, 17, 1-23.

Tate, E., Muñoz, C., & Suchan, J. (2014). Uncertainty and Sensitivity Analysis of the HAZUS-MH Flood Model. *Natural Hazards Review*, 16(2010), 4014030.

Temurshoev, U., Miller, R., & Bouwmeester, M. (2013). A Note on the GRAS Method. *Economic Systems Research*, 25(3), 361-367.

Temurshoev, U., Webb, C., & Yamano, N. (2011). Projection of Supply and Use Table: Methods and their Empirical Assessment. *Economic Systems Research*, 23, 91-123.

ten Raa, T. (1986). Dynamic Input-Output Analysis with Distributed Activities. *Review of Economics and Statistics*, 68(2), 300-310.

Theil, H. (1967). *Economics and Information Theory*. Amsterdam, Netherlands: North-Holland.

Thomas, D., & Kandaswamy, A. (2017). An Examination of National Supply-Chain Flow Time. *Economic Systems Research*. Advance online publication.

Tierney, K. (1997). Business Impacts of the Northridge Earthquake. *Journal of Contingencies and Crisis Management*, 5(2), 87-97.

Tilanus, C. (1968). *Input-Output Experiments, The Netherlands 1948-1961*. Rotterdam, Netherlands: Rotterdam University Press.

Tilanus, C., & Theil, H. (1965). The Information Approach to the Evaluation of Input-Output Forecasts. *Econometrica*, 33(4), 847-862.

Töben, J., & Kronenberg, T. (2015). Construction of Multi-Regional Input-Output Tables using the CHARM Method. *Economic Systems Research*, 27, 487-507.

Tohmo, T. (2004). New Developments in the Use of Location Quotients to Estimate Regional Input-Output Coefficients and Multipliers. *Regional Studies*, 38, 43-54.

United Nations. (2009). *System of National Accounts 2008*. New York: United Nations.

United States Department of Agriculture. (2010). *Field Crops Usual Planting and Harvesting Dates (October 2010)*. Retrieved from http://usda.mannlib.cornell.edu/usda/current/planting/planting-10-29-2010.pdf

University of Tennessee. (2014). *Managing Risk in the Global Supply Chain*. Knoxville: Global Supply Chain Institute. Available from https://haslam.utk.edu/whitepapers/global-supply-chain-institute/managing-risk-global-supply-chain

U.S. Army Corps of Engineers. (2010). *HEC-RAS River Analysis System: User's Manual*. Retrieved from http://www.hec.usace.army.mil/software/hec-ras/documentation/HEC-RAS_4.1_Users_Manual.pdf.

U.S. Department of Commerce. (2013). *Economic Impact of Hurricane Sandy: Potential Economic Activity Lost and Gained in New Jersey and New York*. Retrieved from http://www.esa.doc.gov/sites/default/files/sandyfinal101713.pdf

Vaccara, B. (1970). Changes over Time in Input-Output Coefficients for the United States. In A. Carter and A. Bródy (Eds.), *Applications of Input-Output Analysis Vol. 2* (238-260). Amsterdam, Netherlands: North-Holland.

van Dijk, J., & Oosterhaven, J. (1986). Regional Impacts of Migrants' Expenditures: An Input-Output/Vacancy-Chain Approach. In P. Batey and M. Madden (Eds.), *Integrated Analysis of Regional Systems* (pp. 122-147). London, UK: Pion.

Washington State Department of Transportation. (2008). *Storm-Related Closures of I-5 and I-90: Freight Transportation Economic Impact Assessment Report Winter 2007-2008*. Retrieved from https://www.wsdot.wa.gov/research/reports/fullreports/708.1.pdf

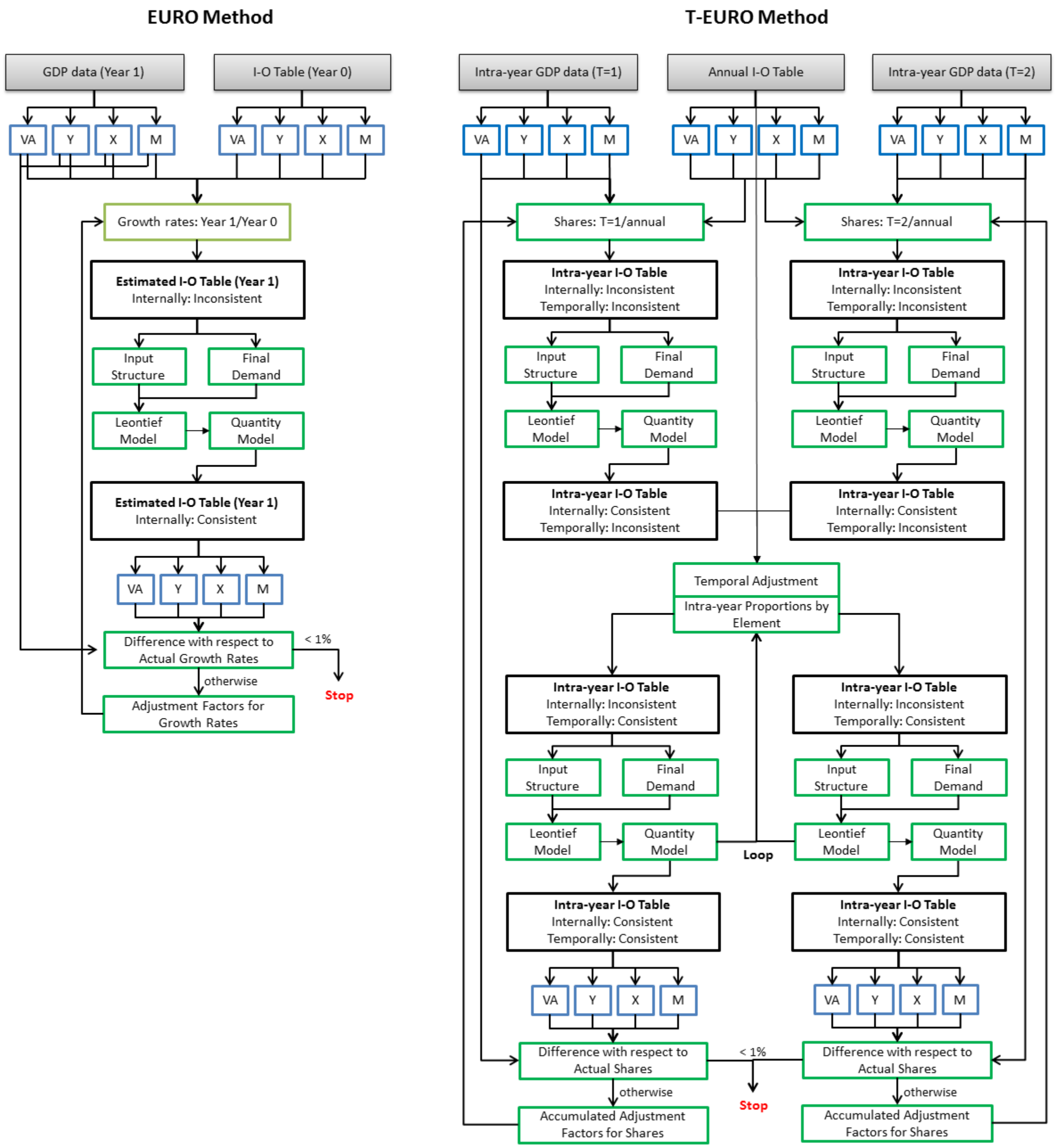
Washington State Employment Security Department. (2018). *Labor Market County Profiles* [Data file]. Available from https://esd.wa.gov/labormarketinfo/county-profiles

Wilson, A. (1970a). Interregional Commodity Flows: Entropy Maximizing Approaches. *Geographical Analysis*, 2, pp 255-282.

Wilson, A. (1970b). *Entropy in Urban and Regional Modelling*. London, UK: Pion.

Wolsky, A. (1984). Disaggregating Input-Output Models. *Review of Economics and Statistics*, 66, 283-291.

APPENDIX A: CHAPTER ONE



Notes: VA: value added by sector; Y: total final demand; X: total exports; M: total imports.

Figure A.1: EURO and T-EURO methods

Table A.1: Results of temporal disaggregation via T-EURO and RAS, 2002

		Technical Coefficient Matrix				Leontief Inverse Matrix			
		No Error	2% Error	5% Error	10% Error	No Error	2% Error	5% Error	10% Error
MAD	T-EURO $(Q)^S$	0.002				0.004			
	T-EURO $(Q)^H$	0.002				0.004			
	RAS	0.001	0.001	0.002	0.003	0.001	0.002	0.004	0.006
MAPE	T-EURO $(Q)^S$	17.379				6.015			
	T-EURO $(Q)^H$	17.322				6.003			
	RAS	7.236	8.353	9.677	13.085	2.217	3.307	6.617	9.803
WAPE	T-EURO $(Q)^S$	7.082				2.587			
	T-EURO $(Q)^H$	7.074				2.584			
	RAS	2.563	3.542	5.971	9.076	0.778	1.372	2.839	4.297
SWAD	T-EURO $(Q)^S$	0.066				0.014			
	T-EURO $(Q)^H$	0.066				0.014			
	RAS	0.019	0.031	0.063	0.093	0.002	0.006	0.014	0.023
PSI	T-EURO $(Q)^S$	0.071				0.026			
	T-EURO $(Q)^H$	0.071				0.026			
	RAS	0.026	0.035	0.060	0.091	0.008	0.014	0.028	0.043

Notes: T-EURO $(Q)^S$: 2002 table derived from the 2002-2005 “annual table” via simultaneous disaggregation
T-EURO $(Q)^H$: 2002 table derived from the 2002-2005 “annual table” via hierarchical disaggregation
RAS: 2002 table derived from the 2002-2005 “annual table”

Table A.2: Results of temporal disaggregation via T-EURO and RAS, 2003

		Technical Coefficient Matrix				Leontief Inverse Matrix			
		No Error	**2% Error**	**5% Error**	**10% Error**	**No Error**	**2% Error**	**5% Error**	**10% Error**
MAD	**T-EURO $(Q)^S$**	0.002				0.002			
	T-EURO $(Q)^H$	0.002				0.002			
	RAS	0.001	0.001	0.002	0.003	0.001	0.001	0.003	0.005
MAPE	**T-EURO $(Q)^S$**	11.273				4.494			
	T-EURO $(Q)^H$	11.260				4.429			
	RAS	8.372	8.999	11.776	11.926	1.902	3.083	5.468	9.325
WAPE	**T-EURO $(Q)^S$**	5.185				1.647			
	T-EURO $(Q)^H$	5.163				1.633			
	RAS	2.244	2.796	5.593	8.793	0.680	1.038	2.103	3.824
SWAD	**T-EURO $(Q)^S$**	0.039				0.007			
	T-EURO $(Q)^H$	0.039				0.007			
	RAS	0.016	0.019	0.043	0.083	0.002	0.004	0.008	0.015
PSI	**T-EURO $(Q)^S$**	0.052				0.016			
	T-EURO $(Q)^H$	0.052				0.016			
	RAS	0.022	0.028	0.056	0.088	0.007	0.010	0.021	0.038

Notes: T-EURO $(Q)^S$: 2003 table derived from the 2002-2005 “annual table” via simultaneous disaggregation
T-EURO $(Q)^H$: 2003 table derived from the 2002-2005 “annual table” via hierarchical disaggregation
RAS: 2003 table derived from the 2002-2005 “annual table”

Table A.3: Results of temporal disaggregation via T-EURO and RAS, 2005

		Technical Coefficient Matrix				Leontief Inverse Matrix			
		No Error	2% Error	5% Error	10% Error	No Error	2% Error	5% Error	10% Error
MAD	T-EURO $(Q)^S$	0.002				0.003			
	T-EURO $(Q)^H$	0.002				0.003			
	RAS	0.001	0.001	0.002	0.003	0.001	0.002	0.004	0.006
MAPE	T-EURO $(Q)^S$	11.064				4.898			
	T-EURO $(Q)^H$	11.073				4.924			
	RAS	5.451	6.069	8.192	11.384	2.484	3.862	7.491	8.971
WAPE	T-EURO $(Q)^S$	5.732				2.062			
	T-EURO $(Q)^H$	5.747				2.078			
	RAS	2.793	3.311	5.793	9.384	0.778	1.270	3.015	4.425
SWAD	T-EURO $(Q)^S$	0.048				0.012			
	T-EURO $(Q)^H$	0.048				0.012			
	RAS	0.018	0.021	0.054	0.099	0.003	0.005	0.015	0.027
PSI	T-EURO $(Q)^S$	0.057				0.021			
	T-EURO $(Q)^H$	0.057				0.021			
	RAS	0.028	0.033	0.058	0.094	0.008	0.013	0.030	0.044

Notes: T-EURO $(Q)^S$: 2005 table derived from the 2002-2005 “annual table” via simultaneous disaggregation
T-EURO $(Q)^H$: 2005 table derived from the 2002-2005 “annual table” via hierarchical disaggregation
RAS: 2005 table derived from the 2002-2005 “annual table”

Table A.4: Industrial disaggregation

Code	Sector
1	Agriculture
2	Mining
3	Manufacturing
4	Utilities and Waste
5	Construction
6	Wholesale Trade
7	Transportation and Warehousing
8	Information Services
9	Financial Services
10	Real Estate
11	Other Services
12	Government, Public Education and Health

	1	2	3	4	5	6	7	8	9	10	11	12	Final Demand	Exports	Total Output
1	5,129	5	27,136	1	5	4	1	0	1	0	665	118	13,820	5,917	52,801
2	184	682	9,885	548	199	4	26	1	0	0	9	6	182	3,849	15,577
3	8,735	2,213	81,810	1,415	9,417	3,061	6,296	1,616	1,339	297	12,326	3,849	92,107	38,056	262,536
4	272	881	6,567	6,250	102	1,289	397	365	304	37	2,153	1,544	8,862	3	29,026
5	0	210	347	4	961	43	10	53	299	856	638	1,919	29,871	201	35,410
6	1,653	396	13,347	342	1,753	1,484	1,336	388	406	71	3,155	1,470	26,066	5,655	57,521
7	700	1,570	7,566	477	434	2,784	2,982	658	467	40	1,799	614	13,975	1,765	35,829
8	84	410	2,201	275	65	793	351	4,277	1,998	71	5,245	3,474	8,600	131	27,975
9	524	274	4,831	308	253	724	582	403	5,874	59	585	6,106	16,928	313	37,765
10	19	406	579	59	141	837	334	595	196	56	891	996	32,399	273	37,781
11	81	1,061	5,628	1,126	646	3,631	2,288	2,622	3,013	327	5,862	5,836	56,934	5,098	94,153
12	23	62	445	155	25	158	84	100	105	11	248	188	82,675	132	84,412
Imports	1,934	937	21,753	833	1,072	1,098	1,226	785	568	75	2,243	1,429	17,816	-	51,770
Taxes	1,632	799	12,847	1,541	1,166	1,244	1,743	1,393	1,195	109	4,330	2,521	25,707	4,067	60,293
Value Added	31,831	5,673	67,593	15,692	19,172	40,367	18,173	14,718	22,002	35,771	54,004	54,342			379,339
Total Output	52,801	15,577	262,536	29,026	35,410	57,521	35,829	27,975	37,765	37,781	94,153	84,412	425,943	65,460	1,262,189

Figure A.2: Estimated IO table, 1st quarter 2004

	1	2	3	4	5	6	7	8	9	10	11	12	Final Demand	Exports	Total Output
1	6,349	7	33,181	1	6	4	1	0	1	0	793	142	16,477	7,658	64,620
2	239	982	12,791	674	245	5	33	2	1	1	11	8	226	5,339	20,556
3	10,560	2,884	96,575	1,597	10,586	3,579	7,209	1,826	1,511	338	14,009	4,411	104,856	47,904	307,846
4	302	1,024	6,963	6,380	103	1,355	410	371	308	38	2,207	1,588	9,092	3	30,144
5	0	259	389	5	1,025	48	10	57	319	925	689	2,086	32,320	240	38,373
6	1,931	493	15,095	370	1,887	1,662	1,466	420	438	77	3,436	1,612	28,438	6,811	64,136
7	798	1,894	8,307	502	454	3,029	3,182	692	490	43	1,906	654	14,825	2,059	38,835
8	94	484	2,366	283	66	844	367	4,394	2,042	74	5,432	3,615	8,920	150	29,131
9	566	309	4,942	301	245	732	578	393	5,675	58	576	6,027	16,696	340	37,439
10	21	472	613	60	142	878	344	604	198	58	911	1,022	33,168	307	38,798
11	93	1,282	6,188	1,189	676	3,955	2,445	2,763	3,167	348	6,219	6,226	60,482	5,957	100,990
12	26	75	495	165	26	174	90	106	110	12	265	202	88,504	156	90,409
Imports	2,340	1,225	25,687	939	1,204	1,283	1,403	886	639	86	2,547	1,636	20,264	-	60,138
Taxes	1,899	992	14,461	1,658	1,248	1,385	1,901	1,498	1,280	118	4,690	2,749	27,895	4,877	66,653
Value Added	39,402	8,174	79,793	16,020	20,458	45,203	19,396	15,120	21,260	36,623	57,299	58,428			417,174
Total Output	64,620	20,556	307,846	30,144	38,373	64,136	38,835	29,131	37,439	38,798	100,990	90,409	462,163	81,802	1,405,241

Figure A.3: Estimated IO table, 2nd quarter 2004

	1	2	3	4	5	6	7	8	9	10	11	12	Final Demand	Exports	Total Output
1	3,840	5	23,668	1	4	3	1	0	1	0	535	93	11,079	5,697	44,926
2	233	1,159	14,645	738	273	5	36	2	1	1	12	9	247	6,300	23,661
3	9,481	3,195	103,316	1,633	11,056	3,729	7,446	1,880	1,584	344	14,287	4,417	106,613	53,032	322,014
4	265	1,125	7,371	6,448	107	1,398	419	378	320	38	2,226	1,573	9,142	4	30,813
5	0	307	446	5	1,147	54	11	63	360	1,011	754	2,247	35,258	284	41,948
6	1,779	563	16,650	390	2,033	1,787	1,562	446	474	81	3,615	1,667	29,826	7,775	68,649
7	715	2,110	8,927	516	477	3,172	3,302	716	517	44	1,952	658	15,140	2,293	40,538
8	85	554	2,609	298	72	908	391	4,675	2,222	78	5,713	3,739	9,352	172	30,866
9	559	385	5,947	347	289	860	673	458	6,780	67	663	6,836	19,131	424	43,418
10	19	529	663	62	150	926	360	629	210	60	939	1,035	34,077	344	40,004
11	82	1,411	6,564	1,205	701	4,089	2,504	2,821	3,298	351	6,287	6,179	60,955	6,551	103,000
12	23	84	528	168	28	181	93	109	116	12	269	202	89,628	173	91,614
Imports	2,210	1,423	28,887	1,010	1,321	1,406	1,524	960	706	92	2,733	1,727	21,682	-	65,683
Taxes	1,801	1,166	16,432	1,802	1,386	1,535	2,088	1,643	1,432	128	5,087	2,934	30,159	5,731	73,323
Value Added	23,833	9,646	85,362	16,190	22,902	48,596	20,128	16,086	25,397	37,698	57,927	58,298			422,064
Total Output	44,926	23,661	322,014	30,813	41,948	68,649	40,538	30,866	43,418	40,004	103,000	91,614	472,290	88,780	1,442,521

Figure A.4: Estimated IO table, 3rd quarter 2004

	1	2	3	4	5	6	7	8	9	10	11	12	Final Demand	Exports	Total Output
1	3,243	4	21,800	1	4	3	1	0	0	0	499	94	10,365	4,771	40,786
2	214	1,022	13,852	701	257	5	34	2	1	1	11	9	235	5,502	21,845
3	9,573	3,038	105,873	1,684	11,229	3,794	7,596	1,995	1,669	357	14,782	4,801	110,261	49,974	326,626
4	268	1,072	7,589	6,683	109	1,430	429	404	339	39	2,316	1,725	9,509	3	31,917
5	0	281	439	5	1,119	53	11	64	364	1,005	748	2,341	34,955	257	41,641
6	1,804	537	17,116	404	2,072	1,824	1,599	475	501	84	3,752	1,816	30,940	7,352	70,276
7	725	2,014	9,193	535	486	3,244	3,386	765	547	45	2,031	720	15,743	2,170	41,604
8	94	562	2,856	329	78	986	426	5,295	2,494	86	6,321	4,331	10,339	173	34,370
9	609	388	6,458	380	312	927	728	513	7,539	74	726	7,823	20,955	423	47,855
10	20	527	714	68	160	989	386	702	232	65	1,021	1,182	37,046	340	43,452
11	85	1,369	6,877	1,271	727	4,253	2,613	3,064	3,553	372	6,655	6,878	64,494	6,302	108,512
12	28	92	629	202	33	214	111	135	142	15	325	254	107,969	189	110,337
Imports	2,176	1,326	28,952	1,018	1,314	1,400	1,520	996	727	93	2,764	1,832	21,913	-	66,031
Taxes	1,818	1,108	16,802	1,855	1,406	1,558	2,126	1,738	1,504	133	5,250	3,173	31,106	5,395	74,970
Value Added	20,127	8,505	87,475	16,782	22,336	49,598	20,639	18,223	28,241	41,083	61,312	73,359			447,681
Total Output	40,786	21,845	326,626	31,917	41,641	70,276	41,604	34,370	47,855	43,452	108,512	110,337	505,832	82,850	1,507,904

Figure A.5: Estimated IO table, 4th quarter 2004

Table A.5: Output multipliers

Sector	2004 Q1	2004 Q2	2004 Q3	2004 Q4	2005 Q1	2005 Q2	2005 Q3	2005 Q4	2006 Q1	2006 Q2	2006 Q3	2006 Q4
Agriculture	1.62	1.61	1.73	1.80	1.75	1.73	1.77	1.81	1.69	1.69	1.71	1.75
Mining	1.94	1.90	1.87	1.90	1.91	1.89	1.86	1.84	1.77	1.80	1.78	1.81
Manufacturing	2.17	2.17	2.15	2.15	2.20	2.22	2.21	2.21	2.18	2.19	2.18	2.17
Utilities and Waste	1.65	1.67	1.66	1.67	1.65	1.67	1.67	1.68	1.64	1.65	1.65	1.65
Construction	1.78	1.80	1.77	1.79	1.80	1.82	1.80	1.80	1.80	1.83	1.80	1.81
Wholesale Trade	1.44	1.44	1.43	1.44	1.45	1.45	1.45	1.44	1.44	1.45	1.44	1.43
Transp. and Warehousing	1.76	1.78	1.77	1.77	1.80	1.81	1.79	1.78	1.76	1.79	1.79	1.79
Information Services	1.67	1.69	1.67	1.66	1.67	1.68	1.67	1.68	1.69	1.70	1.69	1.69
Financial Services	1.62	1.65	1.62	1.61	1.54	1.53	1.49	1.49	1.51	1.52	1.52	1.50
Real Estate	1.09	1.09	1.09	1.09	1.09	1.10	1.09	1.09	1.10	1.10	1.10	1.10
Other Services	1.65	1.66	1.66	1.66	1.65	1.67	1.67	1.66	1.64	1.66	1.65	1.64
Gov., Pub. Edu. and Health	1.53	1.53	1.53	1.49	1.53	1.54	1.55	1.49	1.52	1.53	1.52	1.48

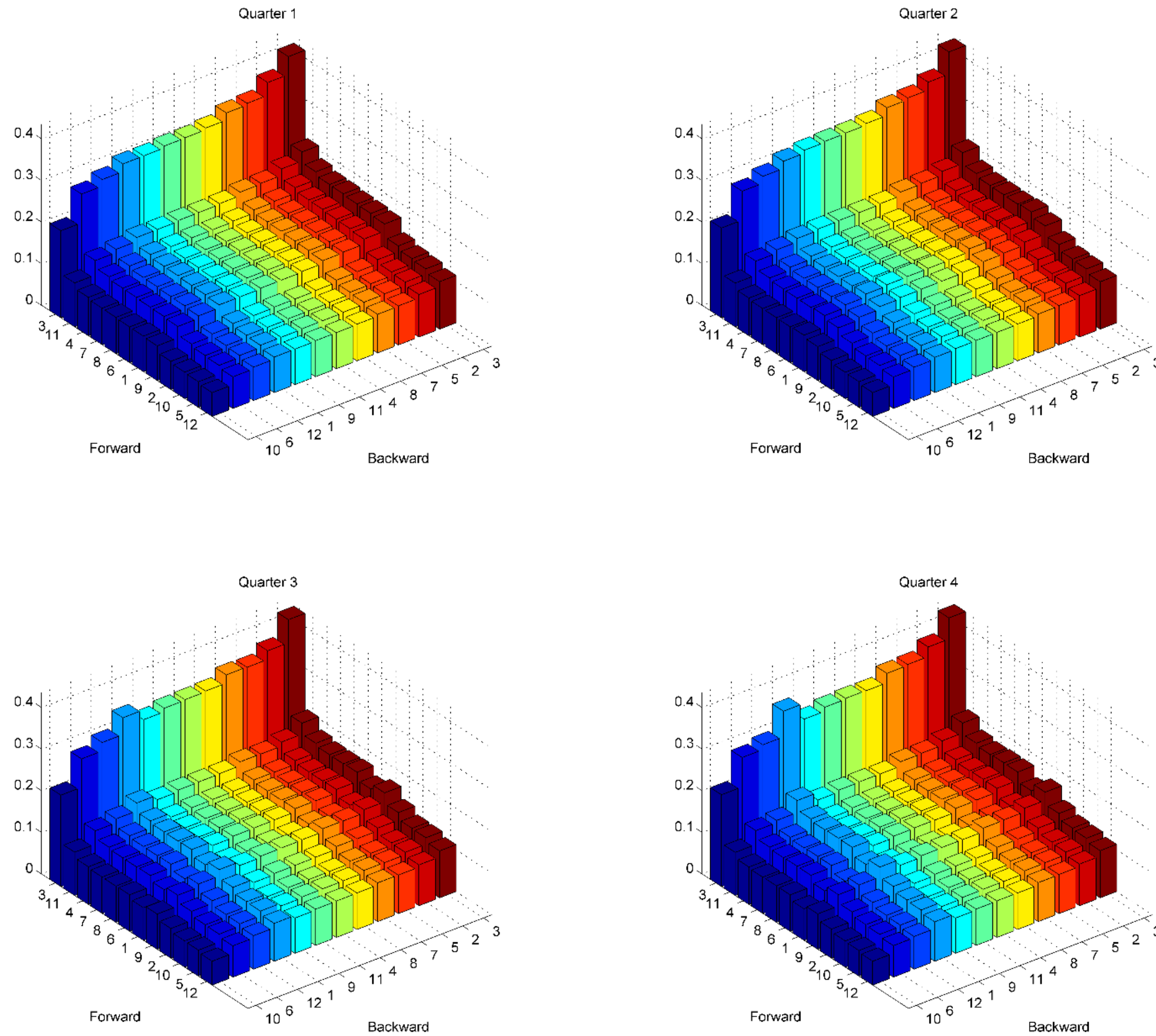


Figure A.6: Economic landscapes by quarter, 2004

APPENDIX B: T-EURO EXAMPLE

Assume the annual IO table (${}^{\mathrm{E}}\mathbf{IOT}^0$) is given by Table B.1 and the available GDP information for each semester of the same year by Table B.2 (hence, $n = 3$, $f = 1$, $t = 2$).

Table B.1: Three sectors example economy's IO Table

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	31	61	13	30	68	**203**
Industry	22	252	66	160	209	**709**
Services	19	115	44	145	230	**553**
Imports	22	43	66			
Taxes	3	9	3			
Value Added	106	229	361			
Output	**203**	**709**	**553**			

Table B.2: GDP information by semester

	Value Added			Totals			
	Agriculture ${}^{\mathrm{E}}\mathbf{v}_1^t$	**Industry** ${}^{\mathrm{E}}\mathbf{v}_2^t$	**Services** ${}^{\mathrm{E}}\mathbf{v}_3^t$	**HH** ${}^{\mathrm{E}}\mathbf{y}_1^t$	**Exports** ${}^{\mathrm{E}}e^t$	**Imports** ${}^{\mathrm{E}}m^t$	**Taxes** ${}^{\mathrm{E}}t^t$
1st Semester ($t = 1$)	50	142	130	150	238	59	7
2nd Semester ($t = 2$)	56	87	231	185	269	72	8

- **Iteration *k = 1***

Following the T-EURO procedure, the first step begins with the calculation of each semester' share according to Equations 1.6-1.10 (Table B.3).

Table B.3: Shares by semester (*k* = *1*)

	Value Added			Totals			
	Agriculture ${}^{\mathrm{S}}\mathbf{v}_1^{t,1}$	**Industry** ${}^{\mathrm{S}}\mathbf{v}_2^{t,1}$	**Services** ${}^{\mathrm{S}}\mathbf{v}_3^{t,1}$	**HH** ${}^{\mathrm{S}}\mathbf{y}_1^{t,1}$	**Exports** ${}^{\mathrm{S}}e^{t,1}$	**Imports** ${}^{\mathrm{S}}m^{t,1}$	**Taxes** ${}^{\mathrm{S}}t^{t,1}$
1st Semester ($t = 1$)	0.472	0.620	0.360	0.448	0.469	0.450	0.467
2nd Semester ($t = 2$)	0.528	0.380	0.640	0.552	0.531	0.550	0.533

The initial flow adjustment is performed by the set of equations presented in Equations 1.11-1.16. This set generates an *internally inconsistent* IO table (see Tables B.4 and B.5). The results for each period follow:

$$\mathbf{Z}^{1,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1} \times {}^{\mathrm{E}}\mathbf{Z}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{Z}^{0} \times {}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1}\right)\right] = \begin{bmatrix} 14.62 & 33.30 & 5.41 \\ 12.01 & 156.26 & 32.35 \\ 7.90 & 56.36 & 15.84 \end{bmatrix}$$

$$\mathbf{m}^{1,1} = 0.5 \times \left[\left({}^{\mathrm{S}}m^{1,1} \times {}^{\mathrm{E}}\mathbf{m}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{m}^{0} \times {}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1}\right)\right] = [10.14 \quad 23.02 \quad 26.75]$$

$$\mathbf{t}^{1,1} = 0.5 \times \left[\left({}^{\mathrm{S}}t^{1,1} \times {}^{\mathrm{E}}\mathbf{t}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{t}^{0} \times {}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1}\right)\right] = [1.41 \quad 4.89 \quad 1.24]$$

$$\mathbf{v}^{1,1} = {}^{\mathrm{E}}\mathbf{v}^{0} \times {}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1} = [50 \quad 142 \quad 130]$$

$$\mathbf{Y}^{1,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1} \times {}^{\mathrm{E}}\mathbf{Y}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{Y}^{0} \times {}^{\mathrm{S}}\hat{\mathbf{y}}^{1,1}\right)\right] = \begin{bmatrix} 13.79 \\ 85.43 \\ 58.57 \end{bmatrix}$$

$$\mathbf{e}^{1,1} = 0.5 \times \left[\left({}^{\mathrm{S}}\hat{\mathbf{v}}^{1,1} \times {}^{\mathrm{E}}\mathbf{e}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{e}^{0} \times {}^{\mathrm{S}}e^{1,1}\right)\right] = \begin{bmatrix} 32.00 \\ 113.85 \\ 95.40 \end{bmatrix}$$

$$\mathbf{Z}^{2,1} = \begin{bmatrix} 16.38 & 27.70 & 7.59 \\ 9.99 & 95.74 & 33.65 \\ 11.10 & 58.64 & 28.16 \end{bmatrix}$$

$$\mathbf{m}^{2,1} = [11.86 \quad 19.98 \quad 39.25]$$

$$\mathbf{t}^{2,1} = [1.59 \quad 4.11 \quad 1.76]$$

$$\mathbf{v}^{2,1} = [56 \quad 87 \quad 231]$$

$$\mathbf{Y}^{2,1} = \begin{bmatrix} 16.21 \\ 74.57 \\ 86.43 \end{bmatrix}$$

$$\mathbf{e}^{2,1} = \begin{bmatrix} 36.00 \\ 95.15 \\ 134.60 \end{bmatrix}$$

Table B.4: Internally inconsistent, temporally inconsistent IO Table (*k = 1*, *t = 1*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.62	33.30	5.41	13.79	32.00	99.12
Industry	12.01	156.26	32.35	85.43	113.85	399.90
Services	7.90	56.36	15.84	58.57	95.40	234.07
Imports	10.14	23.02	26.75			
Taxes	1.41	4.89	1.24			
Value Added	50.00	142.00	130.00			
Output	96.08	415.83	211.59			

Table B.5: Internally inconsistent, temporally inconsistent IO Table (*k = 1*, *t = 2*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.38	27.70	7.59	16.21	36.00	103.88
Industry	9.99	95.74	33.65	74.57	95.15	309.10
Services	11.10	58.64	28.16	86.43	134.60	318.93
Imports	11.86	19.98	39.25			
Taxes	1.59	4.11	1.76			
Value Added	56.00	87.00	231.00			
Output	106.92	293.17	341.41			

The second step converts these adjusted flows into an *internally consistent* table. From $\mathbf{q}_j^{t,1}$'s definition, we have the first approximation of the total output, that will be used in calculating the new input requirement structures:

$$\mathbf{q}^{1,1} = [96.08 \quad 415.83 \quad 211.58]$$

$$\mathbf{q}^{2,1} = [106.92 \quad 293.17 \quad 341.42]$$

These define the following Leontief Model (Equation 1.18) that produces the updated total outputs $\mathbf{x}^{t,1}$:

$$\mathbf{x}^{1,1} = \left(\begin{bmatrix}1 & 0 & 0\\0 & 1 & 0\\0 & 0 & 1\end{bmatrix} - \left(\begin{bmatrix}14.62 & 33.30 & 5.41\\12.01 & 156.26 & 32.35\\7.90 & 56.36 & 15.84\end{bmatrix} \times \begin{bmatrix}1/96.08 & 0 & 0\\0 & 1/415.83 & 0\\0 & 0 & 1/211.58\end{bmatrix}\right)\right)^{-1}$$
$$\times \left(\begin{bmatrix}13.79\\85.43\\58.57\end{bmatrix} + \begin{bmatrix}32.00\\113.85\\95.40\end{bmatrix}\right) = \begin{bmatrix}98.45\\396.08\\233.21\end{bmatrix}$$

$$\mathbf{x}^{2,1} = \begin{bmatrix}105.08\\313.60\\321.15\end{bmatrix}$$

Now, applying the quantity model (Equations 1.19-1.22), we recover *internally consistent* IO tables:

$$\mathbf{Z}^{1,1} = \begin{bmatrix}14.62 & 33.30 & 5.41\\12.01 & 156.26 & 32.35\\7.90 & 56.36 & 15.84\end{bmatrix} \times \begin{bmatrix}1/96.08 & 0 & 0\\0 & 1/415.83 & 0\\0 & 0 & 1/211.58\end{bmatrix}$$
$$\times \begin{bmatrix}98.45 & 0 & 0\\0 & 396.08 & 0\\0 & 0 & 233.21\end{bmatrix} = \begin{bmatrix}14.98 & 31.72 & 5.96\\12.31 & 148.84 & 35.65\\8.10 & 53.69 & 17.46\end{bmatrix}$$

$$\mathbf{m}^{1,1} = [10.14 \quad 23.02 \quad 26.75] \times \begin{bmatrix}1/96.08 & 0 & 0\\0 & 1/415.83 & 0\\0 & 0 & 1/211.58\end{bmatrix}$$
$$\times \begin{bmatrix}98.45 & 0 & 0\\0 & 396.08 & 0\\0 & 0 & 233.21\end{bmatrix} = [10.39 \quad 21.92 \quad 29.48]$$

$$\mathbf{t}^{1,1} = [1.41 \quad 4.89 \quad 1.24] \times \begin{bmatrix}1/96.08 & 0 & 0\\0 & 1/415.83 & 0\\0 & 0 & 1/211.58\end{bmatrix} \times \begin{bmatrix}98.45 & 0 & 0\\0 & 396.08 & 0\\0 & 0 & 233.21\end{bmatrix}$$
$$= [1.44 \quad 4.66 \quad 1.37]$$

$$\mathbf{v}^{1,1} = [50 \quad 142 \quad 130] \times \begin{bmatrix}1/96.08 & 0 & 0\\0 & 1/415.83 & 0\\0 & 0 & 1/211.58\end{bmatrix} \times \begin{bmatrix}98.45 & 0 & 0\\0 & 396.08 & 0\\0 & 0 & 233.21\end{bmatrix}$$
$$= [51.23 \quad 135.26 \quad 143.29]$$

$$\mathbf{Z}^{2,1} = \begin{bmatrix}16.10 & 29.63 & 7.14\\9.82 & 102.41 & 31.66\\10.91 & 62.72 & 26.48\end{bmatrix}$$

$$\mathbf{m}^{2,1} = [11.65 \quad 21.38 \quad 36.92]$$

$$\mathbf{t}^{2,1} = [1.57 \quad 4.40 \quad 1.66]$$

$$\mathbf{v}^{2,1} = [55.04 \quad 93.06 \quad 217.29]$$

Which yields the *internally consistent* tables $\mathbf{OIT}^{1,1}$ (Table B.6) and $\mathbf{OIT}^{2,1}$ (Table B.7):

Table B.6: Internally consistent, temporally inconsistent IO Table ($k = 1$, $t = 1$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.98	31.72	5.96	13.79	32.00	**98.45**
Industry	12.31	148.84	35.65	85.43	113.85	**396.08**
Services	8.10	53.69	17.46	58.57	95.40	**233.21**
Imports	10.39	21.92	29.48			
Taxes	1.44	4.66	1.37			
Value Added	51.23	135.26	143.29			
Output	**98.45**	**396.08**	**233.21**			

Table B.7: Internally consistent, temporally inconsistent IO Table ($k = 1$, $t = 2$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.10	29.63	7.14	16.21	36.00	**105.08**
Industry	9.82	102.41	31.66	74.57	95.15	**313.60**
Services	10.91	62.72	26.48	86.43	134.60	**321.15**
Imports	11.65	21.38	36.92			
Taxes	1.57	4.40	1.66			
Value Added	55.04	93.06	217.29			
Output	**105.08**	**313.60**	**321.15**			

Temporal consistency is achieved via Equation 1.24, that distributes each individual annual flow according to $\mathbf{OIT}^{1,1}$ and $\mathbf{OIT}^{2,1}$. This results in the *temporally consistent* but *internally inconsistent* Tables B.8 and B.9.

Table B.8: Internally inconsistent, temporally consistent IO Table ($k = 1$, $t = 1$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.94	31.54	5.91	13.79	32.00	**98.19**
Industry	12.24	149.29	34.96	85.43	113.85	**395.76**
Services	8.10	53.03	17.49	58.57	95.40	**232.58**
Imports	10.37	21.77	29.30			
Taxes	1.44	4.63	1.36			
Value Added	51.10	135.66	143.46			
Output	**98.19**	**395.92**	**232.47**			

Table B.9: Internally inconsistent, temporally consistent IO Table (*k = 1*, *t = 2*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.06	29.46	7.09	16.21	36.00	**104.81**
Industry	9.76	102.71	31.04	74.57	95.15	**313.24**
Services	10.90	61.97	26.51	86.43	134.60	**320.42**
Imports	11.63	21.23	36.70			
Taxes	1.56	4.37	1.64			
Value Added	54.90	93.34	217.54			
Output	**104.81**	**313.08**	**320.53**			

By repeating step two, these tables are corrected for internal consistency:

$$\mathbf{q}^{1,1} = [98.19 \quad 395.92 \quad 232.47]$$

$$\mathbf{q}^{2,1} = [104.81 \quad 313.08 \quad 320.53]$$

$$\mathbf{x}^{1,1} = \begin{bmatrix} 98.17 \\ 395.69 \\ 232.56 \end{bmatrix}$$

$$\mathbf{x}^{2,1} = \begin{bmatrix} 104.84 \\ 313.31 \\ 320.46 \end{bmatrix}$$

After the quantity model (Equations 1.19-1.22), we recover the *internally consistent* IO tables:

$$\mathbf{Z}^{1,1} = \begin{bmatrix} 14.94 & 31.52 & 5.92 \\ 12.23 & 149.20 & 34.97 \\ 8.09 & 53.00 & 17.49 \end{bmatrix}$$

$$\mathbf{m}^{1,1} = [10.37 \quad 21.76 \quad 29.31]$$

$$\mathbf{t}^{1,1} = [1.44 \quad 4.63 \quad 1.36]$$

$$\mathbf{v}^{1,1} = [51.09 \quad 135.58 \quad 143.51]$$

$$\mathbf{Z}^{2,1} = \begin{bmatrix} 16.06 & 29.48 & 7.09 \\ 9.77 & 102.79 & 31.03 \\ 10.91 & 62.01 & 26.51 \end{bmatrix}$$

$$\mathbf{m}^{2,1} = [11.63 \quad 21.24 \quad 36.69]$$

$$\mathbf{t}^{2,1} = [1.56 \quad 4.37 \quad 1.64]$$

$\mathbf{v}^{2,1} = [54.91 \quad 93.41 \quad 217.50]$

Which yields the *internally consistent* tables $\mathbf{OIT}^{1,1}$ and $\mathbf{OIT}^{2,1}$:

Table B.10: Internally consistent, temporally consistent IO Table (*k = 1, t = 1*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.94	31.52	5.92	13.79	32.00	**98.17**
Industry	12.23	149.20	34.97	85.43	113.85	**395.69**
Services	8.09	53.00	17.49	58.57	95.40	**232.56**
Imports	10.37	21.76	29.31			
Taxes	1.44	4.63	1.36			
Value Added	51.09	135.58	143.51			
Output	**98.17**	**395.69**	**232.56**			

Table B.11: Internally consistent, temporally consistent IO Table (*k = 1, t = 2*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.06	29.48	7.09	16.21	36.00	**104.84**
Industry	9.77	102.79	31.03	74.57	95.15	**313.31**
Services	10.91	62.01	26.51	86.43	134.60	**320.46**
Imports	11.63	21.24	36.69			
Taxes	1.56	4.37	1.64			
Value Added	54.91	93.41	217.50			
Output	**104.84**	**313.31**	**320.46**			

The temporal adjustment is performed a second time on Tables B.10 and B.11 as the mean absolute percentage error (MAPE, as defined by Equation 1.43) between the $\mathbf{OIT}^{1,1} + \mathbf{OIT}^{2,1}$ and ${}^{\mathrm{E}}\mathbf{IOT}^{0}$ (0.003%) is larger than the set threshold of 0.001%. After applying Equation 9 and correcting the internal consistency via step two, we have:

Table B.12: Internally consistent, temporally consistent IO Table (*k = 1, t = 1*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.94	31.52	5.91	13.79	32.00	**98.16**
Industry	12.23	149.20	34.97	85.43	113.85	**395.69**
Services	8.09	53.00	17.49	58.57	95.40	**232.55**
Imports	10.37	21.76	29.31			
Taxes	1.44	4.63	1.36			
Value Added	51.09	135.59	143.51			
Output	**98.16**	**395.69**	**232.55**			

Table B.13: Internally consistent, temporally consistent IO Table (*k = 1, t = 2*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.06	29.48	7.09	16.21	36.00	**104.84**
Industry	9.77	102.80	31.03	74.57	95.15	**313.31**
Services	10.91	62.00	26.51	86.43	134.60	**320.45**
Imports	11.63	21.24	36.69			
Taxes	1.56	4.37	1.64			
Value Added	54.91	93.41	217.49			
Output	**104.84**	**313.31**	**320.45**			

With MAPE = 0.00003%, the current iteration ends. Hence, we recalculate shares using Equationa 1.25-1.29:

Table B.14: Shares by semester (*k = 2*)

	Value Added			Totals			
	Agriculture ${}^{s}\mathbf{v}_1^{t,2}$	Industry ${}^{s}\mathbf{v}_2^{t,2}$	Services ${}^{s}\mathbf{v}_3^{t,2}$	HH ${}^{s}\mathbf{y}_1^{t,2}$	Exports ${}^{s}e^{t,2}$	Imports ${}^{s}m^{t,2}$	Taxes ${}^{s}t^{t,2}$
1st Semester ($t = 1$)	0.482	0.592	0.398	0.471	0.476	0.469	0.495
2nd Semester ($t = 2$)	0.518	0.408	0.603	0.529	0.524	0.531	0.505

And the respective deviations from the true shares:

Table B.15: Deviations from true shares (*k* = *2*)

	Value Added			Totals			
	Agriculture $d^t_{\mathbf{v}_1}$	**Industry** $d^t_{\mathbf{v}_2}$	**Services** $d^t_{\mathbf{v}_3}$	**HH** $d^t_{\mathbf{y}_1}$	**Exports** d^t_e	**Imports** d^t_m	**Taxes** d^t_t
1st Semester ($t = 1$)	0.979	1.047	0.906	0.951	0.987	0.960	0.943
2nd Semester ($t = 2$)	1.020	0.931	1.062	1.044	1.012	1.035	1.056

Assuming an adjustment elasticity of 0.9, and a maximum absolute deviation threshold level of 0.5% error, the correction factors are calculated using Equation 1.30.

Table B.16: Correction factors (*k* = *2*)

	Value Added			Totals			
	Agriculture $c^{t,2}_{\mathbf{v}_1}$	**Industry** $c^{t,2}_{\mathbf{v}_2}$	**Services** $c^{t,2}_{\mathbf{v}_3}$	**HH** $c^{t,2}_{\mathbf{y}_1}$	**Exports** $c^{t,2}_e$	**Imports** $c^{t,2}_m$	**Taxes** $c^{t,2}_t$
1st Semester ($t = 1$)	0.980	1.041	0.925	0.958	0.987	0.966	0.952
2nd Semester ($t = 2$)	1.019	0.943	1.052	1.044	1.012	1.031	1.047

- **Iteration *k* = *2***

The new "corrected" shares are calculated by multiplying the correction factors ($c^{t,2}_{\mathrm{r}}$) with their respective true shares, yielding:

Table B.17: Corrected shares by semester (*k* = *2*)

	Value Added			Totals			
	Agriculture ${\mathrm{s^C}}_{\mathbf{v}_1}^{t,2}$	**Industry** ${\mathrm{s^C}}_{\mathbf{v}_2}^{t,2}$	**Services** ${\mathrm{s^C}}_{\mathbf{v}_3}^{t,2}$	**HH** ${\mathrm{s^C}}_{\mathbf{y}_1}^{t,2}$	**Exports** ${\mathrm{s^C}}_{e}^{t,2}$	**Imports** ${\mathrm{s^C}}_{m}^{t,2}$	**Taxes** ${\mathrm{s^C}}_{t}^{t,2}$
1st Semester ($t = 1$)	0.462	0.645	0.333	0.429	0.463	0.435	0.452
2nd Semester ($t = 2$)	0.538	0.358	0.673	0.573	0.537	0.567	0.558

The first adjustment is made using Equations 1.31-1.36, that generates an *internally inconsistent* IO table (Tables B.18 and B.19). The results for each period follows:

$$\mathbf{Z}^{1,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2} \times {}^{\mathrm{E}}\mathbf{Z}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{Z}^{0} \times {}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2}\right)\right] = \begin{bmatrix} 14.33 & 33.78 & 5.17 \\ 12.18 & 162.59 & 32.28 \\ 7.56 & 56.25 & 14.65 \end{bmatrix}$$

$$\mathbf{m}^{1,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}m^{1,2} \times {}^{\mathrm{E}}\mathbf{m}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{m}^{0} \times {}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2}\right)\right] = [9.87 \quad 23.22 \quad 25.34]$$

$$\mathbf{t}^{1,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}t^{1,2} \times {}^{\mathrm{E}}\mathbf{t}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{t}^{0} \times {}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2}\right)\right] = [1.36 \quad 4.90 \quad 1.17]$$

$$\mathbf{v}^{1,2} = {}^{\mathrm{E}}\mathbf{v}^{0} \times {}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2} = [49.01 \quad 147.75 \quad 120.22]$$

$$\mathbf{Y}^{1,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2} \times {}^{\mathrm{E}}\mathbf{Y}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{Y}^{0} \times {}^{\mathrm{S^C}}\hat{\mathbf{y}}^{1,2}\right)\right] = \begin{bmatrix} 13.37 \\ 85.93 \\ 55.24 \end{bmatrix}$$

$$\mathbf{e}^{1,2} = 0.5 \times \left[\left({}^{\mathrm{S^C}}\hat{\mathbf{v}}^{1,2} \times {}^{\mathrm{E}}\mathbf{e}^{0}\right) + \left({}^{\mathrm{E}}\mathbf{e}^{0} \times {}^{\mathrm{S^C}}e^{1,2}\right)\right] = \begin{bmatrix} 31.47 \\ 115.84 \\ 91.58 \end{bmatrix}$$

$$\mathbf{Z}^{2,2} = \begin{bmatrix} 16.68 & 27.34 & 7.87 \\ 9.86 & 90.32 & 34.04 \\ 11.51 & 59.31 & 29.61 \end{bmatrix}$$

$$\mathbf{m}^{2,2} = [12.15 \quad 19.89 \quad 40.91]$$

$$\mathbf{t}^{2,2} = [1.64 \quad 4.13 \quad 1.85]$$

$$\mathbf{v}^{2,2} = [57.04 \quad 82.07 \quad 242.95]$$

$$\mathbf{Y}^{2,2} = \begin{bmatrix} 16.67 \\ 74.53 \\ 90.35 \end{bmatrix}$$

$$\mathbf{e}^{2,2} = \begin{bmatrix} 36.55 \\ 93.56 \\ 139.14 \end{bmatrix}$$

Table B.18: Internally inconsistent, temporally inconsistent IO Table ($k = 2, t = 1$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.33	33.78	5.17	13.37	31.47	98.12
Industry	12.18	162.59	32.28	85.93	115.84	408.82
Services	7.56	56.25	14.65	55.24	91.58	225.28
Imports	9.87	23.22	25.34			
Taxes	1.36	4.90	1.17			
Value Added	49.01	147.75	120.22			
Output	94.31	428.49	198.83			

Table B.19: Internally inconsistent, temporally inconsistent IO Table ($k = 2, t = 2$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.68	27.34	7.87	16.67	36.55	105.11
Industry	9.86	90.32	34.04	74.53	93.56	302.31
Services	11.51	59.31	29.61	90.35	139.14	329.92
Imports	12.15	19.89	40.91			
Taxes	1.64	4.13	1.85			
Value Added	57.04	82.07	242.95			
Output	108.88	283.06	357.23			

The algorithm repeats the same steps presented above. At the end of this iteration, we have the new $\mathbf{OIT}^{1,2}$ (Table B.20) and $\mathbf{OIT}^{2,2}$ (Table B.21):

Table B.20: Internally consistent, temporally consistent IO Table ($k = 2, t = 1$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.73	31.52	5.76	13.35	31.46	**96.82**
Industry	12.44	153.49	35.28	85.69	115.62	**402.51**
Services	7.77	51.84	16.49	55.02	91.29	**222.41**
Imports	10.14	21.61	28.29			
Taxes	1.40	4.56	1.30			
Value Added	50.35	139.48	135.29			
Output	**96.82**	**402.51**	**222.41**			

Table B.21: Internally consistent, temporally consistent IO Table ($k = 2, t = 2$)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.27	29.48	7.24	16.65	36.54	**106.18**
Industry	9.56	98.51	30.72	74.31	93.38	**306.48**
Services	11.23	63.16	27.51	89.98	138.71	**330.59**
Imports	11.86	21.39	37.71			
Taxes	1.60	4.44	1.70			
Value Added	55.65	89.52	225.71			
Output	**106.18**	**306.48**	**330.59**			

The recalculated shares are:

Table B.22: Shares by semester ($k = 3$)

	Value Added			Totals			
	Agriculture ${}^{s}\mathbf{v}_1^{t,3}$	**Industry** ${}^{s}\mathbf{v}_2^{t,3}$	**Services** ${}^{s}\mathbf{v}_3^{t,3}$	**HH** ${}^{s}\mathbf{y}_1^{t,3}$	**Exports** ${}^{s}e^{t,3}$	**Imports** ${}^{s}m^{t,3}$	**Taxes** ${}^{s}t^{t,3}$
1st Semester ($t = 1$)	0.475	0.609	0.375	0.460	0.470	0.458	0.484
2nd Semester ($t = 2$)	0.525	0.391	0.625	0.540	0.530	0.542	0.516

And the new deviations from the true shares:

Table B.23: Deviations from true shares ($k = 3$)

	Value Added			Totals			
	Agriculture $d_{\mathbf{v}_1}^t$	**Industry** $d_{\mathbf{v}_2}^t$	**Services** $d_{\mathbf{v}_3}^t$	**HH** $d_{\mathbf{y}_1}^t$	**Exports** d_e^t	**Imports** d_m^t	**Taxes** d_t^t
1st Semester ($t = 1$)	0.993	1.018	0.961	0.974	0.998	0.983	0.964
2nd Semester ($t = 2$)	1.006	0.972	1.023	1.022	1.001	1.015	1.034

Assuming an adjustment elasticity of 0.9, and threshold level of 0.5% error, the accumulated correction factors are calculated using Equations 1.37-1.41 and $\prod_{k=2}^{3} c_{\mathrm{r}}^{t,k}$.

Table B.24: Correction factors (k = 3)

	Value Added			Totals			
	Agriculture $c_{\mathbf{v}_1}^{t,3}$	**Industry** $c_{\mathbf{v}_2}^{t,3}$	**Services** $c_{\mathbf{v}_3}^{t,3}$	**HH** $c_{\mathbf{y}_1}^{t,3}$	**Exports** $c_e^{t,3}$	**Imports** $c_m^{t,3}$	**Taxes** $c_t^{t,3}$
1st Semester ($t = 1$)	0.973	1.058	0.893	0.935	0.985	0.950	0.922
2nd Semester ($t = 2$)	1.025	0.919	1.074	1.059	1.012	1.046	1.078

- **Iteration *k* = *3***

The new "corrected" shares are calculated by multiplying the correction factors with their respective true shares, yielding:

Table B.25: Corrected shares by semester (k = 3)

	Value Added			Totals			
	Agriculture ${s^C}_{\mathbf{v}_1}^{t,3}$	**Industry** ${s^C}_{\mathbf{v}_2}^{t,3}$	**Services** ${s^C}_{\mathbf{v}_3}^{t,3}$	**HH** ${s^C}_{\mathbf{y}_1}^{t,3}$	**Exports** ${s^C}_e^{t,3}$	**Imports** ${s^C}_m^{t,3}$	**Taxes** ${s^C}_t^{t,3}$
1st Semester ($t = 1$)	0.459	0.656	0.322	0.419	0.462	0.428	0.430
2nd Semester ($t = 2$)	0.542	0.349	0.688	0.585	0.538	0.575	0.575

The algorithm converges after 6 iterations, when the absolute deviation become less than 0.5% (Table B.26).

Table B.26: Deviations from true shares (k = 7)

	Value Added			Totals			
	Agriculture $d_{\mathbf{v}_1}^{t}$	**Industry** $d_{\mathbf{v}_2}^{t}$	**Services** $d_{\mathbf{v}_3}^{t}$	**HH** $d_{\mathbf{y}_1}^{t}$	**Exports** d_e^{t}	**Imports** d_m^{t}	**Taxes** d_t^{t}
1st Semester ($t = 1$)	1.000	1.000	1.000	0.999	1.001	1.000	0.997
2nd Semester ($t = 2$)	1.000	1.000	1.000	1.001	1.000	1.000	1.003

The final semester tables are then $\mathbf{OIT}^{1,6}$ (Table B.27) and $\mathbf{OIT}^{2,6}$ (Table B.28):

Table B.27: Internally consistent, temporally consistent IO Table (*k = 6, t = 1*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	14.62	31.55	5.67	12.95	31.33	**96.12**
Industry	12.59	156.26	35.51	85.13	117.31	**406.80**
Services	7.57	51.09	15.85	52.10	89.24	**215.84**
Imports	9.99	21.47	27.57			
Taxes	1.34	4.44	1.24			
Value Added	50.01	142.00	130.01			
Output	**96.12**	**406.80**	**215.84**			

Table B.28: Internally consistent, temporally consistent IO Table (*k = 6, t = 2*)

	Agriculture	Industry	Services	HH	Export	Output
Agriculture	16.38	29.45	7.33	17.05	36.67	**106.88**
Industry	9.41	95.74	30.49	74.87	91.69	**302.20**
Services	11.43	63.91	28.15	92.90	140.76	**337.16**
Imports	12.01	21.54	38.43			
Taxes	1.66	4.56	1.76			
Value Added	55.99	87.00	230.99			
Output	**106.88**	**302.20**	**337.16**			

APPENDIX C: CHAPTER TWO

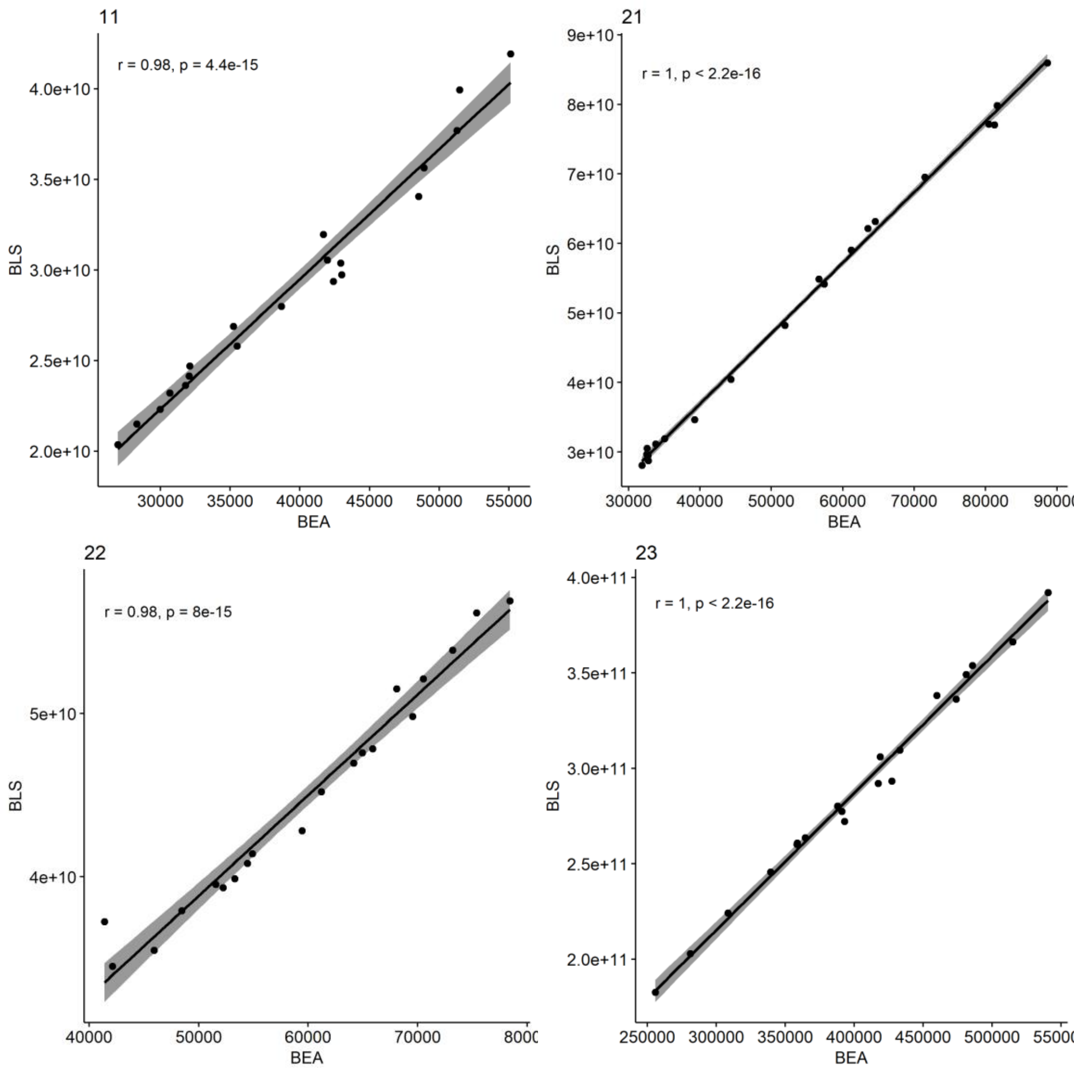


Figure C.1: Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 2-digit aggregation)

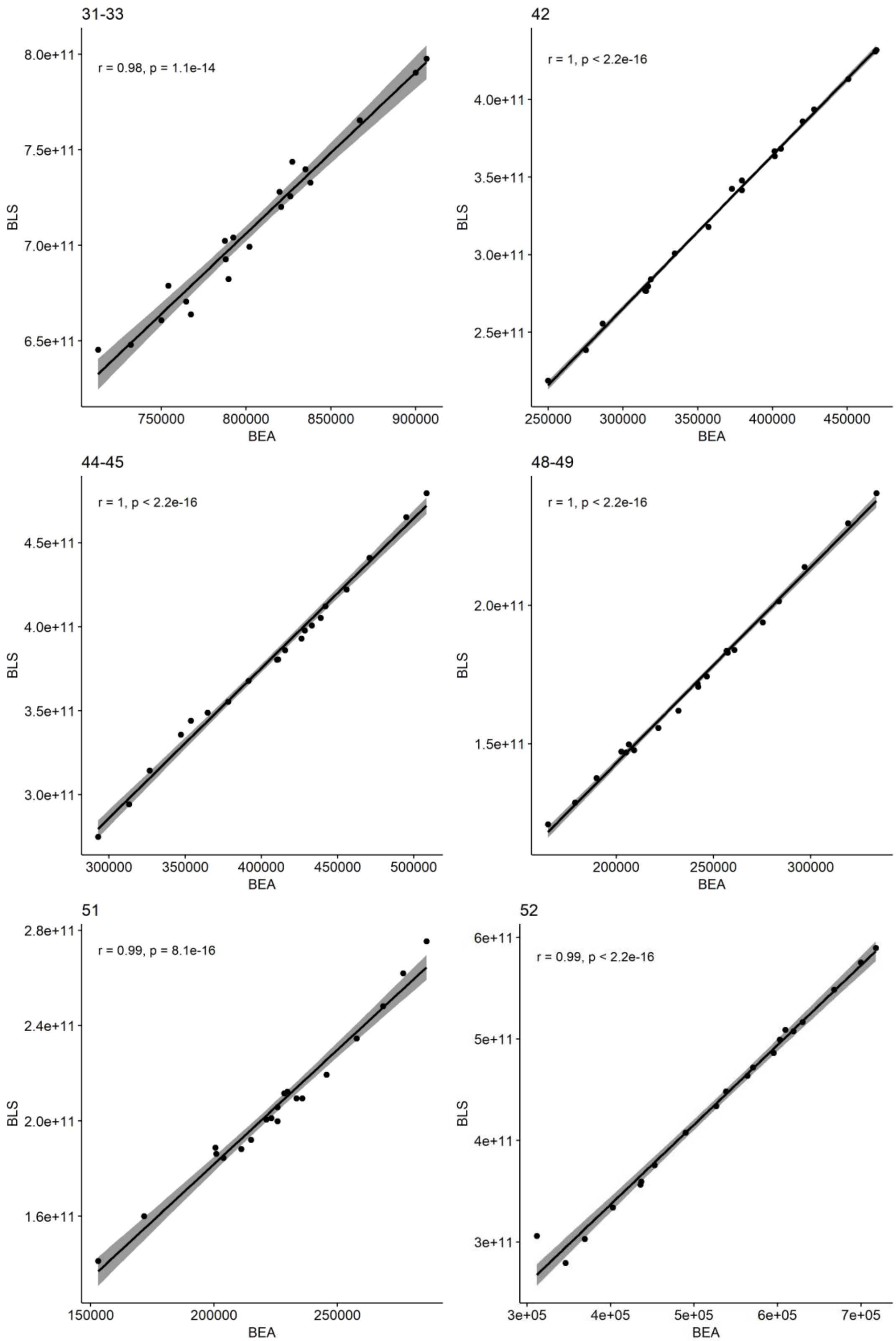


Figure C.1: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 2-digit aggregation)

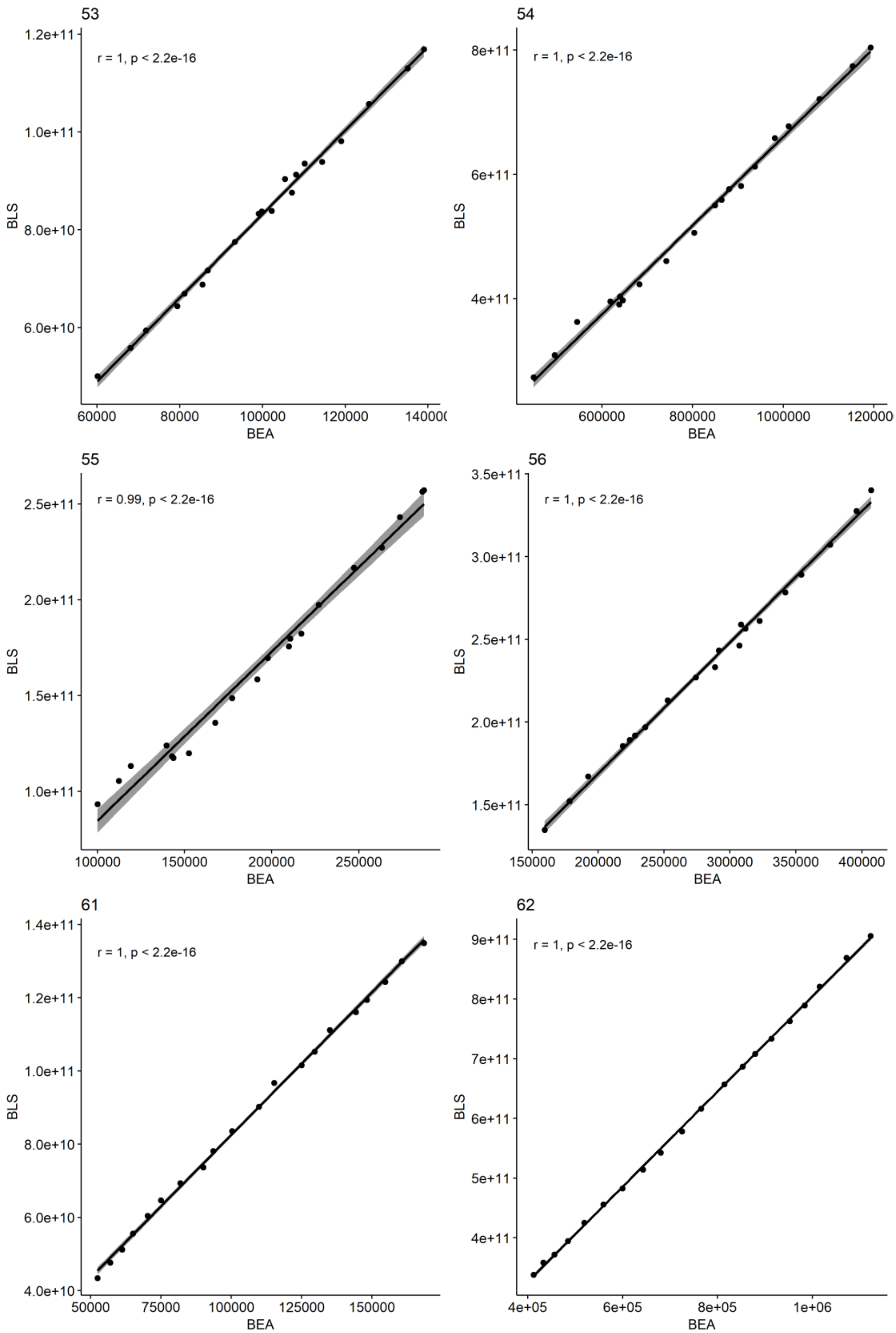


Figure C.1: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 2-digit aggregation)

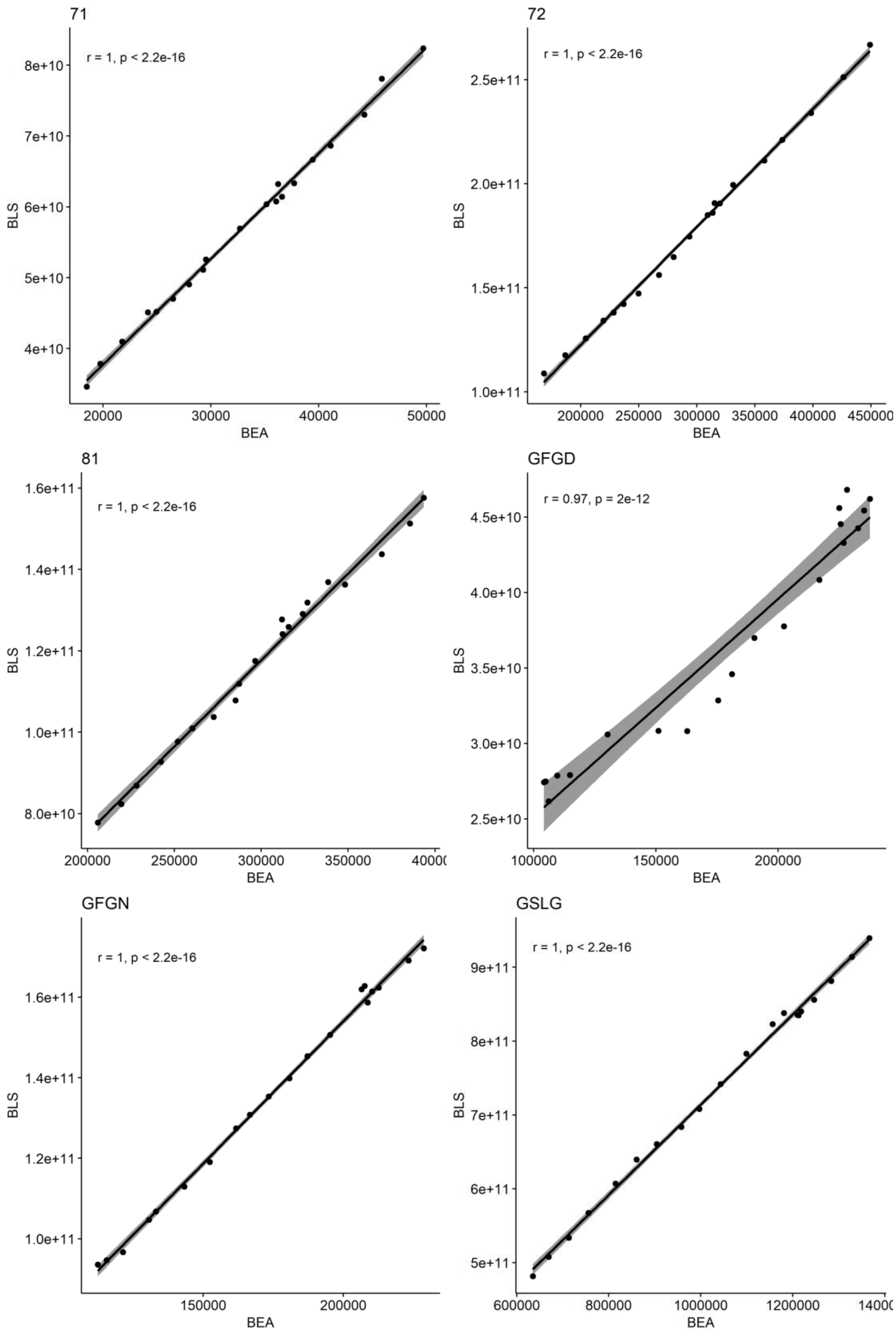


Figure C.1: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 2-digit aggregation)

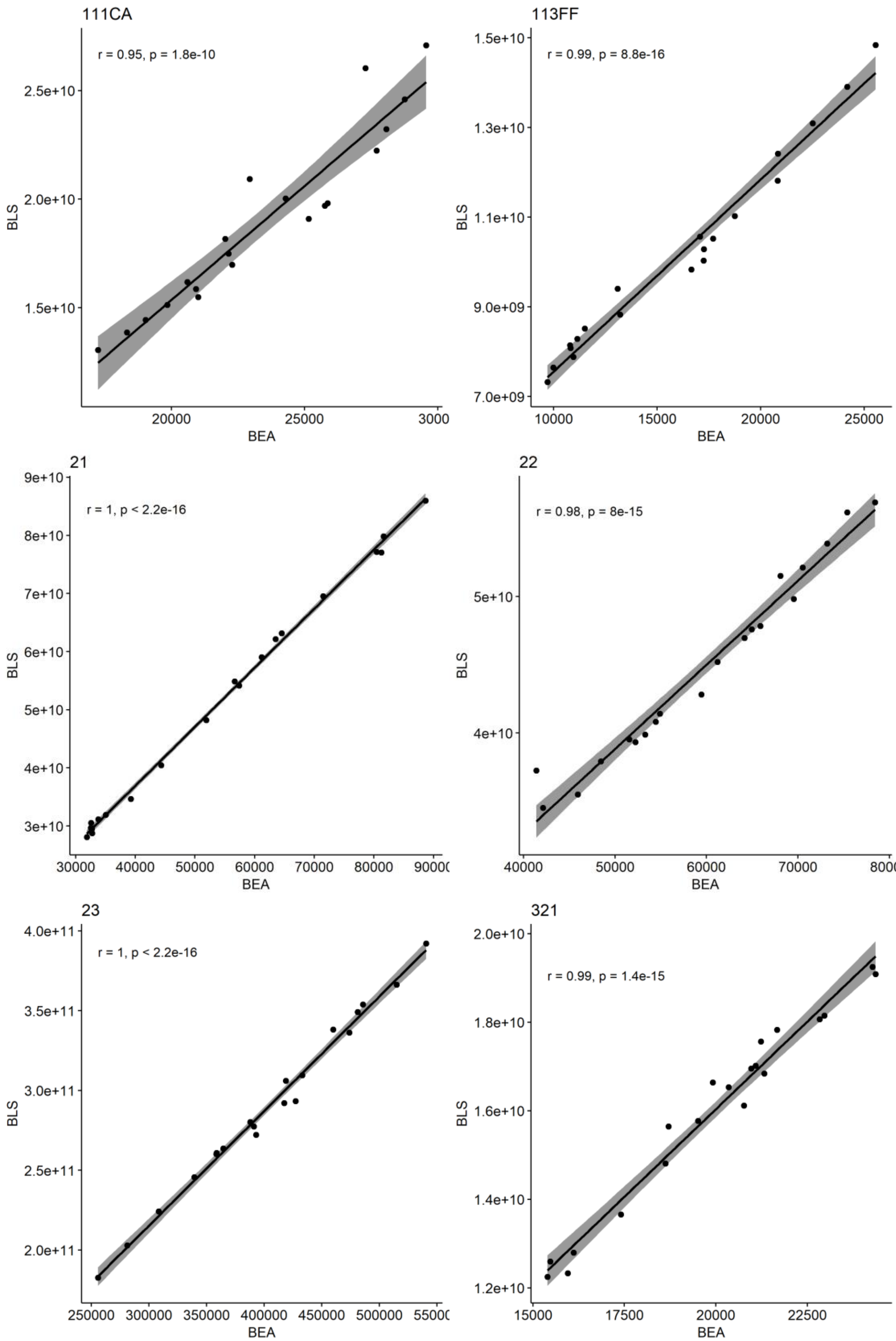


Figure C.2: Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

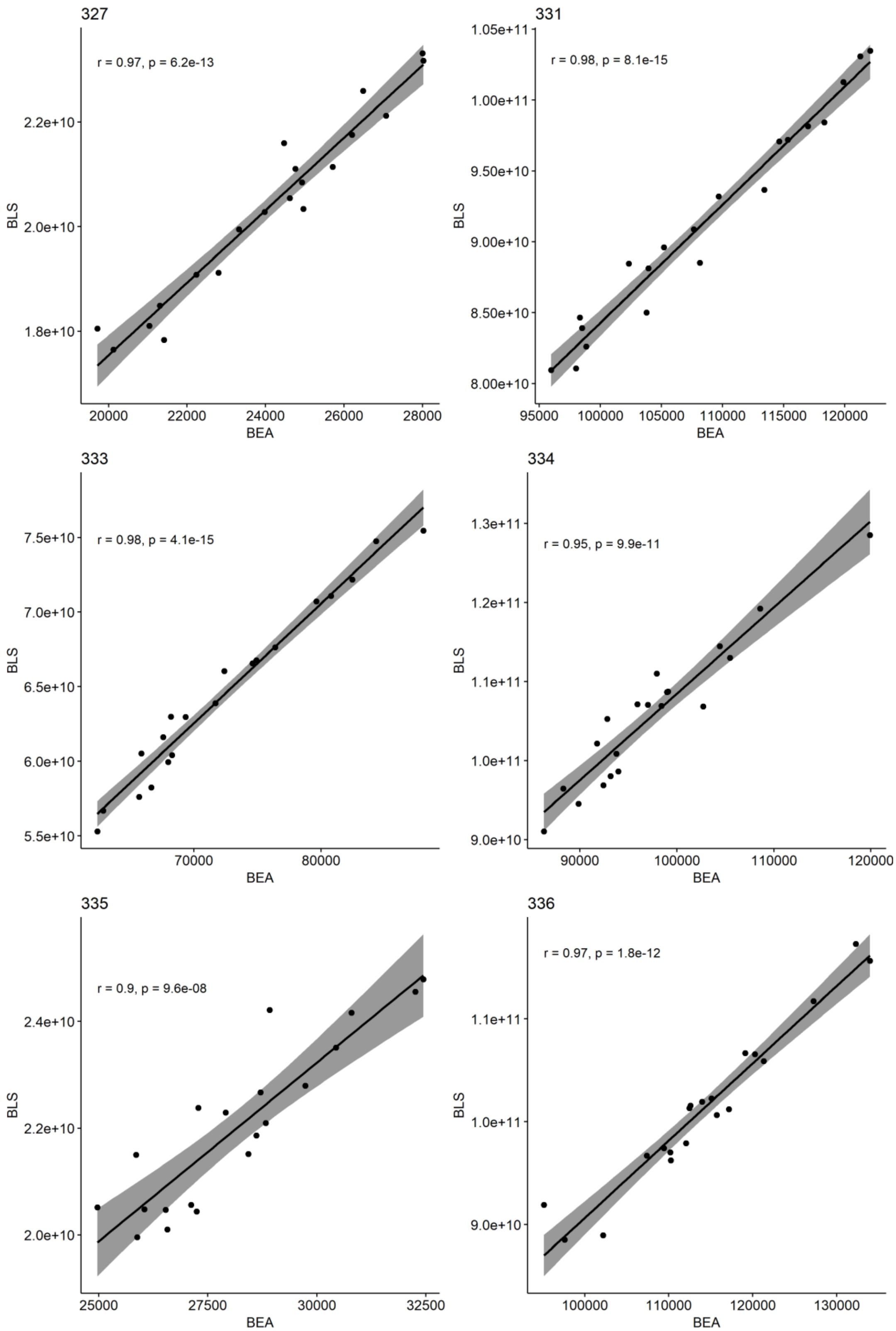


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

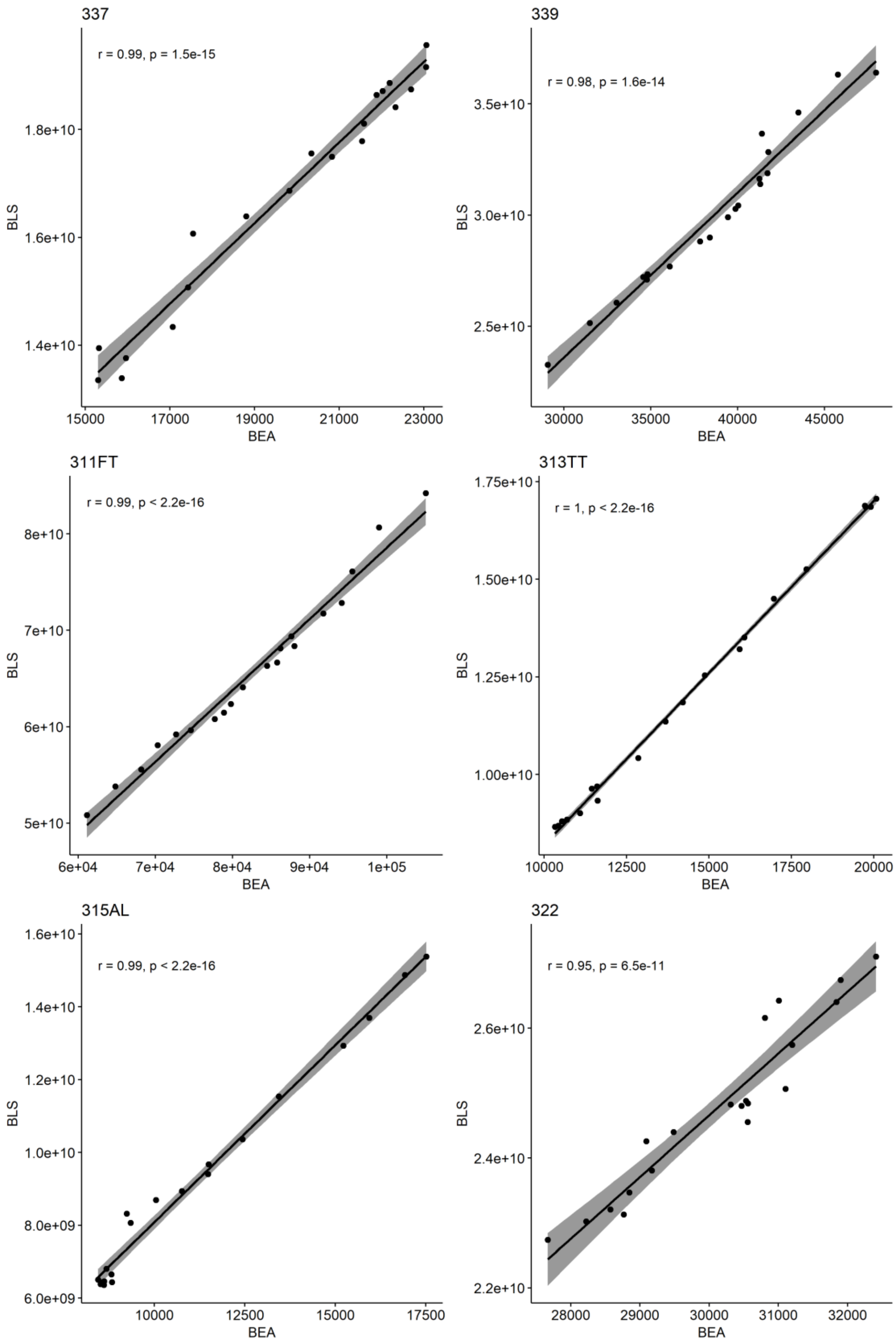


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

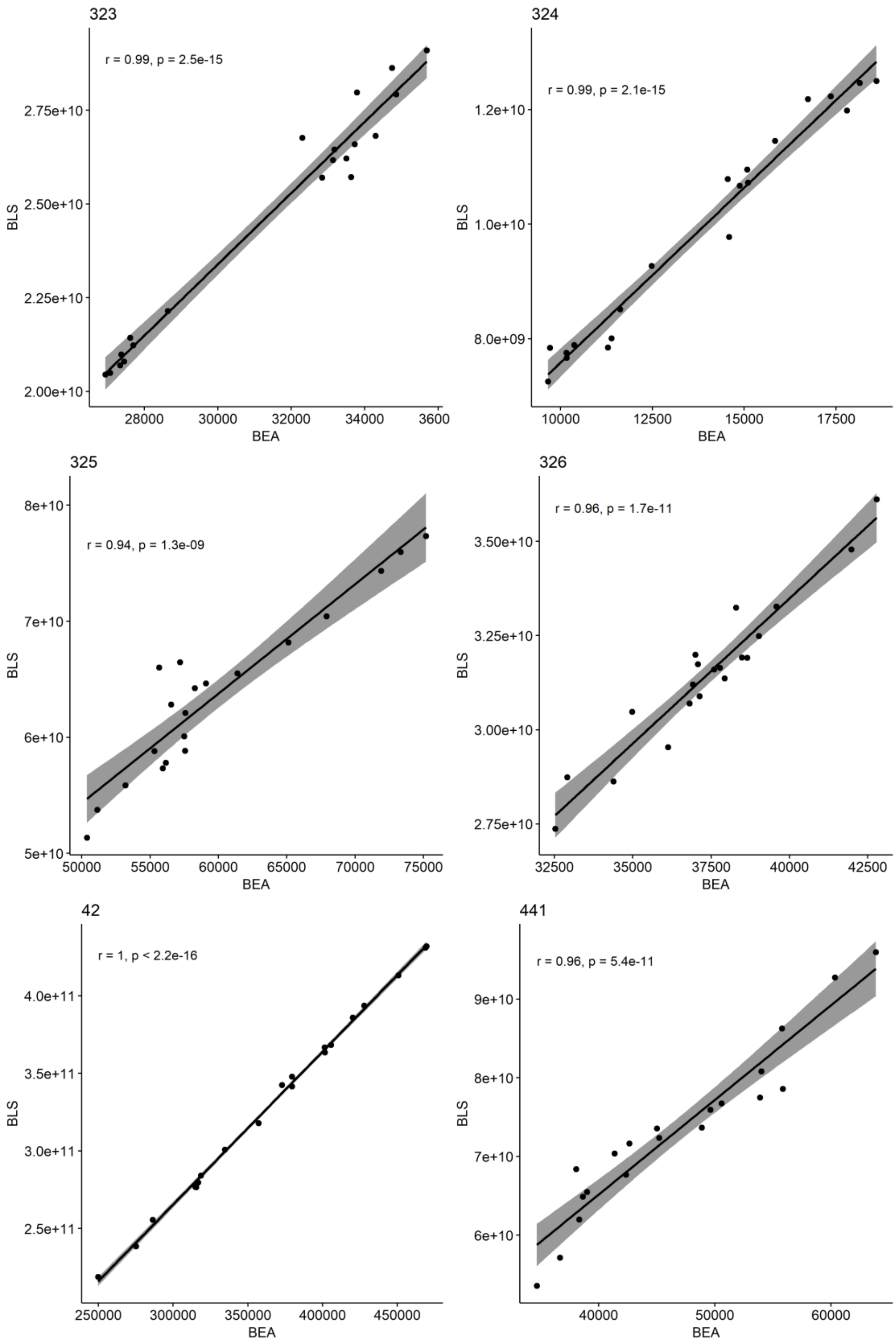


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

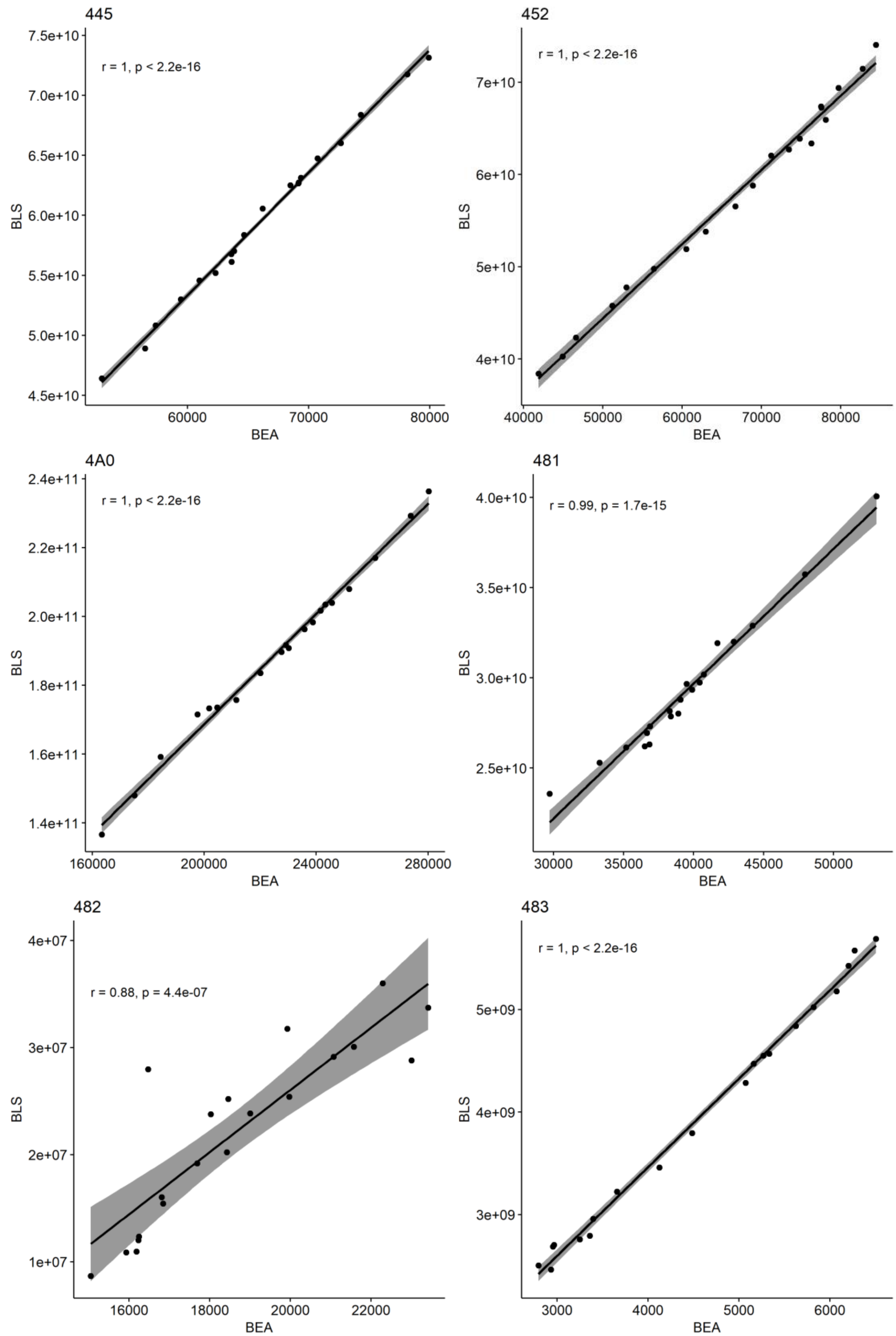


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

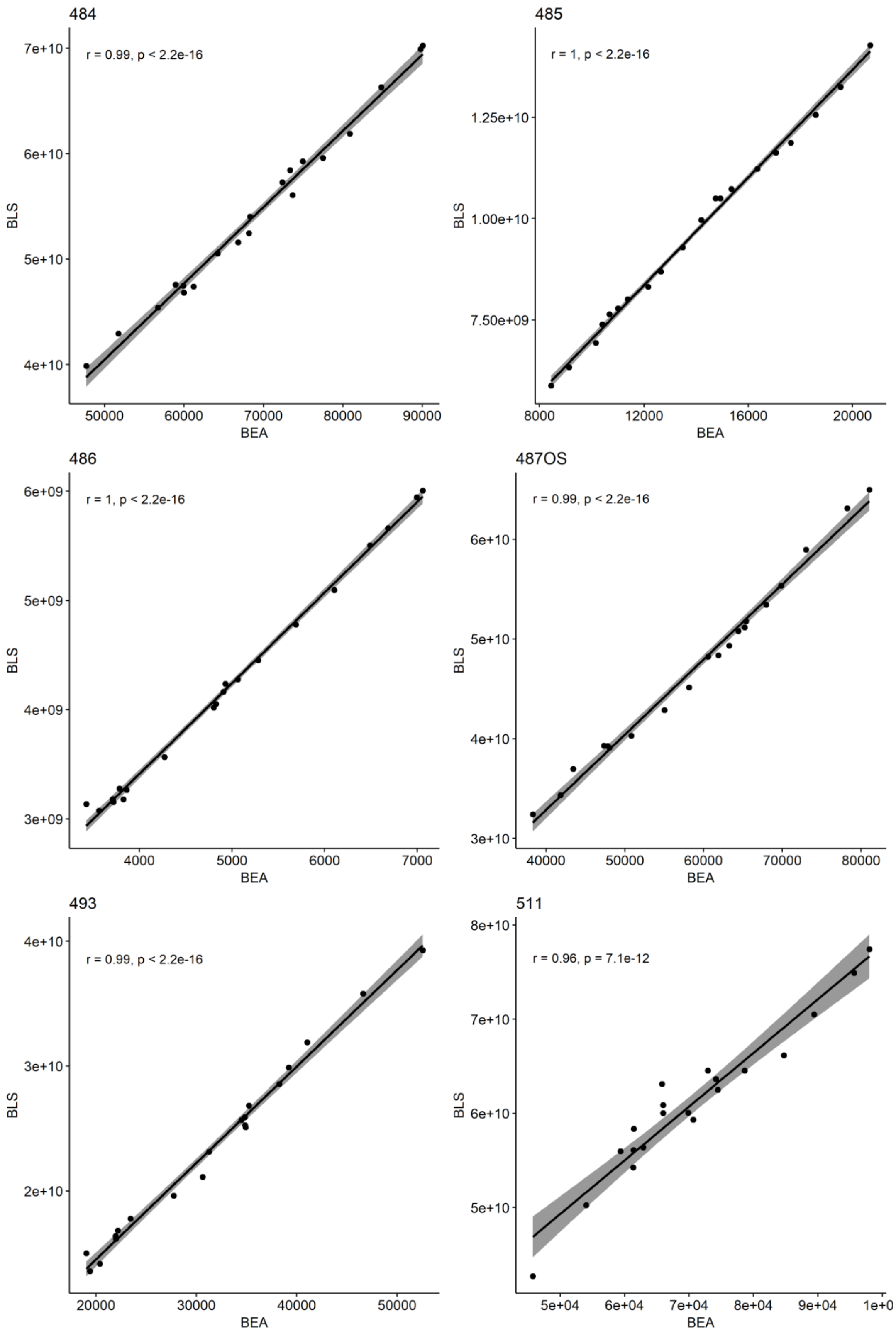


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

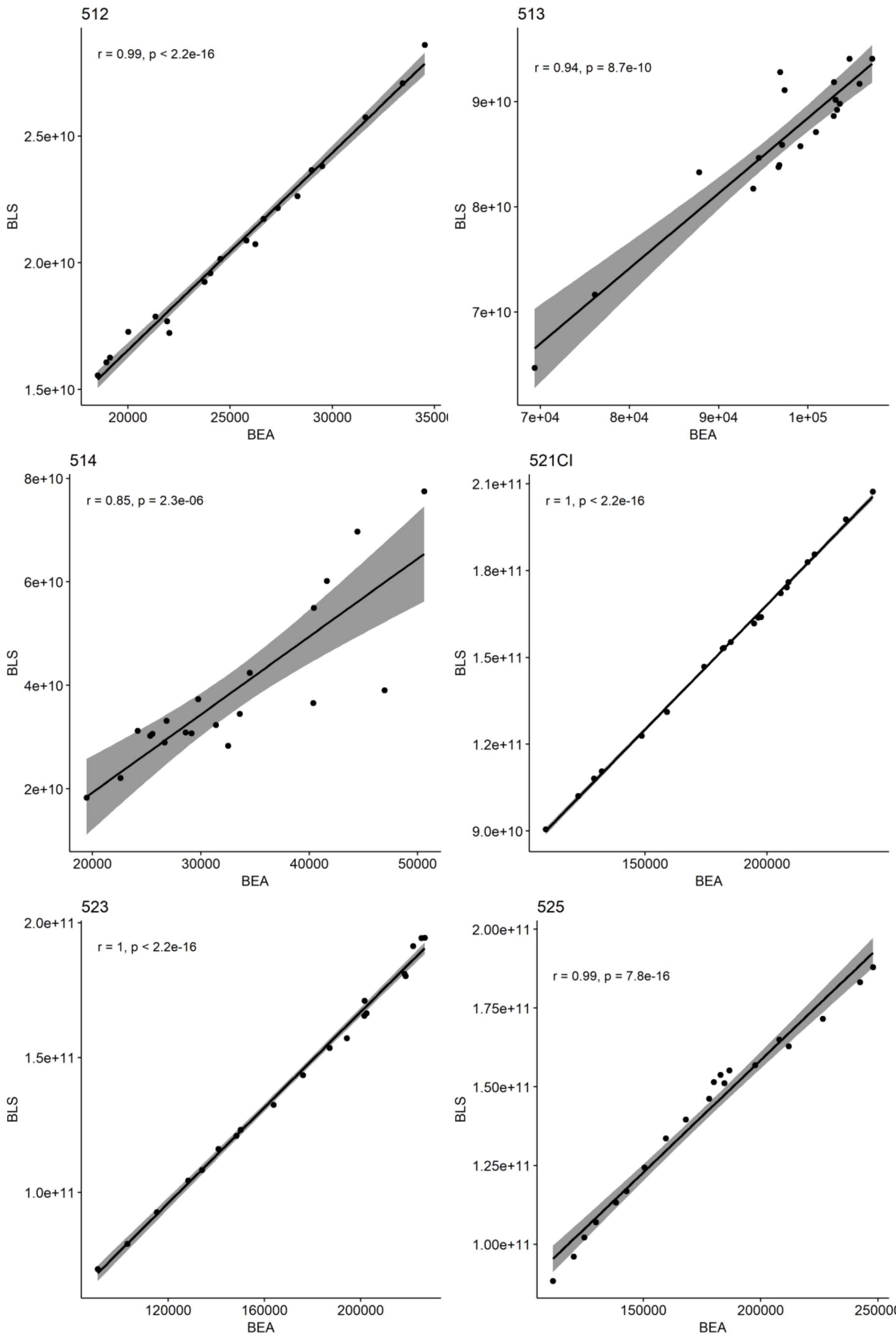


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

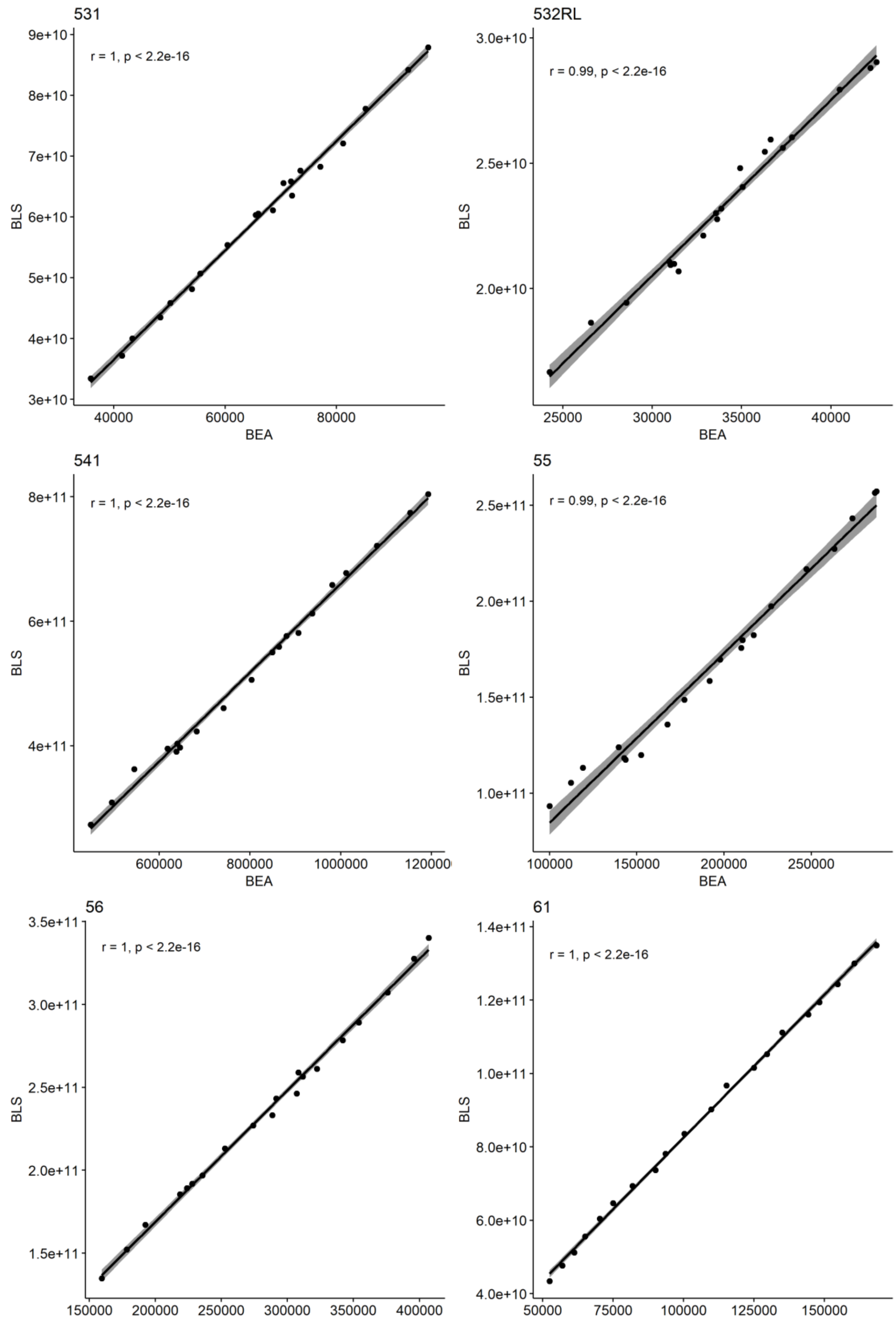


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

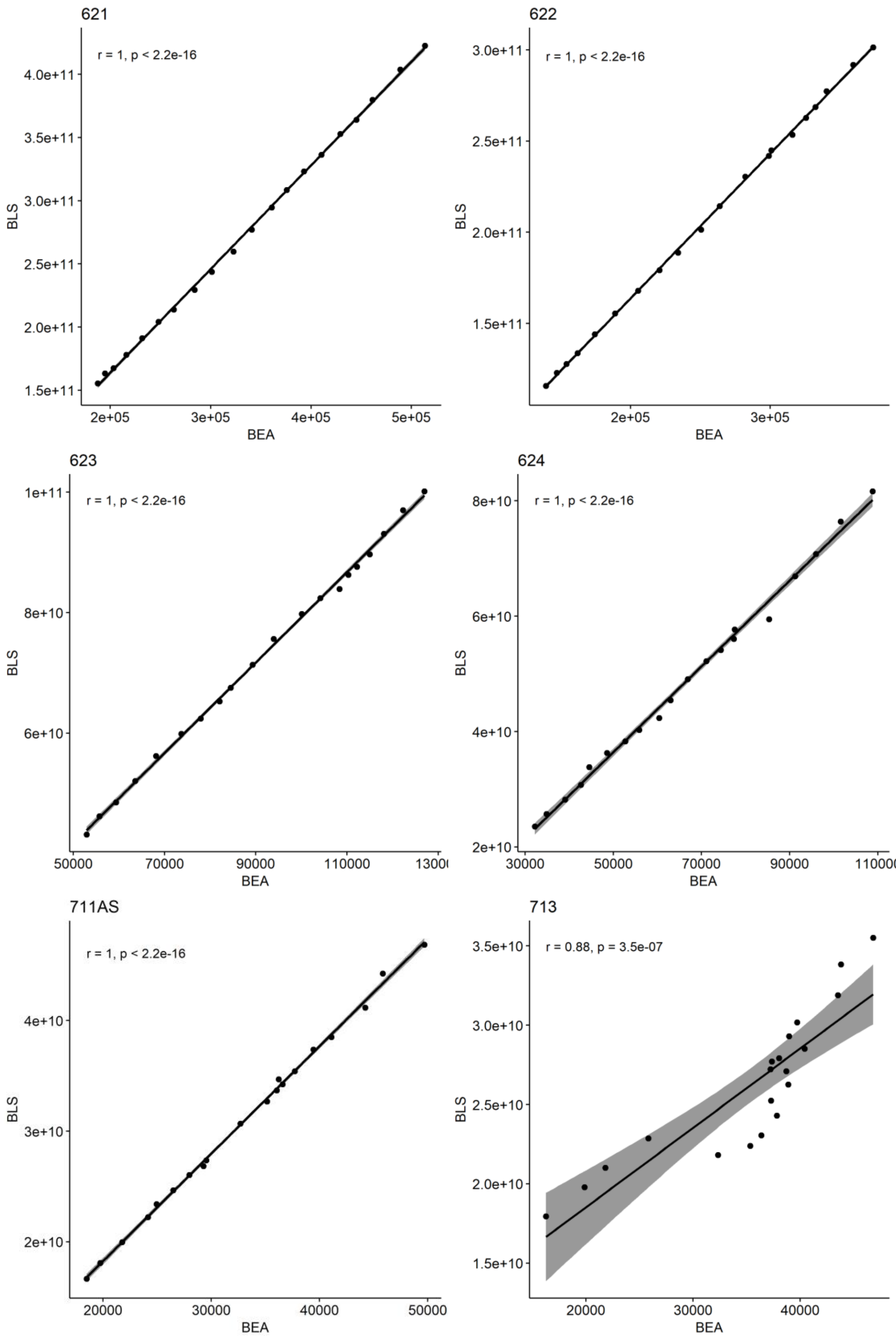


Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

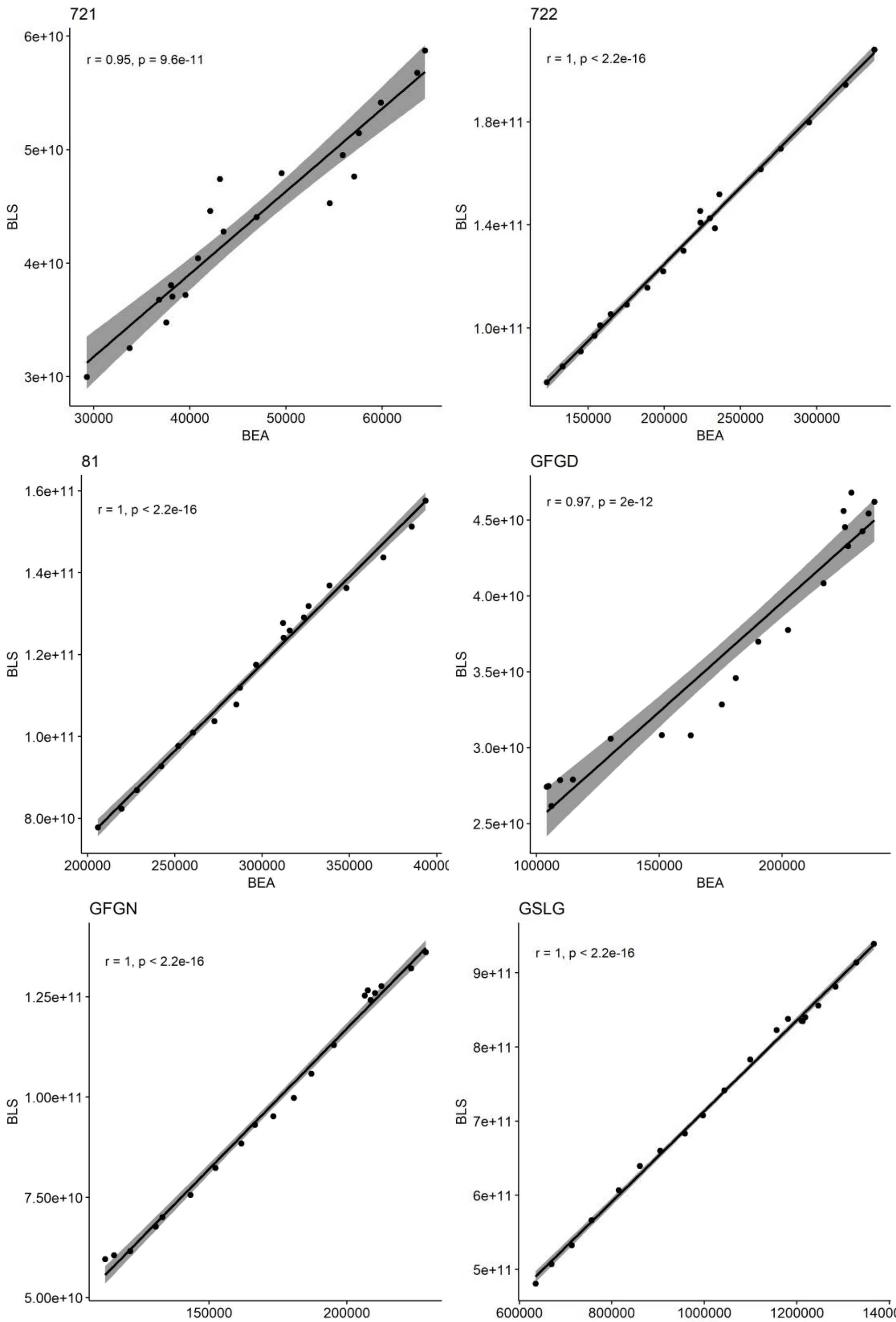


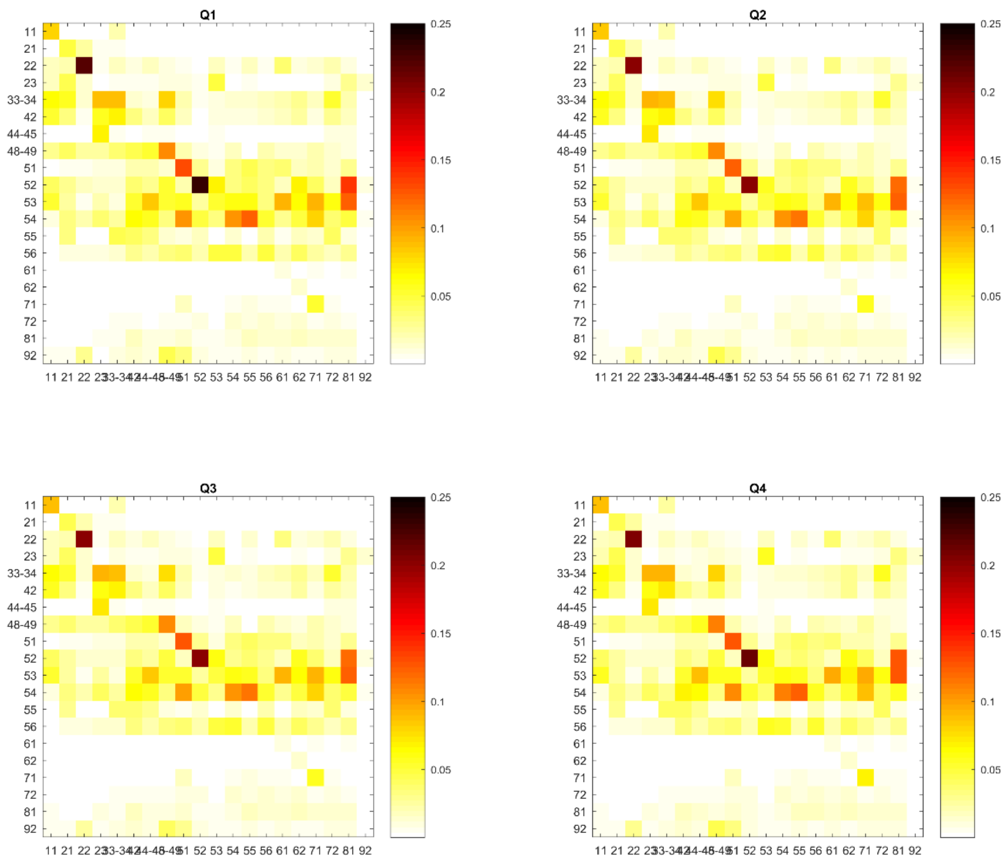
Figure C.2: (cont.) Pearson correlation between BEA and BLS labor compensation series by industry (NAICS 3-digit aggregation)

Table C.1: 60-sector disaggregation detail for the US quarterly IO tables

Code	NAICS	Description
111CA	111, 112	Farms
113FF	113, 114, 115	Forestry, fishing, and related activities
21	21	Mining, Quarrying, and Oil and Gas Extraction
22	22	Utilities
23	23	Construction
321	321	Wood products
327	327	Nonmetallic mineral products
331MT	331, 332	Primary metals and fabricated metal products
333	333	Machinery
334	334	Computer and electronic products
335	335	Electrical equipment, appliances, and components
336	336	Transportation Equipment Manufacturing
337	337	Furniture and related products
339	339	Miscellaneous manufacturing
311FT	311, 312	Food and beverage and tobacco products
313TT	313, 314	Textile mills and textile product mills
315AL	315, 316	Apparel and leather and allied products
322	322	Paper products
323	323	Printing and related support activities
324	324	Petroleum and coal products
325	325	Chemical products
326	326	Plastics and rubber products
42	42	Wholesale trade
441	441	Motor vehicle and parts dealers
445	445	Food and beverage stores
452	452	General merchandise stores
4A0	442, 443, 444, 446, 447, 448, 451, 453, 454	Other retail
481	481	Air transportation
482	482	Rail transportation
483	483	Water transportation
484	484	Truck transportation
485	485	Transit and ground passenger transportation
486	486	Pipeline transportation
487OS	487, 488, 492	Other transportation and support activities
493	493	Warehousing and storage
511	511	Publishing industries, except internet (includes software)
512	512	Motion picture and sound recording industries
513	515, 517	Broadcasting and telecommunications
514	516, 518, 519	Data processing, internet publishing, and other information services

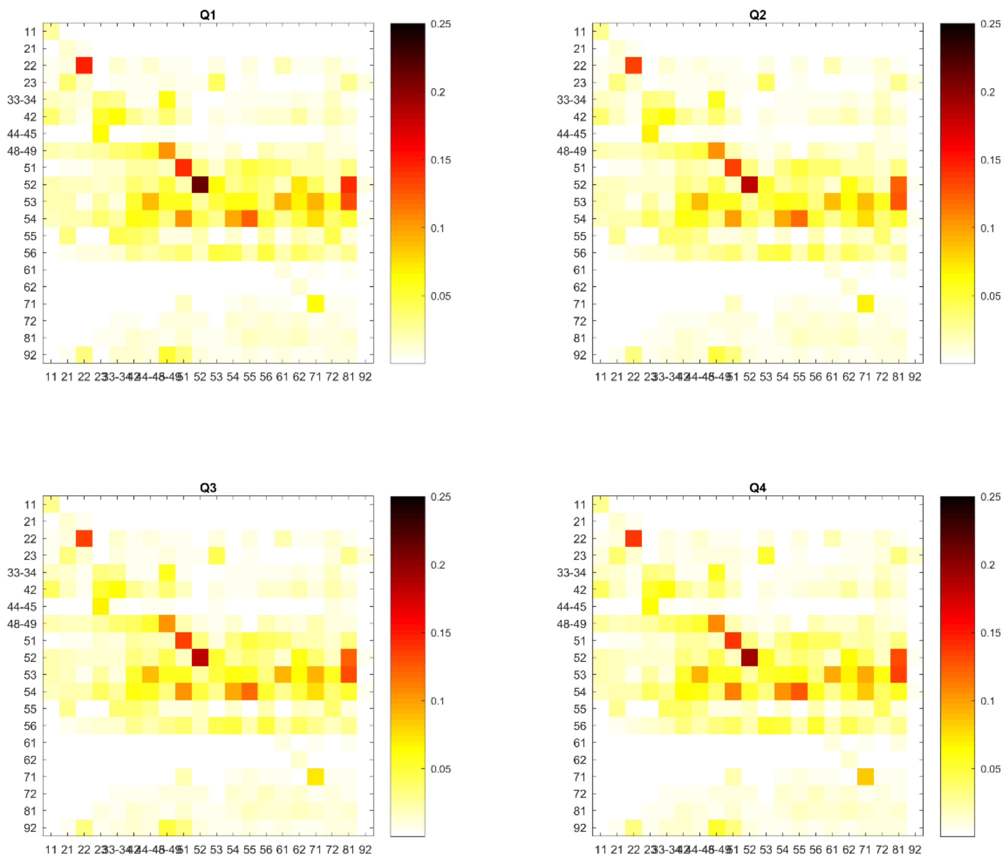
Table C.1: (cont.) 60-sector disaggregation detail for the US quarterly IO tables (cont.)

Code	NAICS	Description
521CI	521, 522	Federal Reserve banks, credit intermediation, and related activities
523	523	Securities, commodity contracts, and investments
525IA	524, 525	Insurance carriers and related activities, funds, trusts, and other financial vehicles
531	531	Real estate
532RL	532, 533	Rental and leasing services and lessors of intangible assets
541	541	Legal services
55	55	Management of companies and enterprises
56	56	Administrative and Support and Waste Management and Remediation Services
61	61	Educational services
621	621	Ambulatory health care services
622	622	Hospitals
623	623	Nursing and residential care facilities
624	624	Social assistance
711AS	711, 712	Performing arts, spectator sports, museums, and related activities
713	713	Amusements, gambling, and recreation industries
721	721	Accommodation
722	722	Food services and drinking places
81	81	Other services, except government
GFGD	928	Federal general government (defense)
GFGN	92, -928	Federal general government (nondefense) and enterprises
GSLG	92	State and local general government and enterprises
IMP		Total Imports
V002		Other value added and adjustments
V001		Compensation of employees
F010		Personal consumption expenditures
F02S		Nonresidential private fixed investment in structures
F02E		Nonresidential private fixed investment in equipment and IP
F02R		Residential private fixed investment
F030		Change in private inventories
F06C		Federal: Consumption expenditures
F06S		Federal: Total gross investment
F10C		State and local: Consumption expenditures
F10S		State and local: Total gross investment
F040		Exports of goods and services



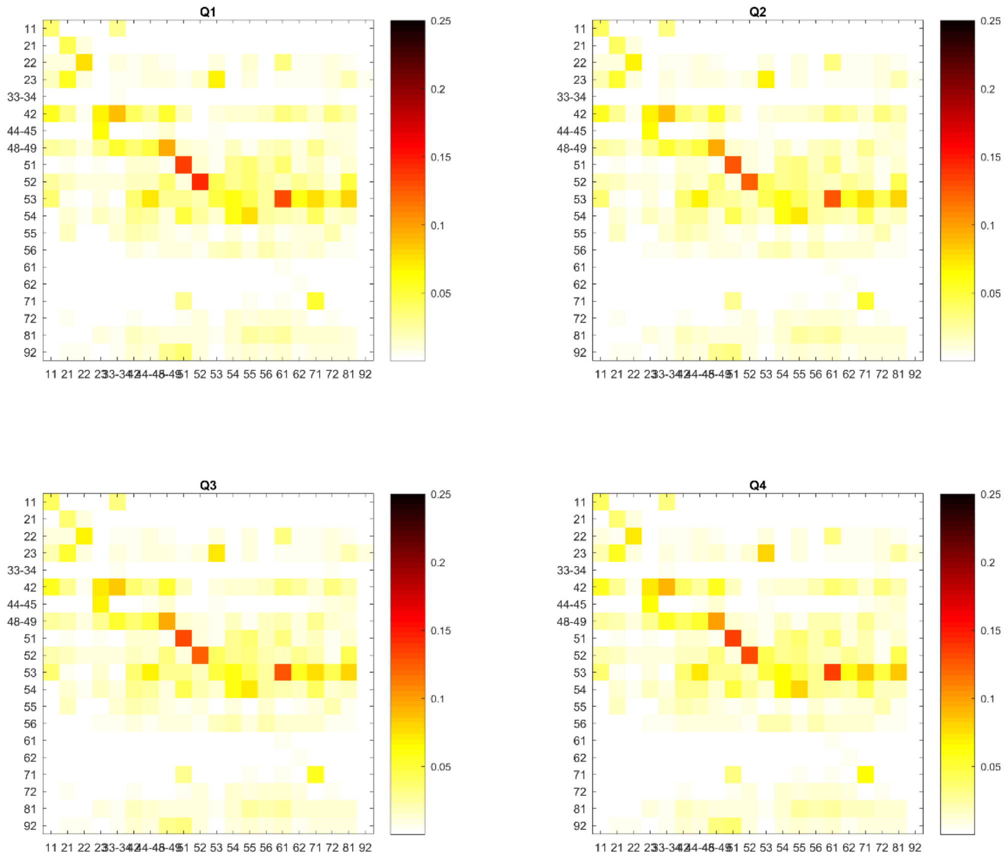
Notes: Calculated via Equation 2.18. Darker colors indicate larger uncertainty.

Figure C.3: Normalized uncertainty measure, interindustrial flows, IL



Notes: Calculated via Equation 2.18. Darker colors indicate larger uncertainty.

Figure C.4: Normalized uncertainty measure, interindustrial flows, Cook County



Notes: Calculated via Equation 2.18. Darker colors indicate larger uncertainty.

Figure C.5: Normalized uncertainty measure, interindustrial flows, Iroquois County

APPENDIX D: CHAPTER THREE

Equation D.1: Simplified extended IO model IV

$$\begin{pmatrix} \mathbf{I}-\widetilde{\mathbf{A}} & -\mathbf{h}_{\mathrm{c}}^{\mathrm{E}} & -s\times\mathbf{h}_{\mathrm{c}}^{\mathrm{U}} \\ -\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} & \mathbf{1} & \mathbf{0} \\ \mathbf{a}^{\mathrm{L}}\times\widehat{\boldsymbol{\rho}} & \mathbf{0} & \mathbf{1} \end{pmatrix}\begin{pmatrix} \mathbf{x}^{\mathrm{A}} \\ x_{\mathrm{H}}^{\mathrm{E}} \\ u \end{pmatrix}=\begin{pmatrix} \mathbf{f}^{\mathrm{A}} \\ f_H \\ l^{\mathrm{T}} \end{pmatrix} \tag{D.1}$$

where:

$\widetilde{\mathbf{A}}$: is a matrix $(n\times n)$ of local direct input requirements

$\mathbf{x}^{\mathrm{A}}$: is a column vector $(n\times 1)$ of total output by industry

$\mathbf{f}^{\mathrm{A}}$: is a column vector $(n\times 1)$ of total final demand by industry

$\mathbf{h}_{\mathrm{c}}^{\mathrm{E}}$: is a column vector $(n\times 1)$ of employed households' expenditure pattern

$\mathbf{h}_{\mathrm{c}}^{\mathrm{U}}$: is a column vector $(n\times 1)$ of unemployed households' expenditure pattern

$\mathbf{h}_{\mathrm{r}}^{\mathrm{E}}$: is a row vector $(1\times n)$ of wage income from employment coefficients

$\mathbf{a}^{\mathrm{L}}$: is a row vector $(1\times n)$ of employment/output ratios

$\boldsymbol{\rho}$: is a column vector $(n\times 1)$ of probabilities indicating the likelihood of previously unemployed indigenous workers filling opened vacancies

s: unemployment benefits

x_H^E: total employed household income

f_H: income from exogenous sources to employed households

u: unemployment level

l^{T}: total labor supply

Table D.1: Additional models' specifications

Model	Assumptions
Static Leontief Demand-Driven Model	Supply constraints converted into demand constraints via: $$\mathbf{f}^{\mathrm{A}}(t) = \big(\mathbf{I} - \boldsymbol{\Gamma}(t)\big) * \mathbf{f}^{\mathrm{A}}(0)$$ Where $\mathbf{I} - \boldsymbol{\Gamma}(t)$ represents the amount of inoperability by sector at time t.
Cochrane's Model	No trade restrictions. Rebalance estimated using: $$\mathbf{x}^{\mathrm{A}}(t) = \Big(\mathbf{I} - \big(\mathbf{I} - \boldsymbol{\Gamma}(t)\big)\widetilde{\mathbf{A}}\Big)^{-1} * \mathbf{f}^{\mathrm{A}}$$
Inventory-DIIM	Resilience coefficients (l) assumed 0.55 (Agriculture) and 0.16 (Services). † Manufacture's resilience coefficient estimated following Barker and Santos (2010) at 0.54. † Repair coefficients (k) estimated following Barker and Santos (2010). † No initial inventories.
Inventory-ARIO (version 4.1)	Same parametrization from Hallegatte (2014), except: • Maximum overproducing capacity††: $\alpha_{max} = 1$ • Number of days of stock: $n_j^i = 60$ • Size of direct losses: 1 • Reconstruction timescale: 5 years • Production reduction parameter††: $\psi = 1$

Notes: † The Inv-DIIM is very sensitive to these parameters, as they inform the speed with which the supply-demand gap closes in each period.
†† The Inv-ARIO model is very sensitive to these parameters, see complete discussion on Hallegatte (2014).

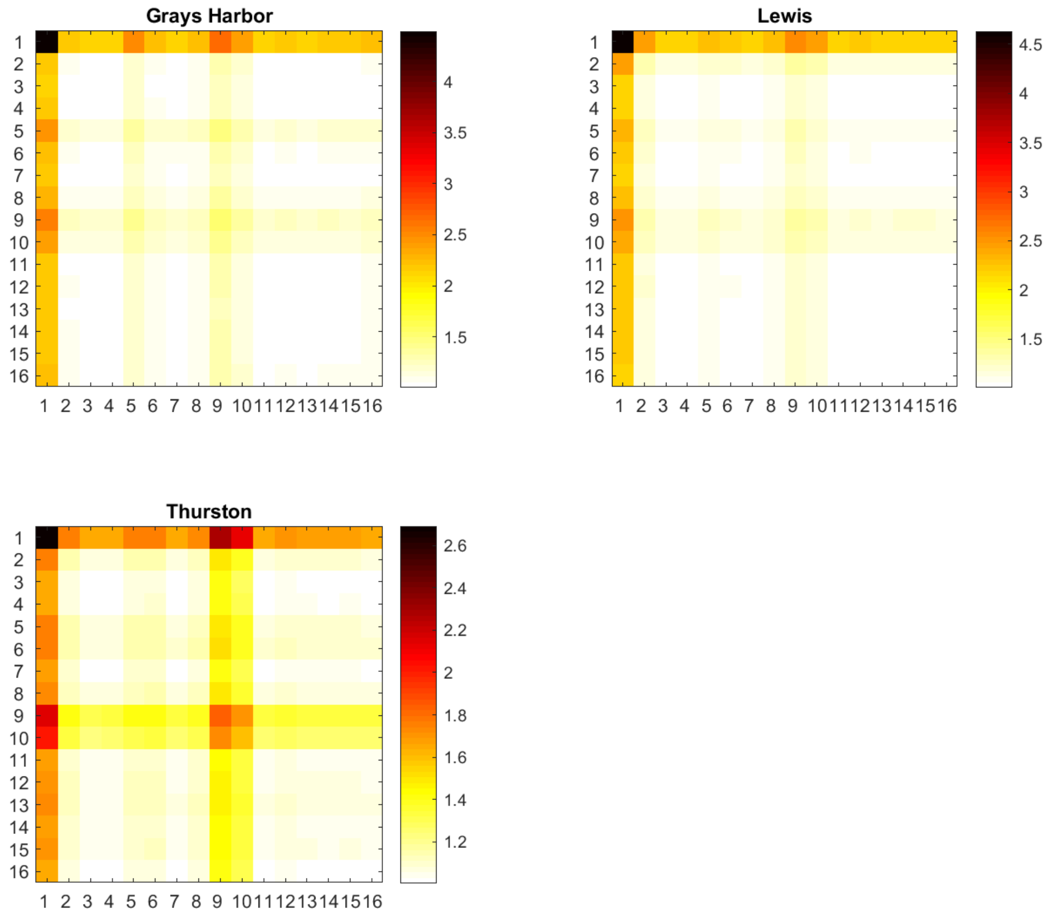
APPENDIX E: CHAPTER FOUR

Table E.1: Main features of alternative input-output methodologies

	LM	RM	SIM	DIIM	Inv-DIIM	Inv-ARIO	GDIO
Type	static	static	quasi-dynamic	dynamic	dynamic	dynamic	dynamic
Causality	demand-driven	demand-driven	demand-driven	demand-driven	demand-driven	demand-driven	demand-driven
Constraints	demand	demand supply trade	demand	demand	demand supply	demand supply	demand supply trade/labor
Inventories	no	no	no	no	yes	yes	yes
Production	simultaneous	simultaneous	time dependent	simultaneous	simultaneous	simultaneous	time dependent
Market Clearing	implicit	implicit	implicit	implicit	implicit	explicit	explicit
Prices	constant	constant	constant	constant	constant	varying[1]	constant
Behavior	perfect foresight	perfect foresight	perfect foresight	backward looking	backward looking	backward looking	backward/forwa rd looking
Regional Purchase Coefficients	fixed	varying	fixed/varying	fixed	fixed	varying[2]	time varying
Induced Effects	traditional	traditional	traditional	traditional	traditional	traditional	demo-economic
Recovery	exogenous	exogenous	exogenous	endogenous	endogenous	endogenous	exogenous
Additional Minimum Data Requirements from LM	-	-	production timing	resilience coeff. final demand*	resilience coeff. repair coeff. inventory level final demand*	inventory level elasticities recovery pace	production timing inventory level trade restrictions demographics

Notes: Traditional induced effects refer to the simple endogenization of households in the IO table as an additional sector.

*Assumptions about what is included in the "potential final demand" in each period post-disaster; [1]price changes do not affect production, only demand behavior; [2]in the ARIO model version only.



Notes: Colors capture for each cell the impact of a 1% change in the value of that cell in the direct input requirement matrix ($\mathbf{A}^P$) on the average change across all the cells of the Leontief Inverse matrix.

Figure E.1: Average fields of influence by county, annual IO table