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The Challenge of Estimating the Impact of Disasters: many approaches, many limitations and a compromise

Andre F. T. Avelino and Geoffrey J. D. Hewings

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Andre Fernandes Tomon Avelino
Regional Economics Applications Laboratory and Department of Agricultural and Consumer Economics, University of Illinois, Urbana, IL
fernan17@illinois.edu

Geoffrey J. D. Hewings
Regional Economics Applications Laboratory, University of Illinois, Urbana, IL
hewings@illinois.edu

Abstract: The recent upward trend in the direct costs of natural disasters is a reflection of both an increase in asset densities and the concentration of economic activities in hazard-prone areas. Although losses in physical infrastructure and lifelines are usually spatially concentrated in a few areas, their effects tend to spread geographically and temporally due to production chains and the timing and length of disruptions. Since the 1980's, several techniques have been proposed to model higher-order economic impacts of disruptive events, most of which are based on the input-output framework. However, there is still no consensus for a preferred model to adopt. Available models tend to focus on just one side of the market or have theoretical flaws when incorporating both sides. In this paper, the Generalized Dynamic Input-Output framework (GDIO) is presented and its theoretical basis derived. It encompasses the virtues of intertemporal dynamic models with the explicit intratemporal modeling of production and market clearing, thus allowing supply and demand constraints to be simultaneously analyzed. Final demand is endogenized via a demo-economic extension to study the impact of displacement and unemployment post-disaster. The key roles of inventories, expectation's adjustment, primary inputs, labor force and physical assets in disaster assessment are explored and previous limitations in the literature are addressed. It will be shown that the dynamic Leontief model, the sequential interindustry model and the traditional input-output model are all special cases of the GDIO framework.

Keywords: Natural disasters, Production chain disruptions, Input-output, Higher-order effects

JEL Classification: C67, Q54, J11

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 *et al*., 2012) in which after the steady-state is disrupted, instead of a gradual transition phase, an accelerated adjustment process (due to recovery efforts) brings the economy to a new steady-state.[1] Even though some activities compress better than others (money flows in relation to construction), it creates an intense transient economic shock (non-marginal) that is spatially heterogeneous and simultaneous depending 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 specific forward and backward linkages effects due to production chronology and schedules, and behavioral changes that affect both composition and the volume of demand (Okuyama, 2009). Timing is, therefore, fundamental in determining the extent of impacts as capacity constraints, inventories and production cycles vary throughout the year (see Avelino, 2017).

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 local economy. 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 internally 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 in the region is positive or negative will depend on the characteristics of the disaster, resilience of local industries, amount of reconstruction and size of interregional linkages. Spillover effects will spread supply chain disruptions and resource allocations for reconstruction to different regions at different times.

Hence, modeling efforts are essential to understand the role of different constraints in the recovery path post-disaster and to better inform mitigation planning. Regional industrial

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

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. 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 and Singhal, 2005). Nonetheless, most firms do not properly quantify these risks, with few developing back-up 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, 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; Richardson *et al*., 2015). The widely used alternative has been the use of input-output (IO) models due to their rapid implementation, easy tractability and integration flexibility with external models, which are essential in the estimation of impacts of post-disaster for recovery aid and planning. The tradeoff between its CGE counterpart is more rigid assumptions on substitutability of goods, price changes and functional forms, which makes IO more appropriate for short-term analysis. A variety of IO models have been proposed to deal with disruptive situations, most of them built upon the traditional demand-driven Leontief model (Okuyama, 2007; Okuyama and Santos, 2014). Nevertheless, most of these models fail to incorporate the aforementioned constraints or do so in an indirect way that may be inconsistent with the IO framework (Oosterhaven and Bouwmeester, 2016; Oosterhaven, 2017).

In this paper, a compromise is offered that encompasses the virtues of *intertemporal* dynamic IO models with the explicit *intratemporal* modeling of production and market clearing, thus allowing supply and demand constraints to be simultaneously analyzed. The so called Generalized Dynamic Input-Output (GDIO) framework is presented and its theoretical basis derived. It combines ideas from the Inventory Adaptive Regional IO Model, Sequential Interindustry Model and demo-economic models. The key roles of inventories, expectations' adjustment, primary inputs and physical assets in disaster assessment are explored and previous limitations in the literature are addressed. The model provides insights into the role of pivotal production chain bottlenecks, resilience of essential industries and interindustrial flow patterns that can guide formulation of better recovery strategies and mitigation planning.

In the next section, a literature review of models focused on disruptive events using the input-output framework is presented. Section 3 describes the basic GDIO framework and its demo-economic extension. Section 4 discusses other models as special cases of the more general framework. Section 5 presents a simple application and the last section offers some concluding comments.

2. Literature Review

Until the 1980's, with exception of the seminal work of Dacy and Kunreuther (1969) and studies on the effects of nuclear warfare (Hirshleifer, 1987), modeling the impacts of disruptions has received limited attention from the economics literature. Nonetheless, several natural and man-made disasters in the last forty years have stimulated new developments in terms of methods, empirical analyses, interdisciplinary approaches and data availability.

In essence, three frameworks have been applied in this endeavor: input-output, computable general equilibrium and econometrics. The first two approaches take advantage of their general equilibrium foundations by facilitating the analysis of the ways in which industrial linkages transmit localized shocks to unaffected sectors in the economy, revealing important nodes in local production chains. A tradeoff between the assumptions and data requirements creates the divide among IO and CGE: linearity and constant prices (or quantities) demand significant less data in the former, while more flexible functional forms in CGE leads to significant data requirements, especially if the parameters are to be estimated econometrically (for more elaboration, see Crawley and Hewings, 2015). Most econometric approaches are rooted in partial equilibrium analysis, preventing the evaluation of spillover effects, but are more suited for forecasting. A major drawback, nevertheless, is the infrequency and wide range of individual magnitudes of disaster events that may create estimation issues.

As noted in the introduction, the IO framework has been widely used in recent years to model disruptive events. Several applications have relied on the traditional static Leontief demand-driven model (for example WSDOT, 2008) and modeled the impact of a disruptive event through exogenous shocks in final demand. However, the assumptions underlying such a simple specification severely restrict its usability in disruption assessments. First, any supply constraint must be introduced as a shock in final demand[2] since the latter is the sole exogenous variable in the model. It also implies that local input requirement coefficients are constant post-disaster, i.e., no domestic/imported substitution effects occur. Secondly, any disruptive impact is contained within the time dimension of the model due to its static nature. Hence, inoperability does not accumulate intertemporally. By construction, the model also assumes production simultaneity, which restricts the temporal scope of economic leakages, and perfect foresight. Thirdly, spatial (in both scope and scale) and temporal aggregation can bias results by ignoring interregional feedbacks and intra-year seasonality. This can be significant as most of these unexpected events are localized in small areas and are characterized as transient phenomena (Donaghy *et al*., 2007).

To address these limitations in dealing with constraints and their sources inside the framework, several extensions have been proposed. In the static framework, in order to explicitly account for local supply constraints and trade post-disaster, rebalancing algorithms were introduced by Cochrane (1997) and Oosterhaven and Bouwmeester (2016). Given supply constraints, final demand requirements and slackness conditions on regional import/exports and inventories, Cochrane's algorithm iteratively rebalances the IO table.[3] Oosterhaven and Bouwmeester's (2016) nonlinear programming formulation minimizes information gains given production caps and demand conditions to determine the new steady state of the system post-disaster. In both models, local inoperability can only be mitigated via trade. Koks and Thissen (2016)'s MRIA model also relies on a nonlinear programming formulation but instead minimizes production costs. Although capacity constraints are set at the industry level, by using supply and

[2] This workaround of transferring supply constraints to final demand, by reducing the latter in some proportion of the capacity restriction has been common in the literature (Oosterhaven, 2017). Notice that it does not recognize the fact that local purchase coefficients might diminish as non-affected industries increase imports, thus biasing upwards the estimated negative impact of the disruption. Moreover, issues arise in sectors with small final demand (e.g. mining) and large capacity constraints.

[3] This algorithm is implemented in HAZUS (HAZards US), a widely used software from the Federal Emergency Management Agency in the US, to evaluate the economic impact of floods, hurricanes and earthquakes (FEMA, 2015).

use tables they allow a reduction in inoperability via local production of by-products by other sectors in addition to reliance on external trade.[4]

Another alternative to incorporate supply constraints in the IO framework is to explicitly model market clearing (in a Marshallian sense). This is done in the Adaptive Regional IO Model (ARIO) model (Hallegate, 2008) by modeling supply and demand conditions separately. Each industry faces a production function and a series of input constraints that bound total output individually and create an unbalance between supply-demand. However, the model also considers price effects on final demand, exports and profits that ignore the general equilibrium framework in which it is embedded (and more specifically the input-output framework), varying independently across sectors and not impacting production decisions.

In terms of dynamics, several studies have proposed intertemporal formulations focused on industrial chronology and flows in order to capture disruption leakages between discrete periods. This is essential as production delays can have ripple effects in different industrial chains and remain in the system for several periods, influencing output *inter-temporally*.

In dealing with the unrealistic assumption of production simultaneity in the basic IO model, Cole (1988, 1989) and Romanoff and Levine (1981) have introduced extensions to account for production timing. The time-lagged model proposed by the former is one of the first studies to incorporate dynamics in disruptive events (industrial plants closure). It assumes heterogeneity in the speed in which shocks reverberate in the economy due to different levels of inertia (lags) at different nodes in the production chain. Therefore, lags are introduced between the flows in the series expansion of the Leontief inverse, reducing feedback speeds and multiplier magnitudes.[5]

Also based on the series expansion of the Leontief inverse, the Sequential Interindustry Model (SIM) introduces production chronology in the IO framework (Romanoff and Levine, 1977). In its original specification, the reference point for production is the period in which orders are placed and industries' scheduling is determined by their specific production mode:

[4] The assumption of Leontief production functions still holds in the model which implies that increased supply of by-products by non-affected sectors generates overproduction of other commodities in the economy. The authors use this overproduction as a measure of local inefficiency during the recovery phase.

[5] The time-lagged model has been criticized in a series of papers by Jackson *et al.* (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.

anticipatory, just-in-time or responsive.[6] Time is discretized, assumed to be the same for all industries, constant through time and synchronized across sectors. This Core SIM is not a truly dynamic model, since it only distributes production through time,[7] and there is no structural change post-disaster. Both issues were further explored in a more complete specification (Levine and Romanoff, 1989; Romanoff and Levine, 1990) including delivery delays, inventories and technology change that was never fully implemented in the disaster literature[8] due to data requirements.[9] Although proposed earlier than Cole's model, just recently it has been applied to disaster events by Okuyama *et al.* (2002, 2004).

Given the quasi-dynamic nature of the SIM, the system's inoperability is only partially captured. In static frameworks, contemporaneous inoperability creates indirect effects *intra-temporally* only, as all flows are contained within a time period. In the SIM, inoperability is projected *inter-temporally* through production timings, i.e., *intra-temporal* impacts are carried over via production lags between time periods. Based on the classic Leontief Dynamic model, the Dynamic Inoperability Input-Output Model (DIIM) proposed by Lian and Haimes (2006) aims at introducing a dynamic framework for disaster assessment that bridges *intra-temporal* and *inter-temporal* inoperability.[10] It modifies the Dynamic Leontief model by replacing the capital formation matrix by a resilience matrix that represents the speed with which the production gap post-disaster is closed. Instead of modeling a growth path between steady-states, the DIIM reflects the spread of capacity constraints in the system from initial disruption until full restoration.

The connection between *intra-temporal* and *inter-temporal* inoperability is achieved by acknowledging that the impact of current inoperability creates contemporaneous supply constraints that also influence the next period, hence accounting for both effects. Note that the

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[6] See complete description of the model in Romanoff and Levine (1977, 1981).

[7] If one accumulates all temporal flows from the Core SIM, they amount to the same output of the traditional IO Model. In fact, the IO model is a special case of the SIM when all industries are just-in-time.

[8] Although Okuyama *et al.* (2004) present this model in their paper, the actual model implemented is the traditional SIM. Okuyama and Lim (2002) implement a toy model of the traditional SIM with inventories.

[9] Another important critique of the SIM is the assumption of perfect knowledge for production scheduling (Mules, 1983). An exercise is performed in Okuyama *et al.* (2002) to relaxed this assumption, but there is no further application of this extension.

[10] The DIIM is the dynamic version of the Inoperability Input-Output Model (IIM) (Santos, 2003; Santos and 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, so no additional insights are gained by applying it.

DIIM schedules a production level for the next period that deviates from current output depending on the contemporaneous mismatch between supply-demand (weighted by the recovery speed). In this sense, all industries operate in anticipatory mode, using the previous period's final demand and production unbalance as expected output level. There is still no explicit modeling of the unbalance between supply and demand and a proportional rationing rule is implicitly assumed to redistribute reduced output.

Barker and Santos (2010) extended the DIIM to include finished goods inventories and their impact on the recovery process. As inventories serve as a way to smooth volatility in the industry, they distinguish between overall inoperability in the system, which accounts for indirect constraints from production chain linkages, and sector-specific inoperability that depends on inventories. Although the impact of pre-disaster inventories is assessed, there is no modeling of inventory formation, nor the impact of material and supply (M&S) inventories in reducing inoperability from the supply perspective.[11] In contrast, the Inventory-ARIO model (Hallegate, 2014), the dynamic version of the ARIO model, incorporates M&S inventories formation and depletion. It is based on the premise that all industries seek to maintain a target level of these inventories similar to "order-point systems" used in managing inventories prior to the 1970s (Ptak and 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 and Smith, 2011). Besides carrying the same theoretical inconsistency on price changes from the ARIO model, several *ad hoc* assumptions on elasticities, inventory levels and other behavioral parameters are required.[12]

Another alternative dynamic framework is the use of regional econometric IO models (REIM) for disaster analysis.[13] The advantage of these models is their forecast capability in terms of structural linkages, which allows implicit coefficient changes, intertemporal effects due

[11] Inoperability can arise from capacity constraints (physical damage) or inputs constraints (disruption in the backward production chain). The Inventory DIIM mitigates the former type of inoperability by embedding finished goods inventories in the model, but does not account for materials and supplies inventories. Notice that in a dynamic framework these stocks are not the same intertemporally, since they are used at different timings.

[12] In a recent study comparing the ARIO, MRIA and a CGE model for the same event (flooding in the Po River basin, Italy) the MRIA outperformed the ARIO model with results closer to those of the CGE run (Koks *et al.*, 2016).

[13] For a complete description of REIM models, see Conway (1990) and Israilevich *et al.* (1997).

to its difference equations structure and nonlinear reaction to given external shocks. An application to the impacts of the 1993 Mississippi Flood in Iowa can be found in Hewings and Mahidhara (1996). Major issues of such approach, however, are the data requirements to build the model, the adjustment functions do not model transition paths, causality is missing in most of the dynamic equations and there is an absence of theoretically grounded feedbacks and constraints in the model's workflow (Donaghy *et al*., 2007).

An important critique to all current dynamic models is time discretization and the impact of such assumption in disaster studies. Donaghy *et al*. (2007) argue that given the transient nature of these shocks and the fact that their duration is usually shorter than the model's time step, there is a temporal aggregation bias. The authors propose a Continuous-Time REIM model that transforms the system of nonlinear difference equations from a REIM to a system of nonlinear differential equations. It allows a consistent way of modeling both stocks and flows, introduces an explicit functional forms for recovery processes, extraction of regional purchase coefficients at any point and, once estimated, the model can be solved for any time interval. Still, data requirements and costs are a major hurdle in implementing REIM models.

In terms of space, several models have captured multiregional feedbacks using a traditional interregional IO framework (Okuyama *et al.*, 1999; Sohn *et al.*, 2004; Richardson *et al.*, 2014). While the spatial aggregation issue of IO models is usually addressed by projecting results at finer geographic units; for example, Yamano *et al.* (2007) apply modified location quotients to disaggregate an IO table from prefecture level to district level in Japan. The economic importance of particular districts and their vulnerability after disruptive events can, then, be assessed to reveal imbalances in first and higher order effects.

Natural disasters also tend to change expenditure patterns both in the affected region (due to layoffs, reduced production, governmental assistance programs) and outside (relief aid). These have been incorporated in Okuyama *et al.* (1999) and Li *et al.* (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 vs micro level larger/smaller networks). Efforts in integrating these include the Southern California Planning Model (Richardson *et al*., 2016) and the National Interstate Economic Model (Richardson *et al*., 2014) combining a MRIO with transportation networks and Rose and Benavides (1998) considering electricity supply.

Finally, another important factor, not considered in any of the available models in the literature, is the role of seasonality in the economic structure. 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 (Avelino, 2017). Hence, fluctuations in production capacity *intra-year* have a significant impact on the magnitude and extension of impacts by affecting inventory levels and sectoral adaptive response.

In sum, several alternatives have been proposed but none has been able to fully and consistently incorporate the constraints created by natural disasters. The ARIO model presents an advance in explicitly modeling supply-demand in a dynamic context, however several theoretical issues were noted. Inventories, when incorporated, usually focus on one type only and the concept of production scheduling has seen limited application. Also, seasonality considerations and demographics dynamics post-event have been largely absent in the literature. The next section introduces a new model that departs from the Inventory-ARIO model and combine the aforementioned points in a consistent and theoretically sound way in order to resolve issues of *inter* and *intratemporal* dynamics, seasonality, inventory formation, demographics and demand-supply constraints.

3. Methodology

When dynamics are introduced in IO analysis, the economic system becomes a combination of *intratemporal* flows and *intertemporal* stocks. The latter are key to exploiting these dynamics and 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 and 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 *per se* is not explicitly modeled, 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).[14]

Flows and stocks need to be organized in a certain way in order to comply with neoclassical assumptions on production sets that are time-relevant. If production is to occur in period t, *irreversibility* requires that all required inputs be available in advance, therefore input's 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.

Based on these assumptions, the length h can be divided into a sequence of events that start with the formation of supply from production and end with demand being realized, markets cleared and goods allocated, thus creating the necessary conditions for production in the next period.[15] An overview of the model is presented in figure 1. First, production takes place with inputs purchased in $t-1$ at a level that depends on current conditions (inventories, available assets, labor and scheduled output). At the end of the period, all industries end production and supply is formed (see section 3.1). Final demand for the period is realized and a market clearing process occurs determining inventories of finished goods and imports for final demand. Then, intermediate demand is generated according to expectations of final demand for $t+1$ and production mode in each industry (see section 3.2). A market clearing process follows.

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

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

Inventories of finished goods and imports for intermediate demand create the conditions for production in the next period (see section 3.3).

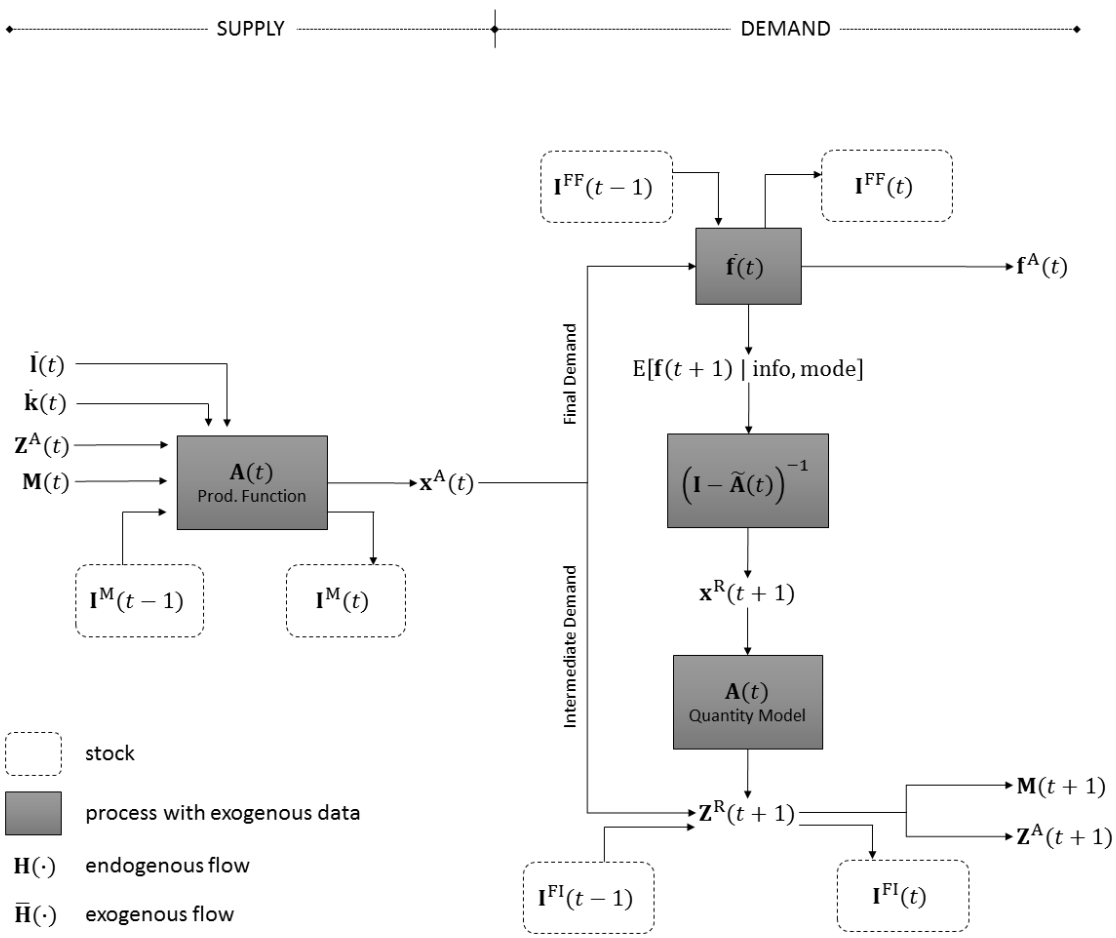

Figure 1. Generalized Dynamic Input-Output Model (GDIO) Overview

The generic formulation of the GDIO model is detailed in figure 1 and Appendices 1 and 2,[16] so no specific functional forms are presented where there is flexibility (although examples are provided). Assume an economy with n industries and T production periods of length h. An

[16] The standard IO notation is used in this paper. 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.

industry $\mu \in 1, \ldots, n$ and time period $t \in 1, \ldots, T$ are taken as reference points for expositional purposes.

3.1. Supply Side

It is imperative to distinguish between a local direct input requirement matrix ($\widetilde{\mathbf{A}}$) and a proper technical coefficient matrix (**A**), as the terminology has often been indiscriminately used in the literature. The former is derived from locally purchased inputs only, while the latter 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 (see Avelino, 2017) – or due to the adoption of alternative production technologies, the choice of which might depend on the availability of local supply.[17]

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 allows for the introduction of supply constraints due to limited input availability, physical damage to capital or displacement of the workforce. Then, production capacity in industry μ is given by available industrial inputs, and 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.[18]

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:

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

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

[18] 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 \$. In this base model, labor force and capital are exogenous to the system. The former is endogenized in section 3.5.

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

$$\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t) \; = f(\mathbf{Z}^{\mathrm{T}}, \mathbf{l}, \mathbf{k}) = \min\left\{\frac{\mathbf{Z}_{1\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{1\mu}(t)}, \dots, \frac{\mathbf{Z}_{\mu\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{\mu\mu}(t)}, \dots, \frac{\mathbf{Z}_{n\mu}^{\mathrm{T}}(t)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{L}}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{K}}(t)}\right\} \tag{2}$$

Note that the only reason for $\mathbf{A}_{ij}(t-1) \neq \mathbf{A}_{ij}(t)$ is a change in production technology as noted earlier. 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 $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$ (to be discussed in more detail) 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 $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$):

$$\mathbf{x}_{\mu}^{\mathrm{A}}(t) = \min\left\{\tilde{\mathbf{x}}_{\mu}^{\mathrm{A}}(t), \;\; \mathbf{x}_{\mu}^{\mathrm{S}}(t) \; - \mathbf{I}_{\mu}^{\mathrm{FI}}(t-1)\right\} \tag{3}$$

After production is completed, unused inputs enter the stock of *materials and supplies inventories* ($\mathbf{I}^{\mathrm{M}}$) at period t. It is assumed that imported inputs are used first in the production process and then local inputs are consumed.[19] 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:

$$\mathbf{I}_{i\mu}^{\mathrm{M}}(t) = \left[\mathbf{Z}_{i\mu}^{\mathrm{T}}(t)\right] - \left[\mathbf{A}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{A}}(t)\right] \quad \forall i \tag{4}$$

3.2. Demand Side

On the demand side, an exogenous final demand vector[20] ($\bar{\mathbf{f}}_{\mu}(t)$) and endogenous intermediate demands ($\mathbf{Z}_{\mu j}^{\mathrm{R}}(t)$) are locally supplied by $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ and any available *finished goods inventory*. It is assumed 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

[19] In this way, there is no changes in inventory for external industries.

[20] Final demand can be fully endogenized in **A** or partially endogenized by linking labor income to household consumption, so that the production level directly influences household expenditures (see section 3.5).

among industries.[21] The amount of $\mathbf{x}_{\mu}^{\mathrm{A}}(t)$ destined for each type of demand is determined by the scheduled total output $\mathbf{x}_{\mu}^{\mathrm{S}}(t)$ and scheduled demands $\mathbf{Z}_{\mu i}^{\mathrm{S}}(t)\,\forall i$, $\mathbf{f}_{\mu}^{\mathrm{S}}(t)$ that were set when purchasing inputs in $t-1$. In the case when $\mathbf{x}_{\mu}^{\mathrm{S}}(t) \neq \mathbf{x}_{\mu}^{\mathrm{A}}(t)$, a rationing scheme $\mathbf{r}(t) \mid \sum_i \mathbf{r}_i(t) = 1$ must be applied (Bénassy, 2002). It 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; Hallegate, 2014). Notice that it is still possible to model this imbalance between supply and demand in an input-output framework as long as t is not too large, as prices may not be able to adjust rapidly. The rationing rule is constrained by:

$$\mathbf{x}_{\mu}^{\mathrm{A}}(t) = \sum_i \mathbf{Z}_{\mu i}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) \tag{5}$$

Given the exogenous final demand $\bar{\mathbf{f}}_{\mu}(t)$, 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:

$$\mathbf{f}_{\mu}^{\mathrm{A}}(t) = \min\left(\bar{\mathbf{f}}_{\mu}(t)\,, \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1)\right) \tag{6}$$

In the case where local supply is insufficient for final demand, imports are required. Imports can be assumed to be sufficient to attend the remaining final demand, or they can be assumed to have a constraint or they 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. In this single region setting, we assume an external import constraint $\mathbf{T}_{i}^{\mathrm{FD}}(t)$ that determines how much trade flexibility there is for finished goods for final demand in the external industry i.[22]

$$\mathbf{m}_{\mu}^{\mathrm{FD}}(t) = \min\left(\bar{\mathbf{f}}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t), \mathbf{T}_{\mu}^{\mathrm{FD}}(t)\right) \tag{7}$$

Sectors that can hold finished goods' inventories[23] update their stocks:

---

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

[22] 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: $\bar{\mathbf{f}}_{\mu}(t+1) = \bar{\mathbf{f}}_{\mu}(t+1) + [\bar{\mathbf{f}}_{\mu}(t) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) - \mathbf{m}_{\mu}^{\mathrm{FD}}(t)]$.

[23] See section 3.6 for notes on inventories.

$$\mathbf{I}_{\mu}^{\mathrm{FF}}(t) = \mathbf{f}_{\mu}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FF}}(t-1) - \mathbf{f}_{\mu}^{\mathrm{A}}(t) \tag{8}$$

Next, industries form expectations regarding final demand in the next period in order to purchase the required inputs at t. They do so by means of an expectation function $\mathrm{E}\left[\bar{\mathbf{f}}_{\mu}(t+1) | \text{ info}\right]$, whose form is to be defined by the modeler, and may include an inventory strategy that varies according to the uncertainty in the system.[24] 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 have a particular case in which $\mathrm{E}\left[\bar{\mathbf{f}}_{\mu}(t+1) \mid \text{info}, \mathrm{JIT}\right] = \bar{\mathbf{f}}_{\mu}(t+1)$, as 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 and Levine, 1981).[25]

The required output for $t+1$ ($\mathbf{x}^{\mathrm{R}}(t+1)$) is determined by its expected final demand via the Leontief model (Eq. 9). After accounting for any labor or capital constraints (Eq. 10), and any available material and supplies inventory, industries determine the total intermediate input requirements in the period $\mathbf{Z}_{i\mu}^{\mathrm{R}}(t)$ (that includes both local and imported goods) (Eq. 11).[26]

$$\mathbf{x}^{\mathrm{R}}(t+1) = \left(\mathbf{I} - \widetilde{\mathbf{A}}(t)\right)^{-1} \left[\mathrm{E}\left[\bar{\mathbf{f}}(t+1) \mid \text{info}, \text{mode}\right] - \mathbf{I}^{\mathrm{FF}}(t)\right] \tag{9}$$

$$\mathbf{x}_{\mu}^{\mathrm{R}}(t+1) = \min\left(\mathbf{x}_{\mu}^{\mathrm{R}}(t+1), \mathbf{l}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{L}}(t), \mathbf{k}_{\mu}(t)/\mathbf{a}_{\mu}^{\mathrm{K}}(t)\right) \tag{10}$$

$$\Longrightarrow \quad \mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1) = \mathbf{A}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{R}}(t+1) - \mathbf{I}_{i\mu}^{\mathrm{M}}(t) \quad \forall i \tag{11}$$

---

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

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

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

where the adjustment parameter σ reflects the reaction of the sectors to such uncertainty.

[26] If an industry is just-in-time, for the model to be consistent with perfect foresight under discretization, technical coefficients and local purchase coefficients in Eq. 9-11 would be indexed $t+1$.

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 and 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 it simplest form, it can 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:

$$\mathbf{Z}_{i\mu}^{\mathrm{A}}(t+1) = \min\left(\mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1), \mathbf{Z}_{i\mu}^{\mathrm{S}}(t) \times \mathbf{r}_i(t) + \mathbf{I}_i^{\mathrm{FI}}(t-1) \times \mathbf{d}_i(t)\right) \quad \forall i \tag{12}$$

In case local supply is insufficient for intermediate demand, imports are required. Besides possible trade constraints, for consistency, the production modes considered previously need to be accommodated. 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.[27] In a multiregional framework, external adjustments are explicitly modeled in the other region.

$$\mathbf{m}_{i\mu}^{\mathrm{I}}(t+1) = \min\left(\mathbf{Z}_{i\mu}^{\mathrm{R}}(t+1) - \mathbf{Z}_{i\mu}^{\mathrm{A}}(t+1), \mathbf{T}_{i\mu}^{\mathrm{I}}(t)\right) \quad \forall i \tag{13}$$

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

$$\mathbf{I}_{\mu}^{\mathrm{FI}}(t) = \begin{cases} \sum_j \mathbf{Z}_{\mu j}^{\mathrm{S}}(t) \times \mathbf{r}_{\mu}(t) + \mathbf{I}_{\mu}^{\mathrm{FI}}(t-1) - \sum_j \mathbf{Z}_{\mu j}^{\mathrm{A}}(t+1) \;, & \text{if } \mu \text{ can hold inventories} \\ 0 \;, & \text{o.w.} \end{cases} \tag{14}$$

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:[28]

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[27] 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.

[28] See footnote 26 regarding the time indexes for JIT industries.

$$\mathbf{x}_{\mu}^{\mathrm{S}}(t+1) = \min\left\{\frac{\mathbf{Z}_{1\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{1\mu}(t)}, \dots, \frac{\mathbf{Z}_{\mu\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{\mu\mu}(t)}, \dots, \frac{\mathbf{Z}_{n\mu}^{\mathrm{T}}(t+1)}{\mathbf{A}_{n\mu}(t)}, \frac{\mathbf{l}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{L}}(t)}, \frac{\mathbf{k}_{\mu}(t)}{\mathbf{a}_{\mu}^{\mathrm{K}}(t)}\right\} \tag{15}$$

$$\mathbf{Z}_{i\mu}^{\mathrm{S}}(t+1) = \widetilde{\mathbf{A}}_{i\mu}(t) \times \mathbf{x}_{\mu}^{\mathrm{S}}(t+1) \quad \forall i \tag{16}$$

$$\bar{\mathbf{f}}_{\mu}^{\mathrm{S}}(t+1) = \min\left(\mathrm{E}\left[\bar{\mathbf{f}}(t+1) \mid \text{info}, \text{mode}\right], \mathbf{x}_{\mu}^{\mathrm{S}}(t+1) - \sum_{j} \mathbf{Z}_{\mu j}^{\mathrm{S}}(t+1)\right) \tag{17}$$

These create the necessary conditions for production in the next period. Note that the disaster significantly impacts anticipatory industries, since they base decisions on 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. 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.

3.4. Recovering the Input-Output Table for the period

Finally, an input-output table can be extracted in each time period according to figure 2. Most of the vectors are determined directly from the previous equations. Interindustrial flows are determined by $\mathbf{Z}(t) = \left(\mathbf{A}(t) \times \hat{\mathbf{x}}^{\mathrm{A}}(t)\right) - \mathbf{M}^{\mathrm{I}}(t)$, as imported inputs are consumed first. Hence, total change in inventories is derived as:

$$\begin{aligned} \Delta\mathbf{I}(t) = {} & \{[\mathbf{Z}(t+1) + \mathbf{I}^{\mathrm{M}}(t)] \times \boldsymbol{\iota} + \mathbf{I}^{\mathrm{FI}}(t) + \mathbf{I}^{\mathrm{FF}}(t)\} \\ & - \{[\mathbf{Z}(t) + \mathbf{I}^{\mathrm{M}}(t-1)] \times \boldsymbol{\iota} + \mathbf{I}^{\mathrm{FI}}(t-1) + \mathbf{I}^{\mathrm{FF}}(t-1)\} \end{aligned} \tag{18}$$

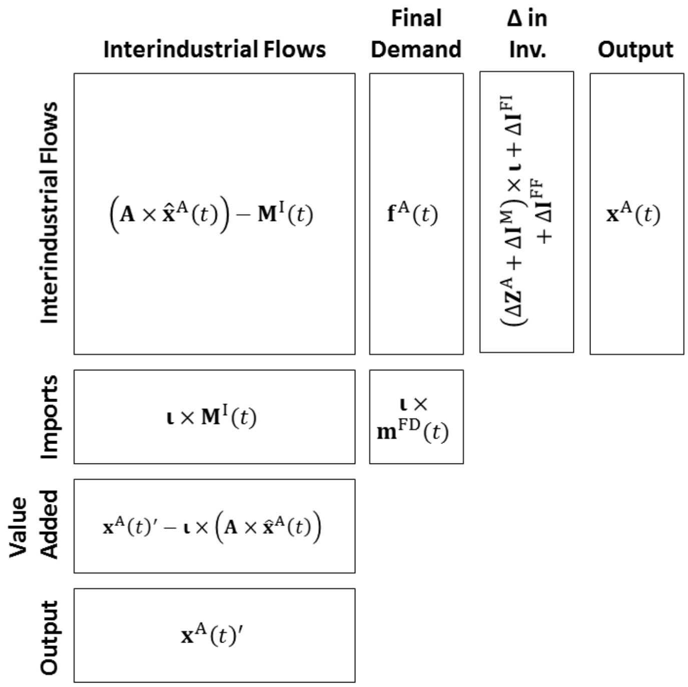

Figure 2. Input-Output Table from GDIO

3.5. Induced Effects: Demo-economic GDIO

The composition and mix of final demand 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, notice that 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 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 and Weeks, 1989; Batey *et al.*, 2001). Of particular interest for disaster analysis is the fact that Type II multipliers artificially inflate induced effects by excluding the expenditure of workers that are unemployed in the region. As highlighted by Batey (2016), by ignoring the consumption of unemployed individuals, 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.

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 (demo-economic) 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 and Oosterhaven, 1986; Madden, 1993).

Therefore, we extend the GDIO model through a demo-economic framework 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 ($\bar{\mathbf{v}}$).[29] We simplify Model IV proposed in Batey and Weeks (1989) by aggregating the intensive and extensive margins. Hence, in its traditional single-region version, the following framework is used:[30]

$$\begin{pmatrix} \mathbf{I}-\widetilde{\mathbf{A}} & -\mathbf{h}_{\mathrm{c}}^{\mathrm{E}} & -s\times\mathbf{h}_{\mathrm{c}}^{\mathrm{U}} \\ -\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} & \mathbf{1} & \mathbf{0} \\ \mathbf{a}^{\mathrm{L}}\times\widehat{\boldsymbol{\rho}} & \mathbf{0} & \mathbf{1} \end{pmatrix} \begin{pmatrix} \mathbf{x}^{\mathrm{A}} \\ x_{\mathrm{H}}^{\mathrm{E}} \\ u \end{pmatrix} = \begin{pmatrix} \mathbf{f}^{\mathrm{A}} \\ f_H \\ l^{\mathrm{T}} \end{pmatrix} \tag{19}$$

where

[29] In many REIMs, 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.

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

$\mathbf{h}_c^{\mathrm{E}}$: is a column vector ($n \times 1$) of employed households' expenditure pattern

$\mathbf{h}_c^{\mathrm{U}}$: is a column vector ($n \times 1$) of unemployed households' expenditure pattern

$\mathbf{h}_r^{\mathrm{E}}$: is a row vector ($1 \times n$) of wage income form 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}: labor supply

This extension is implemented as shown in figure 3 for a single region (see also Appendix 3). Total labor supply $l(t)$ 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 labor $\bar{l}^{\mathrm{E}}(t)$.[31]

$$p(t) = p(t-1) - \bar{n}(t) \tag{20}$$

$$l^{\mathrm{T}}(t) = \tau \times p(t) + \bar{l}^{\mathrm{E}}(t) \tag{21}$$

Note that total labor supply constrains production in Eq. 2 by distributing it among the industries so that $\mathbf{l} = l^{\mathrm{T}} \times \mathbf{l}(0) \times (\boldsymbol{\iota} \times \mathbf{l}(0))^{-1}$. Once the actual total output of industry ($\mathbf{x}^{\mathrm{A}}$) is determined, total employment for the period is estimated by Eq. 22, and total final demand from employed *residents* by Eq. 23. Total unemployment determines the amount of final demand for these households (Eq. 24).

$$l^A(t) = \mathbf{a}^{\mathrm{L}} \times \hat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) \tag{22}$$

[31] 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 ($n(t) = \varphi * \Delta sqft^{\mathrm{RES}}(t-1)$).

$$\mathbf{f}^{\mathrm{HE}}(t) = \mathbf{h}_{\mathrm{c}}^{\mathrm{E}} \times (\mathbf{h}_{\mathrm{r}}^{\mathrm{E}} \times \hat{\boldsymbol{\rho}} \times \mathbf{x}^{\mathrm{A}}(t) + f_H(t)) \tag{23}$$

$$\mathbf{f}^{\mathrm{HU}}(t) = s \times \mathbf{h}_{\mathrm{r}}^{\mathrm{U}} \times \left(l^{\mathrm{T}}(t) - l^{\mathrm{A}}(t)\right) \tag{24}$$

Then, total final demand for the period is estimated by combining *resident* households' expenditures, other final demand components (exogenous) and reconstruction stimulus (exogenous). The new final demand enters back into the base model in Eq. 6.

$$\mathbf{f}(t) = \mathbf{f}^{\mathrm{HE}}(t) + \mathbf{f}^{\mathrm{HU}}(t) + \bar{\mathbf{f}}^{\mathrm{O}}(t) + \bar{\mathbf{v}}(t) \tag{25}$$

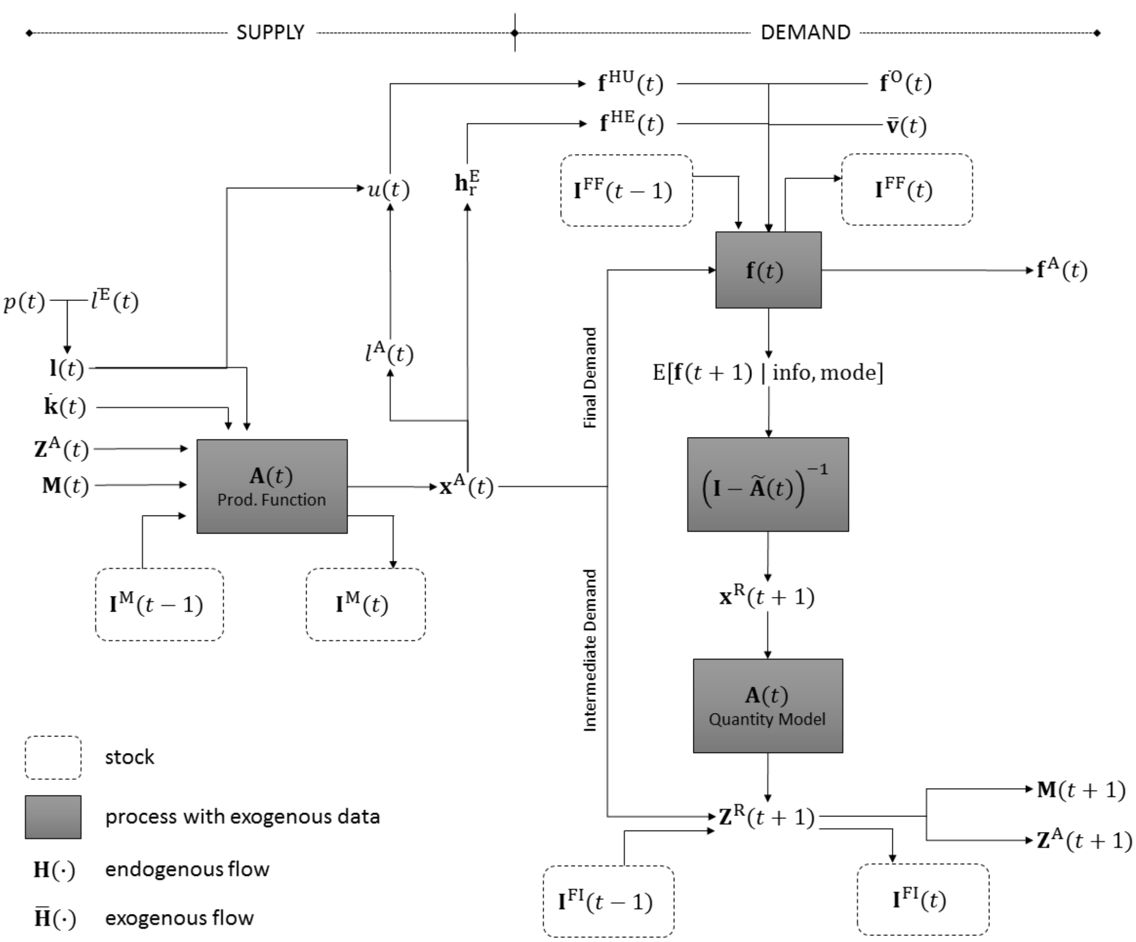

Figure 3. GDIO with Induced Effects

This new specification, however, cannot be solved in the same fashion as the basic GDIO model. Recall that the SIM assumes that, in any period, JIT and responsive industries have perfect information on current and future final demands. When the latter is fully exogenous (as in the basic GDIO), this requirement is easily satisfied. In the demo-economic extension, however, the household's 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 Eq. 9 and the model is solved until $\mathbf{f}(t+1)$ is calculated via Eq. 25. If there is a mismatch between $\mathrm{E}\left[\bar{\mathbf{f}}_{\mu}(t+1) \mid \text{info}\right]$ and $\mathbf{f}_{\mu}(t+1)$ for $\forall \mu \mid$ JIT or Responsive, the prior is updated to $\mathbf{f}_{\mu}(t+1)$ and period t is reiterated. The iteration halts when $\mathrm{E}\left[\bar{\mathbf{f}}_{\mu}(t+1) \mid \text{info}\right] = \mathbf{f}_{\mu}(t+1)$ and the model proceeds.[32]

3.6. A Note on Inventories

First, recall that it is 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. Secondly, 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, packing, etc.) without purchases for resale.

[32] In case of responsive industries with forward lags > 1, the algorithm requires reiterating previous periods when the forward lag is reached.

4. Specific Models

4.1. Traditional Leontief model

The basic GDIO collapses back to Cochrane's model with unrestricted trade when standard assumptions of the demand-driven model are in place. All industries are considered as JIT, which implies that they have perfect foresight over all periods pre- and post-disaster; there are no supply constraints, nor inventories; and the production function drops labor and capital. Under these assumptions, $\mathbf{x}^{\mathrm{S}}(t) = \mathbf{x}^{\mathrm{A}}(t)\ \forall t, i$ i.e., scheduled production always matches actual production since $\mathrm{E}\left[\bar{\mathbf{f}}\ \ (t+1) | \text{ info, mode}\right] = \bar{\mathbf{f}}\ \ (t+1)$ and $\mathbf{Z}^{\mathrm{A}}(t+1) = \mathbf{Z}^{\mathrm{R}}(t+1)\ \forall t$. Although the model is still "dynamic" due to time indexation, periods are independent as no constraints pass between them. Also, regional purchase coefficients are constant since physical damages and labor force restrictions do not affect productivity. To transform it back to the traditional Leontief model, these explicit supply constraints need to be translated into demand reductions via an inoperability coefficient $\boldsymbol{\gamma}_i(t)$ (Oosterhaven and Bouwmeester, 2016), so exogenous final demand becomes Eq. 19 and the traditional result follows.

$$\mathbf{f}_i^{\mathrm{IO}}(t) = \min\left(\bar{\mathbf{f}}_i(t), \left(1 - \boldsymbol{\gamma}_i(t)\right) * \mathbf{f}_i\right) \tag{19}$$

4.2. Dynamic Leontief model

The Dynamic Leontief model follows the same assumptions as before but adds a capital formation component when forming expectations on future final demand in Eq. 9 (Appendix 4). A fully specified system with capital formation (via matrix **B**) is:

$$\begin{aligned}\mathbf{x}^{\mathrm{R}}(t+1) = \left(\mathbf{I} - \widetilde{\mathbf{A}}(t) - \mathbf{B}(t)\right)^{-1}\big[&\mathbf{B}(t) \times \mathrm{E}[\boldsymbol{X}^{\mathrm{R}}(t+2) \mid \text{info, mode}] \\ &+ \mathrm{E}\left[\bar{\mathbf{f}}(t+1) \mid \text{info, mode}\right] - \mathbf{I}^{\mathrm{FF}}(t)\big]\end{aligned} \tag{20}$$

Due to the assumption adopted, it collapses to the usual expression:

$$\mathbf{x}^{\mathrm{R}}(t+1) = \left(\mathbf{I} - \widetilde{\mathbf{A}} - \mathbf{B}\right)^{-1}\left[\mathbf{B} \times \mathbf{x}^{\mathrm{R}}(t+2) + \bar{\mathbf{f}}(t+1)\right] \tag{21}$$

The model becomes dynamic through the capital formation link between periods. However, lack of inventories, simplified production function and perfect information, still do not allow input constraints to be passed between periods nor explicitly account for supply constraints.

4.3. Sequential Inderindustry Model

Following Romanoff and Levine (1977), the same assumptions are applied from the traditional input-output model, but industries are allowed to have different production modes. The expectation function becomes:

$$\mathrm{E}\left[\bar{\mathbf{f}}_{\mu}(t+1) \,|\, \text{info}, \text{mode}\right] = \begin{cases} \bar{\mathbf{f}}_{\mu}(t+k^{a}), & \text{if anticipatory on } k^{a} \text{ periods} \\ \bar{\mathbf{f}}_{\mu}(t+1), & \text{if just in time} \\ \bar{\mathbf{f}}_{\mu}(t-k^{r}), & \text{if responsive on } k^{r} \text{ periods} \end{cases} \quad (22)$$

This quasi-dynamic model reflects production timing, but perfect information does not allow constraints to arise. In fact, as expected, estimated cumulative impacts using the traditional IO model and the SIM are exactly the same, as the latter only "spreads" production through time. Now, it is possible to introduce inventories as in Okuyama *et al*. (2004), to retrieve more realistic results.

4.4. Demo-economic Model

Using the Demo-economic extension and applying the same assumptions as in the traditional IO model (subsection 4.1), the model collapses to the one shown in Eq. 19.

5. Application Example

We illustrate the Demo-economic GDIO with a 3-sector example for a small economy. The IO table for the region is presented in figure 4 and its parametrization in tables 1 and 2. The model runs for 36 periods and we assume an unexpected event in period 13 when 15% of manufacturing becomes inoperable. Recovery happens during the subsequent 5 periods (table 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).[33]

					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 4. Example IO Table, flow values in thousands of dollars

Table 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 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	-

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

Figures 5-7 compare the results of both scenarios. Overall, under full trade flexibility, production losses are lower and recovery faster than in the second scenario, since imports mitigate part of supply restrictions in the economy. The model illustrates the major role that inventories and uncertainty have on losses and, especially, 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 subsequently small impact on services. Agriculture maintains the same production since it is anticipatory, thus overproducing. In the next period, a substantial decline is observed in all sectors due to supply constraints from manufacturing (indirect effects) and lower final demand. Capacity restoration, expectation adjustments and enough inventories of intermediate goods allow a reduction in losses in period 15 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 the service sectors is exacerbated by the increase in unemployed residents who spend a significantly smaller share of their income in this sector than employed residents. The two scenarios diverge from this point forward. The flexibility in trade in the first scenario allows the service sector to overcome local supply restrictions and rebound in the next periods, following the other two sectors. 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, creating inventory and local supply variations together with final demand declines. In time, inventory and final demand heteroscedasticity decline, allowing the economy to rebound.

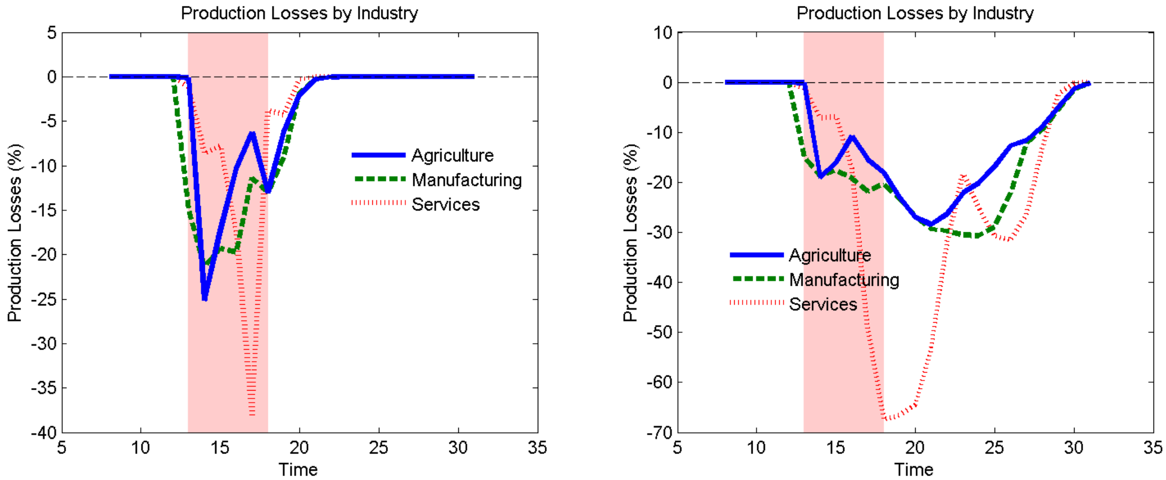

Figure 5. Production losses by industry (flexible: left; restricted: right)

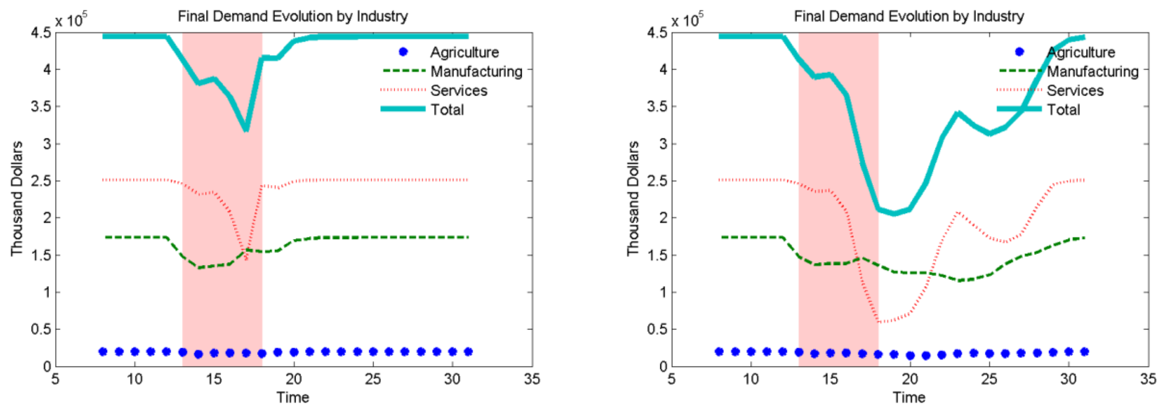

Figure 6. Final demand by industry (flexible: left; restricted: right)

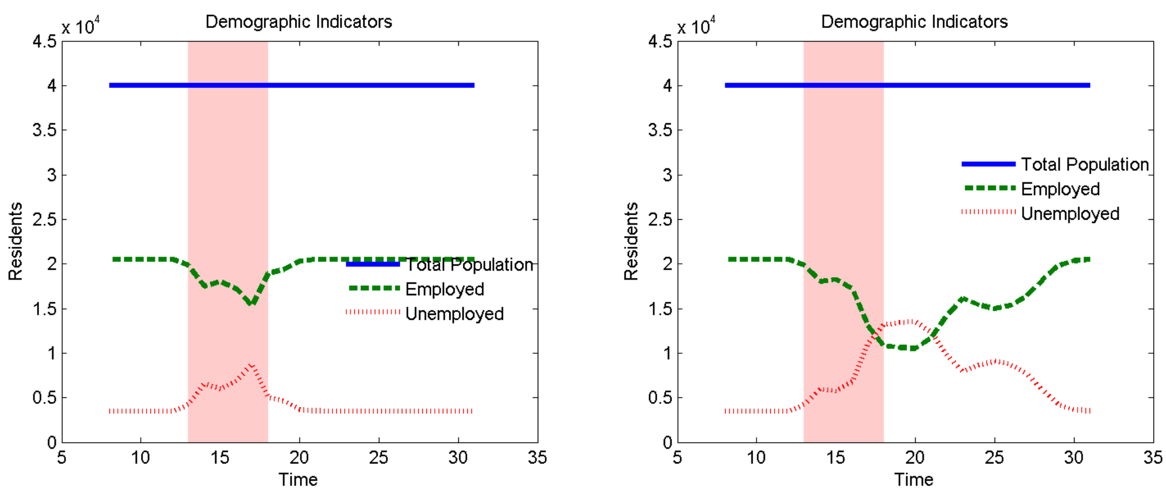

Figure 7. Demographic indicators (flexible: left; restricted: right)

By incorporating intertemporal expectation adjustments via the SIM and a demo-economic framework, this model reflects a non-smooth recovery process in contrast to other models currently available. For example, by assuming no inventories and JIT production for all industries, we simulate Cochrane's model (with the addition of a labor force component) for the same event (figure 8). Notice that the recovery curve is monotonic increasing and such smoothness is a similar feature in the Inventory-ARIO model (see Hallegate, 2014) and the Inventory-DIIM (see Baker and Santos, 2010). The demo-economic GDIO better reflects the transient imbalance dynamics post-disaster until a new steady-state is reached during which uncertainty continues to impact production decisions.

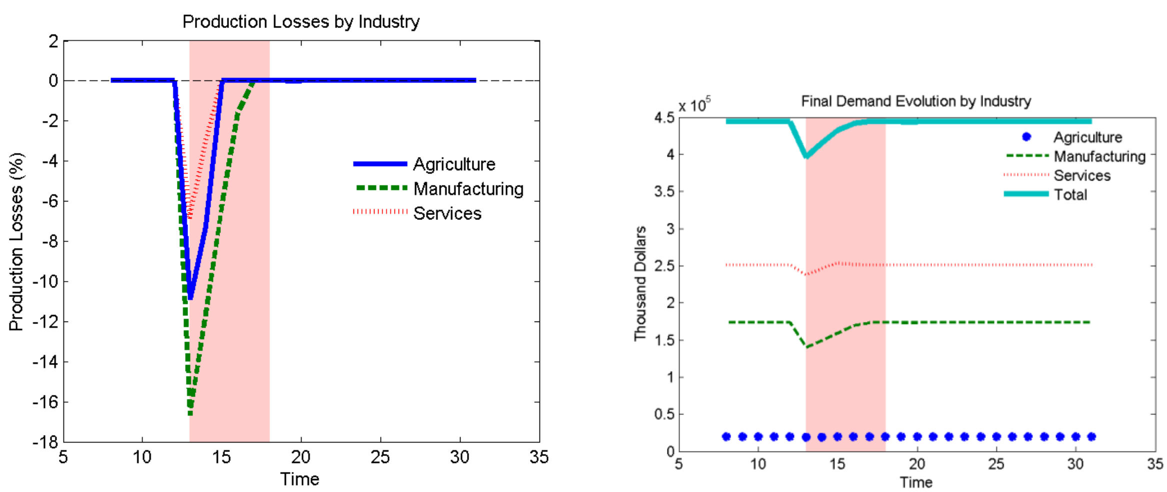

Figure 8. Production losses and final demand, Cochrane's model with labor force

6. Conclusions

Disaster events present unique challenges to economic assessment due to the time-compression characteristic of such phenomena that creates a structural break followed by simultaneous and intense recovery efforts in the affected areas. Due to modern "lean" production systems with high specialization 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. The characteristics of modern production chains tend to exacerbate these problems: component production within the chain is highly specialized with little spare capacity (to exploit scale economies). On the one hand, this improves efficiency but flexibility in sourcing is often very limited creating major problems when there is disruption.

Modeling these interdependent industrial linkages has been the main advantage of the IO framework, especially due to its relatively low data requirements, tractability and connectivity to external models. Nonetheless, given the simplicity of the traditional Leontief demand-driven model, several extensions have been proposed to address issues of supply constraints, dynamics and spatio-temporal limitations but a comprehensive solution is still lacking. On the other hand, CGE models, while offering greater flexibility, may not be able to fully embrace the rigidities in the production chain.

In a step towards a more complete methodology, the GDIO model is proposed in this paper. It derives from insights of the past literature and is shown to be theoretically consistent with the IO framework. It encompasses the virtues of intertemporal dynamic models with the explicit intratemporal modeling of production and market clearing, thus allowing supply and demand constraints to be simultaneously analyzed. The key roles of inventories, production timing, primary inputs and physical assets in disaster assessment are explored and previous limitations in the literature were addressed. Seasonality can be included by using *intra-year* IO tables that can be derived via the T-EURO method (Avelino, 2017). The base model is extended via a demo-economic model to include induced effects post-disaster, accounting for level and mix changes in labor force and household income/expenditure patterns. It is “general” in the sense that simpler models as the Leontief formulation, Dynamic IO, SIM and demo-economic models can be easily derived by using simplifying assumptions. The GDIO model also allows for the extraction of balanced IO tables at each time step; this option might be advantageous in optimizing recovery efforts.

A simple application showed the advantage of the Demo-economic 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.

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