Proceedings of the 2022 Winter Simulation Conference
B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C.G. Corlu, L.H. Lee, E.P. Chew, T. Roeder, and P. Lendermann, eds.

A SYSTEM DYNAMICS MODEL FOR STUDYING THE RESILIENCY OF SUPPLY CHAINS AND INFORMING MITIGATION POLICIES FOR RESPONDING TO DISRUPTIONS

William S. Bland
Andrew E. Hong
Lauren A. Rayson
Jennifer A. Richkus
Scott L. Rosen

The MITRE Corporation
7515 Colshire Drive
McLean, VA 22102-7539 USA

ABSTRACT

Economic shocks are unanticipated events that have widespread impact on an economy and can lead to supply chain disruptions that propagate from one region to another. The COVID-19 pandemic is a recent example. Simulations have been applied to study the impact of COVID-19 shocks on supply chains at the macro level using various approaches. This research has developed a hybrid System Dynamics and Input/Output simulation to model the economic impact of various types of supply chain disruptions. The hybrid model provides results that match historical performance of the U.S. economy under COVID-19 shocks and provides reasonable results when applied to investigate U.S. dependence on foreign trade. Its graphical nature also supports a decision support tool that will allow policymakers to explore the costs and benefits of various policy decisions designed to mitigate the impact of a broad set of potential supply chain disruptions.

1 INTRODUCTION

Economic shocks are unplanned and typically uncontrollable events that have a wide-ranging impact on gross output (Haberman et al. 2015). They can be caused by many different types of triggers, ranging from more predictable scenarios, such as changes in technology, workforce restrictions, and supply and demand shifts to more extreme and unpredictable scenarios involving extreme weather events stemming from environmental and climate shifts. The initiation of a shock may trigger a depletion in supply, demand, or labor within the supply chain in a specific region and industry. This in turn causes a disruption with respect to the flow of supplies between industries, causing production to slow. Slow production in one industry leads to slow production in another, which can easily spread through the supply chain network and propagate across regions. When efficiency and revenue have been optimized over resilience, industries' productions are quickly crippled, leading to depleting sales and eventual shutdown, which dramatically impacts a region's economic well-being (Tang 2006).

Although studies to investigate supply chain interactions after disasters at the sector level have been performed (Cochran 2004, Okuyama et al. 2004, and Hallegatte 2008), disruptions on the scale realized during the COVID-19 pandemic were unanticipated by policy makers and decision makers (Kovacs et al. 2021 and Ivanov 2021). The COVID-19 pandemic has revealed the fragility of supply chains, as its disruptions to labor levels caused supply shortages in certain industries and demand depletions in others

978-1-6654-7661-4/22/$31.00 ©2022 IEEE

(Nikolopoulos et al. 2021). Shortages in individual industries in particular regions cause a ripple effect across other industries and other regions (Li et al. 2021). These shortages can quickly propagate across the supply chain, making it difficult to control the impact of the degraded individual supply nodes. Moreover, local economies are affected by supply nodes from not only their region but also from outside regions that they do not control. As noted above, this is not a COVID-19 specific problem, but instead one that will resurface from other economic shocks in the future (Kovacs et al. 2021). The ongoing risks from shocks like this suggest that modeling approaches are needed to better understand supply chain resiliency at a regional level.

In the initial phases of this research, we incorporated a conventional Input/Output (IO) economic production model into a System Dynamics (SD) framework to create a hybrid SD/IO model to provide detailed insights into the economic impacts associated with supply chain disruptions. The long-term objective is to extend the initial SD model to provide a high-level decision support tool for policy makers to conduct "what-if" analyses to explore the costs and benefits of various policy decisions intended to mitigate the impacts of a broad set of potential supply chain disruptions. The remainder of this paper is structured as follows. Section 2 provides a brief background of efforts to develop simulation models to analyze the impacts of supply chain disruptions. Section 3 summarizes our hybrid SD/IO model development efforts. Section 4 discusses the results of using the hybrid model to study US dependence on imports from China. Section 5 summarizes our conclusions and describes future research plans.

2 BACKGROUND

This section provides a brief background on previous simulation research for analyzing supply chain disruptions with a recent focus on COVID-19 lockdowns. The industrial and academic communities have long recognized the need for holistic modeling of the extended supply chain enterprise and supply chain management. Unfortunately, a major challenge has been an inability to adequately represent the interdependencies among the various components across the supply chain and the associated nonlinearity using traditional modeling approaches (Georgiados 2005, Pettit 2010). Not surprisingly, there have been several recent simulation efforts to evaluate the macroeconomic impacts of supply disruptions like a COVID-19 lockdown.

2.1 Agent Based Models

Agent Based Models (ABM) represent system entities as agents who interact with each other and their environment according to rules from which higher level system behavior can be observed (Swinerd and McNaught 2012). Inoue and Todo developed an ABM to study the lockdown of Tokyo and the potential of the economic impacts to spread to other regions through supply chain propagations of supply and demand shortages (Inoue and Todo 2020). The ABM included over one million firms in Japan to model the outcome of production activities outside of Tokyo when non-essential production activities inside of Tokyo were shut down for varying periods of time. The authors found that a one-month lockdown of Tokyo would lead to an indirect effect on other regions and a 5.3% drop in the country's annual GDP, with an 86% reduction per month in daily production in Japan during that time. Their study demonstrated the severe impact that the degradation of critical supply nodes can have in production in other regions and warrants the use of modeling and simulation to better prepare for these disruptions.

2.2 Input/Output Models

IO models have been fundamental to regional economic analysis since the 1930's (Seung and Waters 2005), in part because they provide a detailed treatment of production and the flow of real goods and services through the economy (Berg et al. 2015). They have been applied to study multiregional impacts from supply chain shortages at the macro level (Albino et al. 2022), multiregional production impacts from localized disruptions stemming from port operations (Thekdi et al. 2016), and natural disasters such as earthquakes (Huang et al. 2022). The analysis of IO models has been performed at local levels as well as national levels, although their accuracy is much greater at the national level due to more input/output data being captured at the national level.

Pichler and his team developed a comprehensive IO model to address the primary impacts of the COVID-19 pandemic within the United Kingdom (UK) (Pichler et al. 2020). The authors included an examination of how social distancing measures and remote labor requirements related to the COVID-19 lockdown can impact both supply and demand through economic constraints and output restrictions. They determined the criticality of inputs for 55 separate industries by leveraging a survey by industry analysts. These criticality measures were incorporated with remote labor indexes to quantify the labor and production that could still be performed from home.

This model, subsequently referred to as the UK IO model, used data from the World Input-Output Database (WIOD). The WIOD provides gross output, intermediate consumption, and final demand data at the national level (Timme et al. 2015). This model also used consumption demand data from the Congressional Budget Office and inventory data from the Bureau of Economic Analysis. Details of the critical inputs, outputs, controllable factors, and uncontrollable factors associated with the UK IO model are described in Section 3.

2.3 System Dynamics Models

SD is a computer modeling methodology that represents complex nonlinear dynamic feedback systems for the purpose of generating insights and improving system performance. It was created in 1957 by Jay W. Forrester of the Massachusetts Institute of Technology as a method to help managers better understand and apply control theory and management science. (Groesser 2012). SD models typically contain a structure of stocks, flows, and feedback loops, with stocks filling and depleting over time based on flows influenced by feedback loops. Stocks represent accumulated inventories within the system and flows represent the movement of inventories between stocks.

There are three primary approaches to use SD models for economic modeling. These include creating an economic model in an SD format from scratch, translating an existing economic model into an SD format, and a hybrid approach where an existing economic model is translated into an SD format and improved by modifying it to better adhere to the principles of SD modeling (Radzicki 2009).

Creating an SD model from scratch entails identifying and linking the relevant pieces of a system's structure and simulating the behavior generated by that structure. This approach usually yields models that are very large and realistic, and they can produce valuable counter-intuitive results. Unfortunately, they may not be readily accepted by formal economists (Radzicki 2009). Translating an existing economic model into an SD format enables well-known economic models to be represented in a common format, making them easier to understand. This can be relatively straight-forward for economic models based on difference equations or ordinary differential equations but can be challenging for written or mathematical economic models (Radzicki 2009).

Creating a hybrid SD/IO model attempts to blend the advantages of the first two approaches (Radzicki 2009). Hybrid simulation involves the use of multiple simulation paradigms and is becoming an increasingly common approach to model modern, complex systems (Swinerd and McNaught 2012). Two recent efforts to create a hybrid SD/IO model addressed the ecological-economic system surrounding the Seine estuary (Cordier et al. 2017, Uehara et al. 2018). These efforts showed that integrating IO with SD allows the estimation of indirect and induced economic impacts of ecosystem modifications on other economic sectors involved in the supply chain. They also allowed description of a detailed economic structure that could identify whether specific economic sectors were advantaged or disadvantaged. In addition, they allowed the static property of IO to be reduced and the incorporation of feedback loops between an ecosystem and an economic system (Cordier et al. 2017).

3 HYBRID SD/IO MODEL DEVELOPMENT

This section describes our efforts to create a hybrid SD/IO model by incorporating the UK IO model described above into an SD framework. We first describe the underlying IO model structure, then introduce the equations within the IO model, and finally describe how we incorporated the underlying IO model structure and equations into an SD framework.

3.1 Underlying IO Model Dynamics

The underlying IO model involves producers experiencing supply-side shocks caused by a nationwide COVID-19 lockdown, where non-essential workers who are unable to work from home become unproductive, resulting in lower productive capacity. At the same time, demand-side shocks hit as consumers adjust their consumption preferences due to the lockdown. This underlying IO model partitioned the overall economy into 55 separate industries to allow for more accurate modeling of the performance characteristics associated with each individual industry.

A high-level conceptual model depicting the primary relationships between key variables in the underlying IO model is presented in Figure 1. The economic system begins in an equilibrium state, where inventory, labor, supply, and demand have all reached a balance (left panel of Figure 1). At some point in time, supply and/or labor shocks are introduced to represent a supply chain disruption (center panel of Figure 1). At some later point in time, the supply and/or labor shocks are removed, and the economic system eventually returns to a new equilibrium state (right panel of Figure 1).

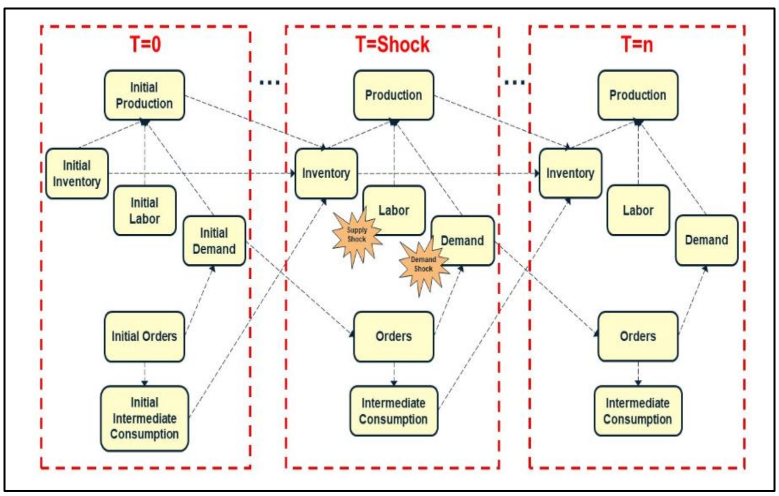

Figure 1. A high-level conceptual model of the dynamics within the underlying IO model.

3.2 Underlying IO Model Structure

The most significant variables and user-defined parameters employed in the underlying IO model are described in Table 1 and Table 2, respectively.

Table 1. Table of major IO model variables.

Notation	Description	Calculation
$Z_{ij,t}$	Intermediate consumption by Industry *i* of Industry *j* goods, in dollars	Equation (1)
$S_{ij,t}$	Inventory levels of Industry *i* goods held by Industry *j*, in dollars	Equation (2)
$O_{ij,t}$	Final demand from Industry *j* for Industry *i* goods, in dollars	Equation (3)
$d_{i,t}$	Aggregate demand for Industry *i* goods, in dollars	Equation (4)
$c_{i,t}^{d}$	Household demand for Industry *i* goods, in dollars	Equation (5)

$x_{i,t}$	Total production (gross output) of Industry *i* goods, in dollars	Equation (6)
$l_{i,t}$	Labor compensation for production of Industry *i* goods, in dollars	Equation (9)
A_{ij}	Cost of Industry *i* goods used to produce a dollar of Industry *j* goods (Recipe Matrix)	Historical Data
$f_{i,t}^d$	Non-household demand for Industry *i* goods, in dollars	Historical Data
n_j	Number of days of targeted inventory for Industry *j* goods	Historical Data

Table 2. Table of major IO model parameters

Notation	**Description**	**Nominal Value**
τ	Speed of inventory adjustment	10
γ_H	Upward labor hiring adjustment	1/30
γ_F	Downward labor hiring adjustment	1/15
ρ	Consumption adjustment	0.987
m	Share of labor income used to consume goods	0.82
Δs	Change in savings rate	0.5

The equations and associated explanations that follow define how the major model components of intermediate consumption, inventories, orders, demand, production, and labor compensation are calculated at each time step.

$$Z_{ij,t} = O_{ij,t} \frac{x_{i,t}}{d_{i,t}} \tag{1}$$

$$S_{ij,t+1} = S_{ij,t} + Z_{ij,t} - (A_{ij} x_{j,t}) \tag{2}$$

$$O_{ij,t} = (A_{ij} d_{j,t-1}) + \frac{1}{\tau}(n_j Z_{ij,0} - S_{ij,t}) \tag{3}$$

$$d_{i,t} = \sum_{j=1}^{N} O_{ij,t} + c_{i,t}^d + f_{i,t}^d \tag{4}$$

$$log\, \tilde{c}_t^d = \rho \log \tilde{c}_{t-1}^d + \frac{1-\rho}{2} log\big(m\tilde{l}_t\big) + \frac{1-\rho}{2} log\big(m\tilde{l}_t^p\big) + \tilde{\epsilon}_t \tag{5}$$

$$x_{i,t} = min\{x_{i,t}^{cap}, x_{i,t}^{inp}, d_{i,t}\} \tag{6}$$

$$x_{i,t}^{cap} = \frac{l_{i,t}}{l_{i,0}} x_{i,0}^{cap} \tag{7}$$

$$x_{i,t}^{inp} = \frac{\sum_j S_{ji,t}}{\sum_j A_{ji}} \tag{8}$$

$$l_{i,t} = \begin{cases} l_{i,t-1} + (\gamma_H\, \Delta l_{i,t}), & if\ \Delta l_{i,t} \geq 0 \\ l_{i,t-1} + (\gamma_F\, \Delta l_{i,t}), & if\ \Delta l_{i,t} < 0 \end{cases} \tag{9}$$

The term $Z_{ij,t}$ defined in (1) represents the value of intermediate consumption by Industry *i* of Industry *j* goods at time *t*. This is calculated as the fraction of orders placed by Industry *j* for Industry *i* goods that were fulfilled at time *t* ($O_{ij,t}$). The term $x_{i,t}/d_{i,t}$ represents the proportion of the aggregate demand for Industry *i* goods at time *t* ($d_{i,t}$) that Industry *i* was able to produce at time *t* ($x_{i,t}$).

The term $S_{ij,t+1}$ defined in (2) represents the inventory value update at each time step. This is calculated by taking the value of the existing inventory of Industry *j* goods at Industry *i* at time *t*, adding the value of

Industry j goods obtained by Industry i at time t ($Z_{ij,t}$), and subtracting the value of Industry j goods used to produce the gross output at time t ($A_{ij}x_{j,t}$). The term A_{ij} is called the Recipe Matrix and defines the cost of Industry i goods used to produce a dollar of Industry j goods.

The term $O_{ij,t}$ defined in (3) represents the number of orders placed by Industry j for Industry i goods at time t. This is calculated using two components: i) the previous time step demand for Industry j scaled by the recipe matrix ($A_{ij}d_{j,t-1}$), and ii) the inventory growth needed to maintain target inventory levels, which is controlled by the inventory replenishment rate τ and the target inventory n_j.

The term $d_{i,t}$ defined in (4) represents the demand for Industry i goods at time t. This is calculated as the total number of orders from all other industries for Industry i goods at time t ($\sum_{j=1}^{N} O_{ij,t}$) plus the household demand for Industry i goods at time t ($c_{i,t}^{d}$) and the non-household demand for Industry i goods at time t ($f_{i,t}^{d}$). As defined in (5), household demand is calculated as a function of the change of permanent income expectations, labor income, share of labor income used to consume goods, and adjustments to new consumption levels. Non-household demand consists of government or foreign entity demand, which are not affected by the dynamics of the model and are based on historical data.

The term $x_{i,t}$ defined in (6) represents the total production of Industry i goods at time t and is calculated as the minimum of production capacities due to labor ($x_{i,t}^{cap}$), production capacities due to inventory $\left(x_{i,t}^{inp}\right)$, and total demand ($d_{i,t}$). The labor production capacity defined in (7) is directly impacted by available labor. The inventory production capacity defined in (8) is directly impacted by available inventory and represents a linear production function. This equation can be adjusted to represent other production functions.

The term $l_{i,t}$ defined in (9) represents labor compensation to workers in Industry i at time t and is calculated as a function of prior labor spending, the desired change of labor supply, and a factor that limits the speed of hiring or firing actions. If the desired change of labor supply is positive, an upward (hiring) labor factor (γ_H) is applied, otherwise, a downward (firing) labor factor (γ_F) is applied.

3.3 Implementation of the Underlying IO Model Within an SD Framework

Our hybrid SD/IO model was developed using Stella Architect v2.1.5. To facilitate model development and implementation of future enhancements, we organized the model into four separate modules as shown in Figure 2.

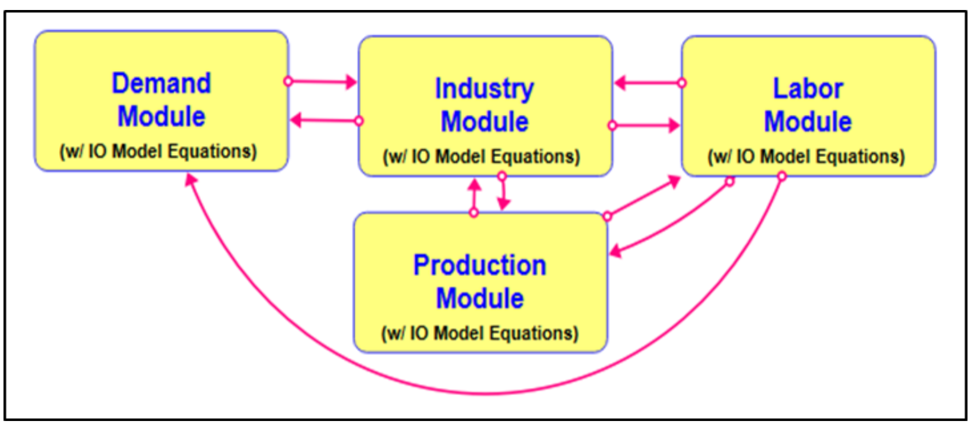

Figure 2. Modular hybrid SD/IO model structure.

The major variables driving the economy (intermediate consumption, inventories, orders, demand, and production) are calculated in the Industry Module, depicted in Figure 3. The other three modules perform detailed calculations of the complex demand, labor, and production interactions and their outputs are used to inform the Industry Module calculations. Since the Industry Module contains the critical elements of the model, that is the only figure provided due to space limitations.

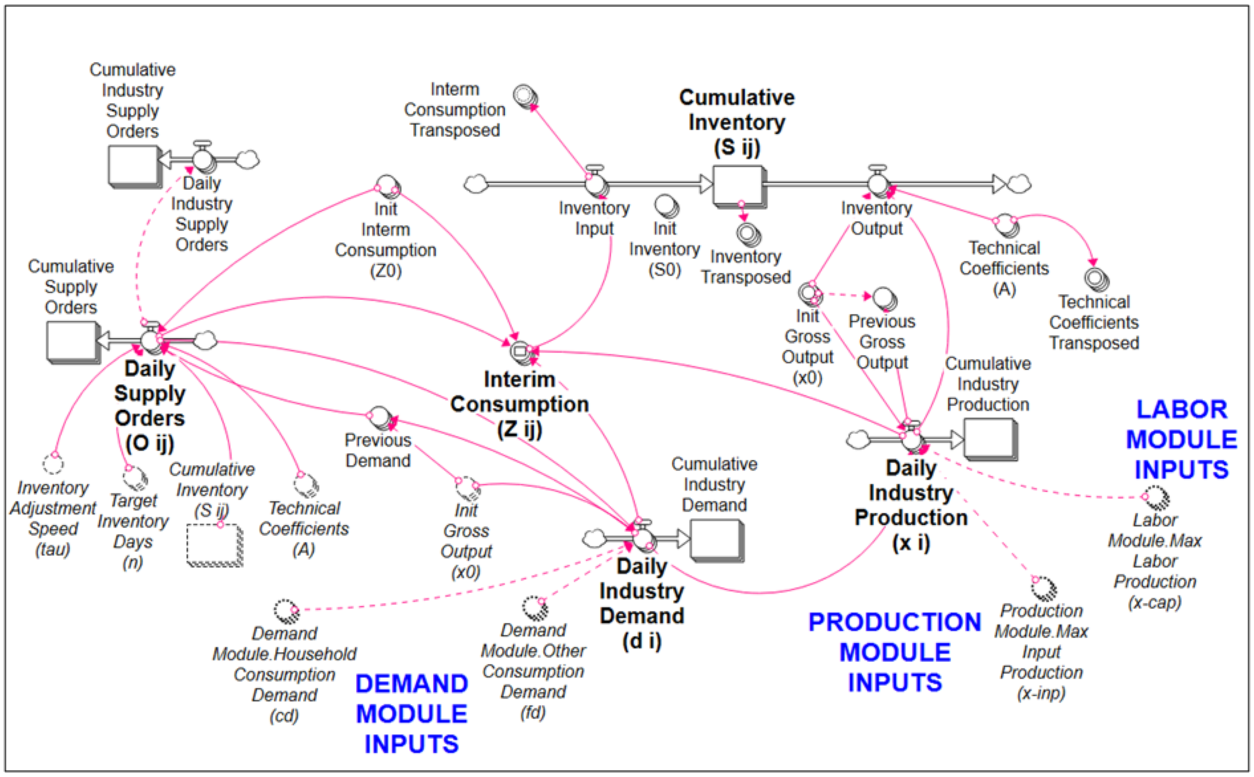

Figure 3**.** Industry module structure includes major variables driving the economy and demonstrates linkages with demand-, production-, and labor-related variables located in other modules.

We began by establishing the model settings for the simulation, choosing a daily time step to match the UK IO model. We next created stocks for Inventory, Supply Orders, Demand, and Production, the main components shown in Figure 1. SD models can capture the complex behavior of a system such as nonlinear dynamics and feedback but are less well suited for detailed disaggregation at economic sector levels (Cordier et al. 2017), so we introduced arrays for demand (the *i* term in the IO model equations in Section 3.2) and supply (the *j* term in the IO model equations in Section 3.2). Arrays are represented in Figure 3 by stacked icons. These arrays effectively created 55 replicas of the model structure, one for each of the 55 individual industries, allowing us to track industry-level performance while also aggregating total overall economic performance.

We next created converters for the model parameters, constants, and other non-stock related elements referenced in the underlying IO model equations. We also created converters for control features, like "shock_start_time" and "shock_end_time". These control features allow the user to make quick adjustments to tailor the specific simulation runs without having to modify hard-coded information and will be extremely useful for implementation within the envisioned decision support tool.

Next, we incorporated the underlying IO model equations to define the specific industry-level inflows, outflows, and feedback information associated with each of the stocks at each time step. We then organized all model input data into Excel import files that the model would reference to establish starting conditions. This data included the Recipe Matrix (A_{ij}), initial values for inventory, intermediate consumption, production, demand, and labor compensation; and all industry-specific parameters. Finally, we created the necessary elements for calculating model performance summaries and generating the desired visualizations.

3.4 Model Verification and Validation Activities

After the model was developed, we performed some initial tasks towards verification and validation (V&V) of the hybrid model. Verification means "ensuring that the computer program of the computerized model and its implementation are correct" (Sargent 1998) and validation means "substantiation that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model" (Schlesinger et al. 1979). There is clearly more to do in terms of official V&V of the model, but these initial tasks provide evidence that we are "building the right model" and "building the model right."

First, we had multiple team members do a one-to-one comparison of the equations and model parameters used in our model against those used in the UK IO model. Once the equations and model parameters were confirmed, we next compared the results of the hybrid model to the impacts of a COVID-19 lockdown on the UK economy produced by the UK IO model.

We loaded the hybrid SD/IO model with the same initial data as the UK IO model and then ran the model with the same parameters as the UK IO model. The hybrid model identified significant drops in demand, production/gross output, and labor compensation when the lockdown began, with steady recovery once the lockdown was lifted, all consistent with the UK IO model results. The SD/IO hybrid model also identified that each industry operated differently, with some significantly impacted by a lockdown (e.g., Accommodation-Food Industry) and others barely impacted (e.g., Retail Industry), also consistent with the UK IO model results. Since the hybrid model provided consistent results when addressing the UK economy, we next compared the results of the hybrid model to historical impacts of a COVID-19 lockdown on the US economy.

We loaded the SD/IO model with US data from the WIOD and configured the model to implement a lockdown for 90 days and observed changes in GDP during that 90-day period. The simulation results were then compared against historical GDP numbers for a 90-day period during which the US was under a COVID-19 lockdown (U.S. Bureau of Economic Analysis 2022). As depicted in Table 3, the historical data showed a GDP loss of 19% while our model predicted a GDP loss of 14%. This difference is most likely attributable to the fact that each of the states implemented COVID-19 lockdowns in their own unique way, with different durations and severity, while our model represents a consistent implementation across the entire nation for the full 90 days.

Table 3. Comparison of historical versus simulated GDP loss during lockdown.

US Q1 GDP	US Q2 GDP	% GDP Change	% Model Change
21,481,367	19,477,444	-19%	-14%

Next, we observed the impacts on total production/gross output from different COVID-19 lockdown scenarios in the US. In the left side of Figure 4, the green solid line shows the system in equilibrium, with no disruptions. The blue dashed line shows the impact of instituting a lockdown at T=100 and keeping it in place indefinitely. This scenario results in a nearly 20% drop in total production when the lockdown begins, after which the system settles into a new equilibrium near 85% of the original equilibrium level. The red dotted line shows the impact of instituting a lockdown at T=100 but then lifting it at T=150. This scenario results in the same 20% drop in total production when the lockdown begins but lifting the lockdown results in a steady recovery to near 95% of the original equilibrium level. These results are consistent with trends found within the UK economy with the UK IO model.

We also observed the impacts on total labor compensation from these same three lockdown scenarios. As depicted by the dashed blue line in the right-hand side of Figure 4, a gradual dip occurs when the lockdown starts, because of decreased demand and labor needs. The dotted red line shows a sharp recovery once the lockdown ends, with industries hiring additional staff to address the increasing demand. These results are also consistent with trends found within the UK economy with the UK IO model.

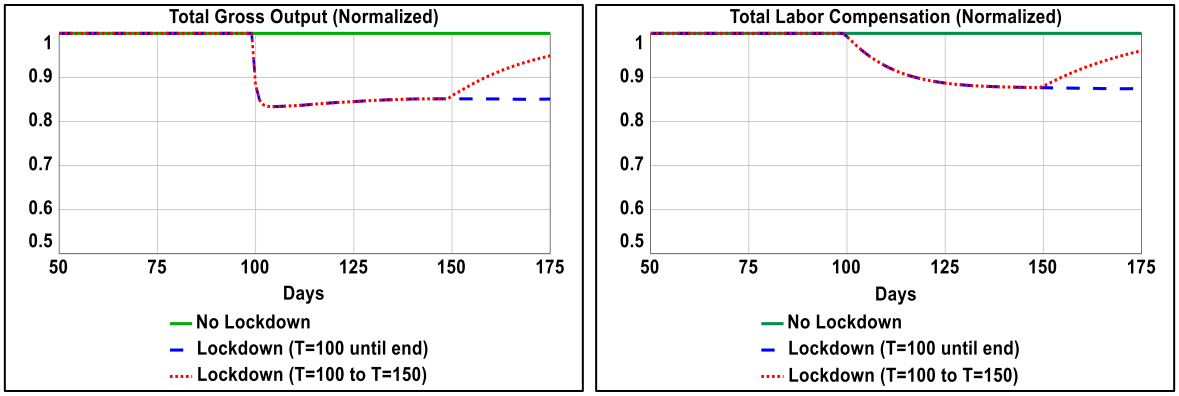

Figure 4. Total production (normalized) and total labor compensation (normalized) results associated with various lockdown scenarios.

Finally, we observed production results for each of the 55 individual industries when both supply-side and demand-side shocks are applied and then removed. As depicted in Figure 5, we see varying dips in production for each industry when the lockdown starts and varying degrees of recovery for each industry when the lockdown ends, the same phenomenon produced by the UK IO model. This is because each industry has a unique sensitivity to the applied shocks, has a different starting inventory, and requires different fixed dollar inputs to produce one dollar of output. As before, the Accommodation-Food Industry was among the most adversely impacted and the Retail Industry was among the least impacted. The Manufacturing-Transport Industry is the green line that never seems to recover. Understanding this will require additional investigation.

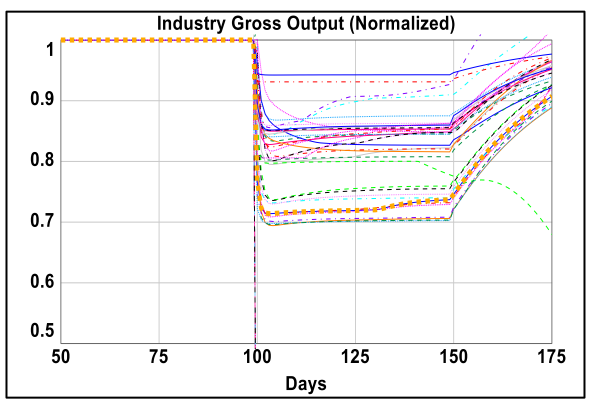

Figure 5**.** Industry production (normalized) results show varying performance across the 55 industries.

These results provide convincing evidence that our hybrid SD/IO model accurately implements the underlying IO equations from the UK IO model. Not only could our model replicate the overall trends that the UK IO model found in the UK economy related to a COVID-19 lockdown, but it could accurately represent historical US GDP losses resulting from the COVID-19 lockdown. In addition, the trends that our model identified for the US economy were consistent with trends identified for the UK economy.

4 APPLYING THE MODEL TO STUDY FOREIGN DEPENDENCE

As a test of the hybrid SD/IO model's applicability beyond representing lockdown supply chain disruptions, we used the model to examine the dependence of the US economy on imports, specifically from China. The first step in doing this was to identify the portion of US imports that came from China. The WIOD was used to identify the total dollar volume of imports to the United States and isolate the proportion which originated from China. Imports from China constitute a different percentage of total US imports for each industry, with the average across all 55 industries being approximately 10%. Next, lockdown effects were turned off, the model was configured to represent a loss of China imports across several different scenarios, and the total production/gross output and total labor compensation were plotted.

In the total production/gross output plot shown in the left side of Figure 6, the solid green solid line shows the system in equilibrium, with no disruptions in China imports. The blue dashed line shows the impact of losing China imports at T=100 through the end of the simulation. This scenario results in a nearly 20% drop in total production when the loss of China imports begins, followed by a steady recovery to over 95% of the original equilibrium level. The red dotted line shows the impact of losing China imports at T=100 but then restoring them at T=150. This scenario results in the same nearly 20% drop in total production when the loss of China imports begins, followed by a sharp recovery to the original equilibrium level once the China imports are restored.

In the total labor compensation plot shown in the right side of Figure 6, the dashed blue line shows that losing China imports results in an initial 5% drop in total labor compensation, followed by a steady recovery to over 95% of the original equilibrium level. The dotted red line shows a sharp recovery to the original equilibrium level once China imports are restored.

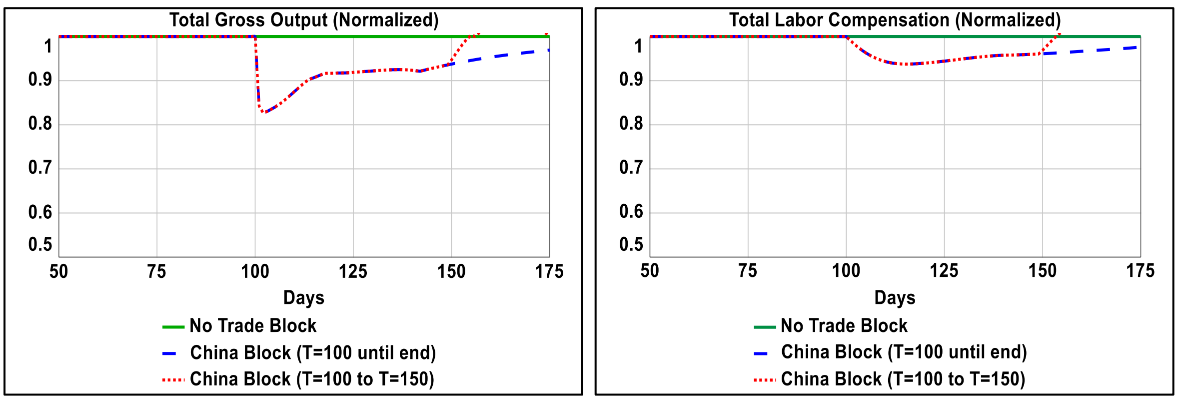

Figure 6**.** Total production (normalized) and total labor compensation (normalized) results associated with various lockdown scenarios.

These results are justifiable, given that China imports represent only 10% of total US imports and the ability of the US to replace these imports from other regions over time. However, the model shows that each industry is affected differently, with some having a relatively minor impact (e.g., Retail Industry) and others having a more significant impact (e.g., Fishing Industry). These differences are because each industry makes up a different percentage of US imports from China, has a different starting inventory, and requires different fixed dollar inputs to produce one dollar of output.

5 CONCLUSIONS AND FUTURE WORK

This research demonstrated that we could successfully incorporate a comprehensive economic IO model within an SD framework and use the resulting hybrid model to provide insights into the economic impacts associated with various supply chain disruptions. We demonstrated that the economic system performance predicted by our hybrid SD/IO model is consistent with that predicted by the UK IO model. We also demonstrated that our model provides results that are relatively consistent with historical impacts on the US GDP resulting from a COVID-19 lockdown. Finally, we were able to use our model to examine the dependence of the US economy on China imports and found the results were reasonable.

One area for future research will involve further partitioning the total inventory flow to allow for regional applications. As mentioned in Section 2.2, the underlying IO model already partitions the total inventory flow into 55 separate industry sub-flows. This is fine for performing national-level analyses, but we intend to further partition each industry sub-flow to allow our model to represent the impact of supply chain disruptions at the regional (state) level. We are currently searching for appropriate state-level data but have also developed an approach to "regionalize" national level data (Hong et al. 2022 and Rosen et al. 2022) and are working to update the model to address both national and regional economies.

These additional partitions will also facilitate applying transportation or processing delays at specific ports, another area for future research. The underlying IO model does not address source-to-port, port-to-port, or port-to-destination transportation delays, or port processing delays. These delays could induce a shock dramatically impacting regional and national economies and could be studied after applying these additional partitions to our model. We are currently searching for appropriate port-level processing and transportation delay data so we can update our model to address the impacts of these delays on national and regional economies.

Another area for future research involves expanding our model into a high-level decision support tool that policy makers can use to conduct "what-if" analyses to explore the costs and benefits of various policy decisions intended to mitigate the impacts of a broader set of potential supply chain disruptions. Such a decision support tool would allow users to set values and model settings associated with proposed policies, run the model, and then observe how the national and/or regional economies performed for each policy.

ACKNOWLEDGMENTS

The authors would like to acknowledge Bridgette Clark of the MITRE Corporation for helping bridge this research towards government policy decisions and David Rodgers of the Mobile Area Chamber of Commerce in Mobile, Alabama, for helpful feedback on the model decision recommendations and on design factors for the simulation framework. This effort was funded by MITRE's independent research and development program.

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AUTHOR BIOGRAPHIES

WILLIAM S. BLAND is an operations research analyst for the Operations Research Department of The MITRE Corporation with over 25 years of application experience. His research interests include modeling and simulation, decision support systems, and data visualization. He holds a PhD in Systems Engineering from the University of Virginia, an MS in Systems Management from Florida Institute of Technology, and a BS in Electrical Engineering/Computer Science from the United States Military Academy. His email address is wbland@mitre.org.

ANDREW E. HONG is a statistician for the Operations Research Department of The MITRE Corporation. His research interests include statistics, machine learning, and optimization. He holds a PhD. in Statistics from the University of Pennsylvania and a BS in Statistics from Carnegie Mellon University. His email address is ahong@mitre.org.

LAUREN A. RAYSON is an economist in The MITRE Corporation’s Transportation Innovation Center. Her research interests include policy analysis, data analysis, and data visualization, with an emphasis on state and local issues. She holds an MS in Data Analytics & Policy from Johns Hopkins University and a BA in Economics and Political Science from the University of Vermont. Her email is lrayson@mitre.org.

JENNIFER A. RICHKUS is an environmental scientist and strategist at MITRE. Her research interests include circular economies and climate-resilient critical infrastructure. She holds an MS in Environmental Science and Policy from Johns Hopkins University and a BS in Biology from the University of Texas at Austin. Her email address is jasrichkus@mitre.org.

SCOTT L. ROSEN is the Chief Engineer for the Operations Research Department of The MITRE Corporation with more than 15 years of application experience. His research interests include simulation-based analysis, multi-criteria decision making, and supply chain modeling. He holds a PhD and MS in Industrial Engineering and Operations Research from Pennsylvania State University and a BS in Industrial and Systems Engineering from Lehigh University. His email address is srosen@mitre.org.