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A HYBRID SYSTEM DYNAMICS/INPUT-OUTPUT MODEL FOR STUDYING THE IMPACT OF TRANSPORTATION DELAYS ON THE RESILIENCY OF NATIONAL SUPPLY CHAINS

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ABSTRACT

In today's globally interconnected economy, transportation delays that impact a specific industry's supply chain can quickly propagate to other industries, dramatically impacting inventory levels and economic production on the local, state, national, and global levels. This research proposes a hybrid System Dynamics and Input-Output simulation model that represents the impact of transportation delays on the flow of goods across industries and between geographic regions. The model is applied to a case study involving the port of Los Angeles to quantify the direct and indirect effects of a 30- and 60-day delay in container movement on gross output across the 55 major industries in the United States. The capability to predict the scope and scale of the economic impact resulting from various transportation delays provides decision makers the opportunity to conduct preliminary what-if analyses which can support the development of potential mitigation strategies before the actual shock occurs.

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.

This is more than a COVID-19 specific problem, however, and is one that will resurface from other types of economic shocks in the future (Kovacs 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. The risks from these shocks suggest that modeling approaches are needed to better understand supply chain resiliency at different regional levels.

Previous work involved the development of a hybrid System Dynamics and Input-Output (SD/IO) simulation model to represent the economic impact of various types of supply chain disruptions, described in Bland et al. (2022). A comprehensive IO model was incorporated into an SD framework that allowed the

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estimation of direct and indirect economic impacts of supply chain disruptions. The underlying IO model involved producers experiencing supply-side, labor induced shocks caused by a nationwide COVID-19 lockdown, where non-essential workers who were unable to work from home became unproductive, resulting in lower productive capacity. Concurrently in this model, demand-side shocks hit as consumers adjusted their consumption preferences due to the lockdown.

One shortcoming of the previous hybrid SD/IO modeling approach is that it did not include any variables to account for delays when moving supplies between industries; other previous IO modeling approaches did not incorporate these transportation delays either. However, the real world typically experiences ordering delays, transportation delays, and/or production delays, all of which would impact the economic system performance and can result in their own type of economic shock. Since these delays can lead to shocks on the local, state, national, and global levels and propagate from regions and industries that are initially impacted, it is necessary to introduce a mechanism to represent transportation delays.

Section 2 provides a brief overview of our original model and explains the reason for updating the model to represent transportation delays. Section 3 summarizes our model development efforts. Section 4 discusses the results of our transportation delay case study involving the ports of Los Angeles and Long Beach. Section 5 summarizes our conclusions and describes future research plans.

2 BACKGROUND

This section provides a brief background on why we chose a hybrid SD/IO modeling approach, an overview of the modeling methodology from the original hybrid SD/IO model, and a conceptual overview describing out approach to introduce transportation delays into the hybrid SD/IO model.

2.1 Rationale for SD/IO Approach

There is widespread agreement that SD is a useful approach for modeling supply chains. Supply chains are complex and dynamic systems and SD is a proven approach for simulating them and supporting long-term, strategic decision-making (Rebs et al. 2018). SD is well suited for examining strategic transportation issues and could provide a useful tool for supporting policy analysis and decision-making (Shepherd 2014). SD models can be used to identify effective policies and optimal parameters for various strategic decision-making problems (Georgiadis et al. 2005).

The foundational IO model was primarily focused on modeling the impact of social distancing measures and remote labor requirements related to the COVID-19 lockdown and their impacts on both supply and demand through economic constraints and output restrictions (Pichler et al. 2020). Other relative IO models that incorporated different variants of Cobb Douglas and Constant Elasticity of Substitution production functions include Barrot et al. (2020), which examines the impact of non-essential industries, and Fadinger and Schymik (2020), Bonadio et al. (2021), and Baqaee and Farhi (2020), which consider the impact lockdown and work from home effects procedures on gross output. Hong et al. (2022) also provides an IO approach that was integrated with a Genetic Algorithm search procedure to determine additional inventory allocations across industries that minimize the shock of gross output reduction.

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). Creating a hybrid SD/IO model attempts to blend the advantages of creating an economic model in SD from scratch and translating an existing economic model into an SD format (Radzicki 2009).

2.2 Original Model Dynamics

The original hybrid SD/IO model used a daily time step for the simulation and utilizes stocks for Inventory, Supply Orders, Demand, and Production. Arrays were introduced for demand and supply (the i and j term in the model equations below). 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. Converters were then created for the model parameters, constants, and other non-stock related elements in the model as well as for control features, like “start_time” and “stop_time”. These control features allow the user to make quick adjustments to tailor the specific simulation runs without having to modify hard-coded information. Next, the underlying IO equations from Pichler et al. 2020 were incorporated into the variable equations to define the specific industry-level inflows, outflows, and feedback information associated with each of the stocks at each time step.

The most significant variables employed in the model are described in Table 1. These variables pertain to the areas of labor/production capacity, intermediate consumption, demand, and inventory.

Table 1. Table of major model variables.

Notation	Description
$x_{i,t}$	Total production (gross output) of products from Industry i
$d_{i,t}$	Aggregate demand for products from Industry i
$l_{i,t}$	Labor utilized for production of Industry i
$Z_{ij,t}$	Intermediate consumption by Industry i of Industry j
A_{ij}	Fixed dollar inputs of Industry i used to produce 1 dollar of Industry j
$S_{ij,t}$	Inventory levels of Industry i products held by Industry j
$O_{ij,t}$	Final demand from Industry j for products from Industry i
n_j	Number of days of targeted inventory for Industry j
$c_{i,t}^{d}$	Household demand for products from Industry i
$f_{i,t}^{d}$	Non-household demand for products from Industry i

In addition to these variables, there are several input parameters that can be adjusted by the user, to include: τ (speed of inventory adjustment), γ_H (upward labor hiring adjustment), γ_F (downward labor firing adjustment, ρ (consumption adjustment), m (share of labor income used to consume goods), and Δs (change in savings rate). Some nominal values of these variables for perspective are τ = 10, γ_H= 1/30, γ_F= 1/15, ρ = 0.987, m= 0.82, and Δs= 0.5. Inventories are updated at each time step according to (1). Orders, intermediate consumption, demand, and production (gross output) are calculated at each time step according to (2), (3), (4), and (5), respectively.

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

$$O_{ij,t} = (A_{ij}d_{j,t-1}) + \frac{1}{\tau}(n_j Z_{ij,0} - S_{ij,t}) \tag{2}$$

$$Z_{ij,t} = O_{ij,t}\frac{x_{i,t}}{d_{i,t}} \tag{3}$$

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

$$x_{i,t} = min\{x_{i,t}^{cap}, x_{i,t}^{inp}, d_{i,t}\} \tag{5}$$

Household demand is 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 and is calculated at each time step according to (6). Non-household demand consists of government or foreign entity demand, which are not affected by the dynamics of the model. Household and non-household demands are referenced by (4) to determine the overall demand at each time step.

$$\log \tilde{c}_t^d = \rho \log \tilde{c}_{t-1}^d + \frac{1-\rho}{2} \log\left(m\tilde{l}_t\right) + \frac{1-\rho}{2} \log\left(m\tilde{l}_t^p\right) + \tilde{\epsilon}_t \tag{6}$$

Labor spending is a function of prior labor spending, the desired change of labor supply, and a factor that limits the speed of hiring or firing actions and is calculated for each time step according to (7). If the desired change of labor supply is negative, the downward labor (firing) factor is applied, otherwise the upward labor (hiring) factor is applied. Labor spending is referenced by (8) to determine the labor production capacity at each time step in the production module.

$$l_{i,t} = \begin{cases} l_{i,t-1} + (\gamma_H \, \Delta l_{i,t}), & if \; \Delta l_{i,t} \geq 0 \\ l_{i,t-1} + (\gamma_F \, \Delta l_{i,t}), & if \; \Delta l_{i,t} < 0 \end{cases} \tag{7}$$

Labor production capacity is directly impacted by available labor and is calculated at each time step according to (8). The input production capacity is directly impacted by available inventory and the selected production function. Assuming a linear production function, the input production capacity is calculated for each time step according to (9). Both production constraints are referenced by (5) to determine the production or gross output produced at each time step.

$$x_{i,t}^{cap} = \frac{l_{i,t}}{l_{i,0}} x_{i,0}^{cap} \tag{8}$$

$$x_{i,t}^{inp} = \frac{\sum_j s_{ji,t}}{\sum_j A_{ji}} \tag{9}$$

For a more detailed description of the original hybrid SD/IO model, see Bland, et al. (2022).

2.3 Modeling Transportation Delays

Delays affecting a specific industry can dramatically propagate to other industries, harming economies on the local, state, and national levels. As shown in Figure 1, there could be ordering delays, transportation delays, and/or production delays, all of which would impact the economic system performance.

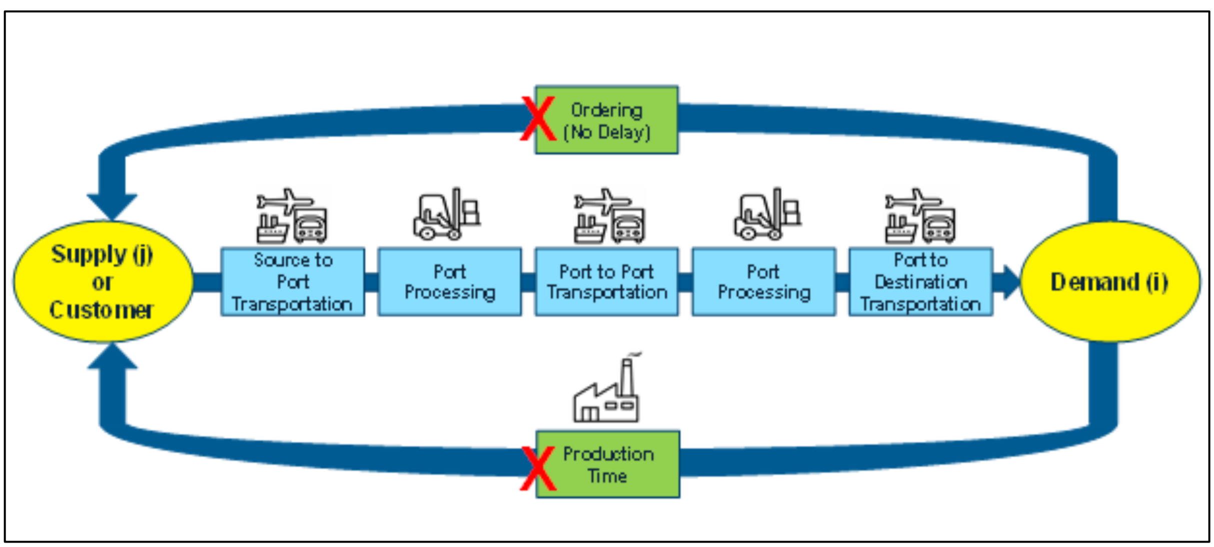

Figure 1. Potential sources of delay.

Recent examples of how transportation delays have impacted the global economy in recent years:

- One of the world's largest container ships ran aground in the Suez Canal in April 2021, halting traffic for nearly a week (Leggett 2021).
- Heavy floods in Europe and China during July 2021 devasted rail lines, disrupting the flow of raw materials and finished products (Tan 2021).
- A three-week long trucker protest in Canada during February 2022 snarled traffic, disrupted retail businesses, and blocked border crossings with the US (Gordon 2022).

Each of the blue boxes in Figure 1 represents a potentially complex supply chain issue contributing to overall transportation delays. Since the purpose of this paper was to investigate the overall impacts of transportation delays on the supply chain and not identify specific solutions for each of the potential transportation delays, all the blue boxes were aggregated into a single "Transportation Delay" issue. Tackling these individual supply chain issues will be part of our future work.

3 METHODOLOGY

This section describes the extensions to the original hybrid SD/IO model that were implemented to represent the impact of transportation delays. This involved creating Industry-Port sub-flows, modifying some of the original I/O equations, and modifying the flow of inventory inputs for each Industry.

3.1 Implementing Port Sub-Flows Within the Model

In the original model, the overall economy was partitioned into 55 separate Industry sub-flows to allow for accurate modeling of the performance characteristics associated with each individual Industry. Investigating the impact of transportation delay issues, however, required the ability to further partition the economy into Industry-Port sub-flows to provide a more detailed representation of the distribution of supplies from each industry through each port.

Data from the U.S. Bureau of Economic Analysis (2022) was examined to identify the percentage of imported supplies entering the U.S. for each of the 55 industries. Individual sub-flows were created to account for supplies entering the U.S. through the top 10 ports. In addition, a sub-flow was created to account for supplies entering the U.S. through all other US ports, and another sub-flow was created to account for supplies from all domestic sources. A Port Matrix variable was introduced into the hybrid SD/IO model that defined the percentage of incoming supplies provided to each Industry via each of the 12 sub-flows described above. In effect, this variable defined a total of 660 separate Industry-Port sub-flows (12 ports * 55 industries).

As an example of the complexity of this issue, Figure 2 depicts a partial view of the flow of supplies modeled in the hybrid IO/SD model. The figure visualizes the Bureau of Economic Analysis (BEA) data for 36 separate Industry-Port sub-flows, representing the movement of supplies for six of the 55 modeled industries from six of the 12 modeled ports. Notice the different widths of the flows as well as the different heights of the boxes. The width of the flow and height of each Industry and Port box represents the relative volume of supplies.

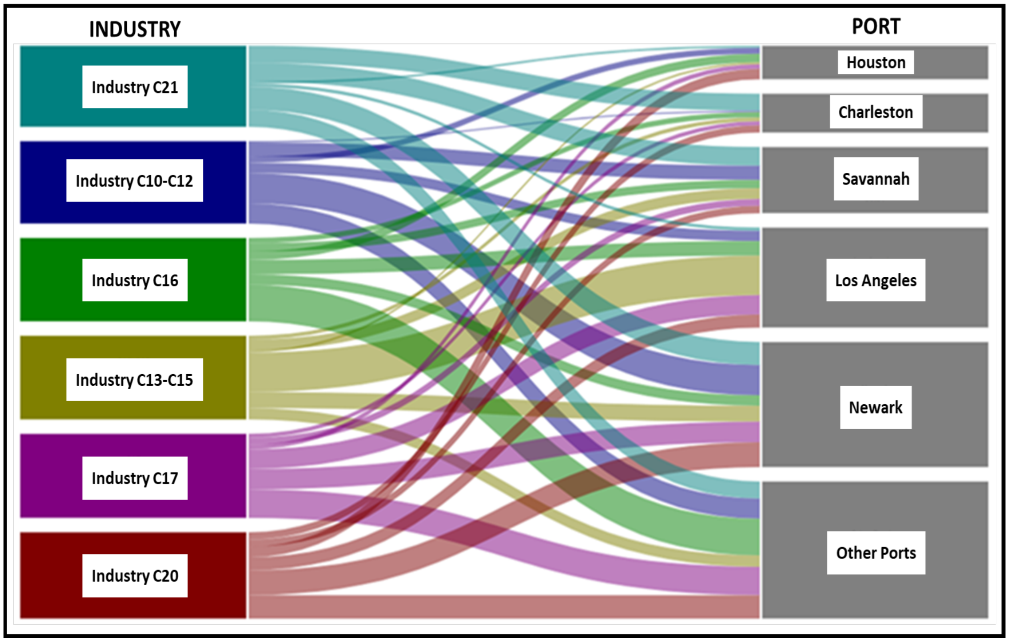

Figure 2**.** Visualization of BEA data showing supply flows for six industries from six ports.

3.2 Implementing a Transportation Delay Mechanism Within the Model

In the original version of the model, supplies defined by the supply orders variable were passed directly into inventory from the intermediate consumption variable, as shown in (1). Implementing a transportation delay mechanism required modifying the flow of inventory inputs into inventory and some of the associated I/O equations. This was accomplished by splitting the flow of inputs into each industry's inventory into two separate sub-streams: one for on-time delivery and one for delayed delivery, each controlled by a set of user-defined transportation delay-related parameters. Supplies in the on-time delivery sub-stream replenish the inventory immediately while supplies in the delayed delivery sub-stream replenish the inventory after an appropriate user-defined delay. To manage the flow of incoming supplies between these two sub-streams, we introduced five additional user-specified variables, defined in Table 2.

Table 2. Transportation Delay Variables.

Notation	Description
PD_p	User defined delays per each Port p, in days
t_{Start_Delay}	Port Delay Start Time
t_{Stop_Delay}	Port Delay Stop Time
$OTD_{jip,t}$	On-Time Delivery inputs from Industry j to Industry i, via Port p
$DD_{jip,t}$	Delayed Delivery inputs from Industry j to Industry i, via Port p

The intermediate consumption term in (1) was replaced by the sum of on-time delivery and delayed delivery to form a new equation representing the inventory level for each industry at the next time step:

$$S_{ij,t+1} = S_{ij,t} + \sum_{p=1}^{P}(OTD_{jip,t} + DD_{jip,t}) - (A_{ij}x_{j,t}) \tag{10}$$

The left side of Figure 3 shows the original model with intermediate consumption connecting directly to the inventory input variable. The right side of Figure 3 shows the new on-time delivery and delayed delivery variables established between the intermediate consumption and inventory input variables and the new Transportation Delay-related variables described in Table 2.

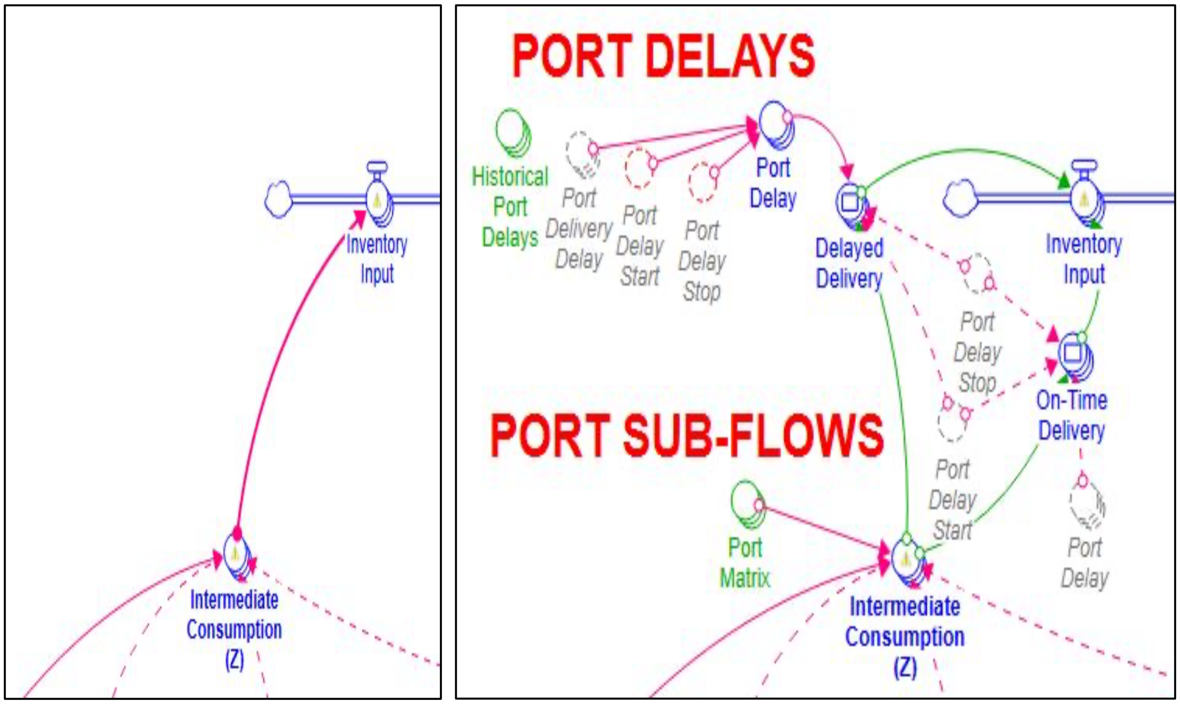

Figure 3**.** Original and updated inventory inputs modeling.

The logic for managing the two sub-streams is depicted in Table 3. At each time step, the inventory input is the sum of the on-time delivery and delayed delivery sub-streams.

Table 3. On-time delivery and delayed delivery logic.

Time Period	**Until Port Delay Start**	**From Port Delay Start until (Port Delay Start + Port Delay)**	**From (Port Delay Start + Port Delay) until Port Delay Stop**	**From Port Delay Stop until (Port Delay Stop + Port Delay)**	**After Port Delay Stop**
On-Time Delivery	Intermediate Consumption	0	0	Intermediate Consumption	Intermediate Consumption
Delayed Delivery	0	0	Delayed Intermediate Consumption	Delayed Intermediate Consumption	0

The model was then run under different port delay scenarios to investigate whether the transportation delay logic was being implemented properly. Figure 4 is an output example depicting inventory inputs for Industry C13-C15 traversing the port of Los Angeles under the following parameter settings: Port Delay Start Time = 100, Port Delay Stop Time = 150, and Port Delay = 30 days.

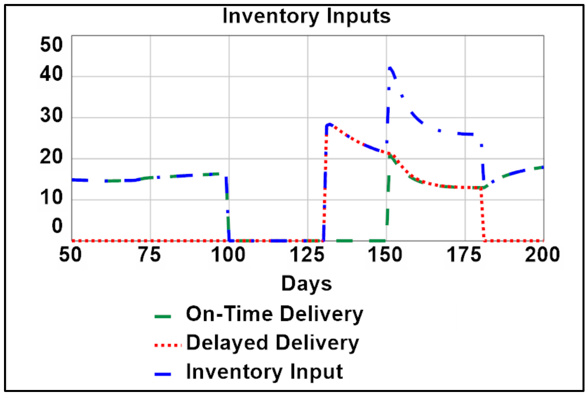

Figure 4. Industry C13-C15 incoming inventory flows.

Note there are only on-time delivery inputs from T=0 to T=100, no inputs from T=100 to T=130, only delayed delivery inputs from T=130 to T=150, both delayed delivery and on-time delivery inputs from T=150 to T=180, and only on-time delivery inputs after T=180. This is consistent with the logic described in Table 5.

4 TRANSPORTATION DELAY CASE STUDY

The case study centered around the port of Los Angeles since it is one of the busiest U.S. seaports for shipping container imports in the United States. This port has faced massive shipping container backlogs recently as well as threats of labor strikes. Each of these situations would have tremendous impacts on the time required for container vessels to load and unload containers and for containers to be efficiently stored and moved out of the port for land transportation to their destination. As an example, the Wall Street Journal (Anguiano 2021) reported that there were five ships waiting to dock and unload at this port in October 2020, but the backlog swelled to 109 ships in January 2022. Unfortunately, we were thus far unable to find reliable data describing specific industry-level data about the impacts of these delays against which to compare our simulation data. As a result, we were only able to provide the simulation results and explain them in terms of the underlying IO equations. We will continue our search for this data and report on it in a future paper.

4.1 Impact of an LA Port Delay on Industries with Inputs Traversing the Port of Los Angeles

Since 38% of the supplies in the Manufacture of Textiles, Wearing Apparel and Leather Products Industry (C13-15) come through the port of Los Angeles, we focused on this industry for this aspect of the case study. A transportation delay at this port should have some impact on the Industry C13-C15 supply chain as well as on other industries that are deeply connected to this industry through intermediate consumption. For the case study, the following parameter settings were invoked: Port Delay Start Time = 100, Port Delay Stop Time = 150, and Port Delays = 30 and 60 days.

The left side of Figure 5 shows the Industry C13-C15 inventory inputs over time. The green line represents the No LA Port delay baseline. For the 30-day LA Port delay case (red line), the dip in inventory inputs occurs once the LA Port delay starts at T=100 and the initial surge that starts at T=130 when delayed delivery inputs start arriving. The secondary surge then begins once both delayed delivery and on-time delivery inputs start arriving when the LA Port delay stops at T=150. It then returns to the baseline once delayed delivery inputs end at T=180. For the 60-day LA Port delay case (blue line), this pattern also occurs but is shifted to the right and magnified due to the extended period without Inventory Inputs.

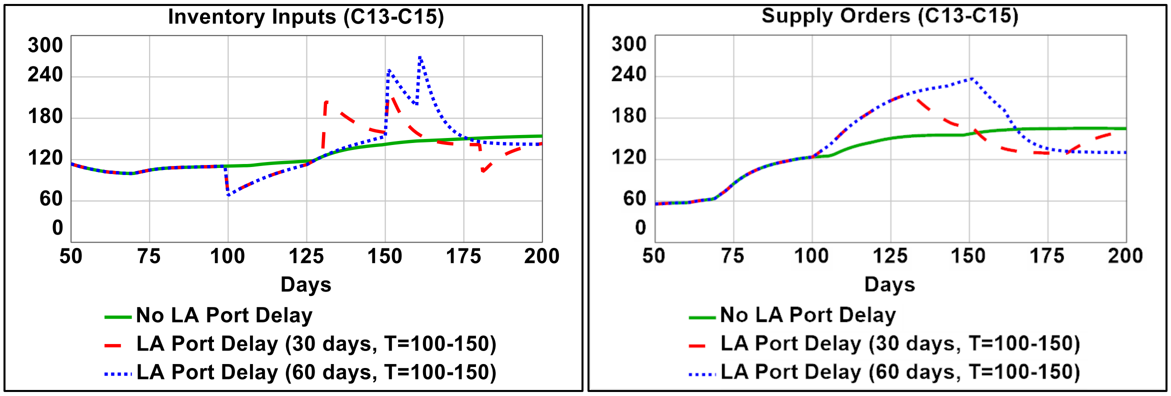

Figure 5. Industry C13-C15 inventory inputs and supply orders.

The right side of Figure 5 shows the Industry C13-C15 supply orders over time. For the 30-day LA Port delay case, the increase in supply orders starting at T=100 is consistent with (2). Production continues during this period but there are no inventory inputs, so supply orders must be increased to maintain the defined target inventory level ($n_j Z_{ij,0}$). The decrease in supply orders starting at T=130 and continuing through T-180 is consistent with the arrival of delayed delivery inputs and then on-time delivery inputs to replenish the Inventory. For the 60-day LA Port delay case, this pattern also occurs but is shifted to the right and magnified due to the extended period without Inventory Inputs.

The left side of Figure 6 shows the Industry C13-C15 demand over time. For the 30-day LA Port delay case, the increase in demand starting at T=100 and the decrease in demand starting at T-150 follow the expected trend from (4) since supply orders are a major component of demand. For the 60-day LA Port delay case, this pattern extends to the right and is magnified due to the extended period without inventory inputs.

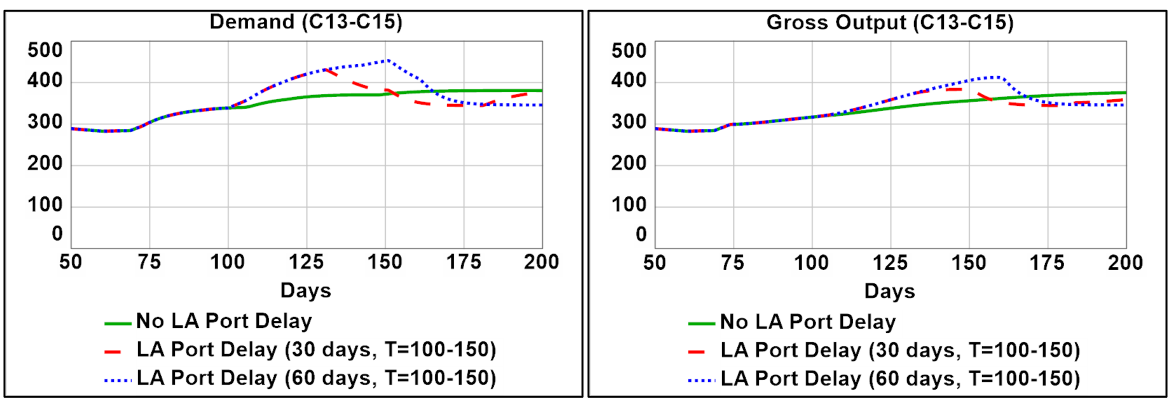

Figure 6. Industry C13-C15 demand and gross output.

The right side of Figure 6 shows the Industry C13-C15 gross output or production over time. For the 30-day LA Port delay case, the minor impacts on gross outputs depicted in this figure are due to the large inventory on hand, which prevents the input production capacity represented by (9) from becoming a constraint in calculating gross outputs in (5). Examining the model results, demand was the major driver of gross outputs, leading to the increase in gross outputs starting at T=100 and the decrease in gross output starting at T-150. For the 60-day LA Port delay case, this pattern extends to the right and is magnified due to the extended period without inventory inputs.

4.2 Impact of an LA Port Delay on Industries without Inputs Traversing the Port of Los Angeles

We investigated the national impacts of an LA Port delay on industries that do not have inputs that traverse the port of Los Angeles. Industry E36 (Water collection, treatment, and supply) was selected for analysis due to its high dependence on Industry C13-C15 and Industry L68 (Real estate activities) for its lack of dependence on Industry C13-C15. The following plots show the results of the same LA Port delay as the preceding section, with a Port Delay Start Time = 100, Port Delay Stop Time = 150, and Port Delays = 30 and 60 days.

Figure 7 shows the Industry E36 demand and gross output over time. While this industry does not have inputs traversing the port of Los Angeles, there is a noticeable increase in demand and gross outputs starting at T=100. This can be attributed to this industry's dependence on Industry C13-15. As shown in the previous section, the delayed delivery of goods through the port of Los Angeles caused an increase in supply orders, which led to an increase in demand, which in turn led to an increase in gross outputs. These increased gross outputs led to an increase in demand for Industry E36, which led to an increase in gross outputs.

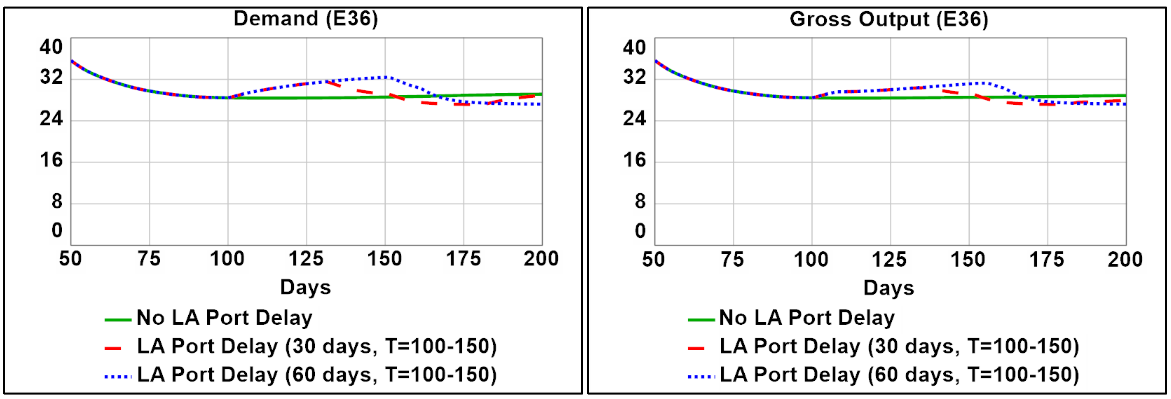

Figure 7. Industry E36 demand and gross output.

Figure 8 shows the Industry L68 demand and gross output over time. As expected, since this Industry is not dependent on Industry C13-C15 and does not have supplies traverse the port of Los Angeles, there is no impact on demand and gross output, confirming expectations this industry is not sensitive to an LA Port delay. However, it is still necessary to apply the model to investigate these possible effects because the structure of the intermediate consumption network could still lead to this industry being impacted at a certain point in time.

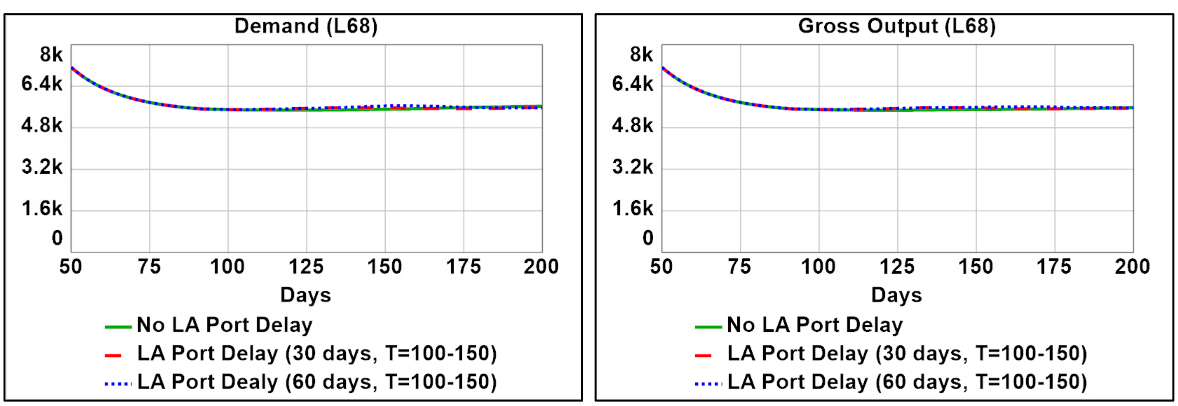

Figure 8. Industry L68 demand and gross output.

5 CONCLUSIONS AND FUTURE RESEARCH

This research proposed an extended hybrid SD/IO simulation model to provide insights into the economic impacts of transportation delays. The model measures the direct impacts on individual industries due to excessive transportation delays between orders with respect to goods traversing specific US ports that are experiencing an abnormal dwell time. Moreover, the model was shown through a case study involving the Port of Los Angeles to capture the potential indirect impacts on industries from the propagating effects of intermediate consumption between industries.

The capability to measure the impact of these transportation delay shocks highlights the importance of developing mitigation strategies to improve the resilience of the national supply chain to withstand these shocks. Three possible mitigation strategies could be distributing an industry's incoming supply across multiple ports rather than concentrating them all in one port, prioritizing efforts to reduce potential delays at the most active ports and increasing target inventory levels to provide a hedge against delayed supply deliveries.

While the case study provided results that are consistent with the IO equations, the results highlight the need to investigate whether other equations besides (1) should also be adjusted to address transportation delays. The existence of delays in a supply chain induces a bullwhip effect, increases system instability, and reduces overall system performance (Chen et al. 2023). Updating additional IO equations could reduce these supply chain impacts and improve supply chain performance.

The supply order calculation described in (2) does not consider past supply orders that are in the delayed delivery sub-stream and have not yet made it into inventory. This leads directly to the large increase in Industry C13-C15 supply orders shown in the right side of Figure 5. Future efforts to update (2) to account for delayed delivery inputs could reduce the bullwhip effect caused by near-term over-ordering. This would reduce unnecessary excess inventory holding costs and lead to a more efficient and resilient supply chain.

REFERENCES

Anguiano, D. 2021. "Southern California's Notorious Container Ship Backup Ends". Retrieved from *The Guardian*; https://www.theguardian.com/us-news/2021/sep/22/cargo-ships-traffic-jam-los-angeles-california, accessed March 10, 2023.

Baqaee, D. and E. Farhi. 2020. "Nonlinear Production Networks with an Application to the Covid-19 Crisis" (No. w27281). *National Bureau of Economic Research*.

Barrot, J.N., B. Grassi, and J. Sauvagnat. 2021. "Sectoral Effects of Social Distancing". In *AEA Papers and Proceedings* (Vol. 111, pp. 277-81).

Bland, W, S. Rosen, A. Hong, L Rayson, and J. Richkus. 2022. "A System Dynamics Model for Studying the Resiliency of Supply Chains and Informing Mitigation Policies for Responding to Disruptions". In *Proceedings of the 2022 Winter Simulation Conference,* edited by B. Feng, G. Pedrielli, Y. Peng, S. Shashaani, E. Song, C. G. Corlu, L. H. Lee, E. P. Chew, T. Roeder, and P. Lendermann, 1235-1246. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Bonadio, B., Z. Huo, A.A Levchenko, and N. Pandalai-Nayar. 2021. "Global Supply Chains in the Pandemic". *Journal of International Economics*, *133*, p.103534.

Chen, D., H. Feng, Y. Huang M. Tan, Q. Chen, and X. Wei. 2023. "Robust Control of Bullwhip Effect for Supply Chain System". *IEEE Access* 11:61409-61058.

Fadinger, H. and J. Schymik. 2020. "The Effects of Working from Home on Covid-19 Infections and Production; A Macroeconomic Analysis for Germany". *Covid Economics*, *9*(24), pp.107-139.

Georgiadis P., D. Vlachos, and E. Iakovou. 2005. "A System Dynamics Modeling Framework for the Strategic Supply Chain Management of Food Chains". *Journal of Food Engineering* 70:351–364

Gordon, J. 2022. "Canada's Trucker Protests Leave Businesses and Taxpayers with Hefty Bills." Retrieved from *Reuters*; https://www.reuters.com/business/autos-transportation/canadas-trucker-protests-leave-businesses-taxpayers-with-hefty-bills-2022-02-24/, accessed March 14, 2023.

Habermann, M., J. Blackhurst, and A.Y. Metcalf. 2015. "Keep Your Friends Close? Supply Chain Design and Disruption Risk". *Decision Sciences* 46(3):491-526.

Hong, A. L. Rayson, W. Bland, J. Richkus, and S. Rosen. 2022. "Regionalized Modeling of Supply Chain Resiliency for Analyzing Incentive Options". In *Proceedings of the 2022 IEEE International Systems Conference*.

Kovacs, G. and I.F. Sigala. 2021. "Lessons Learned from Humanitarian Logistics to Manage Supply Chain Disruptions". *Journal of Supply Chain Management* 57(1):41-49.

Leggett, T. 2021. “Egypt's Suez Canal Blocked by Huge Container Ship”. Retrieved from *BBC News*; https://www.bbc.com/news/world-middle-east-56505413, accessed March 15, 2023.

Li, Y., K. Chen, S. Colignon, and D. Ivanov. 2021. “Ripple Effect in the Supply Chain Network: Forward and Backward Disruption Propagation, Network Health and Firm Vulnerability”. *European Journal of Operational Research* 291(3):1117-1131.

Fadinger, H. and J. Schymik, 2020. "The Effects of Working from Home on COVID-19 Infections and Production - A Macroeconomic Analysis for Germany," CRC TR 224 Discussion Paper Series crctr224_2020_167, University of Bonn and University of Mannheim, Germany.

Pichler, A., R. Pangallo, R. Maria del Rio-Chaona, F. Lafond, and J. D. Farmer. 2020. “Production Networks and Epidemiological Spreading: How to Restart the UK Economy?”. *INET Oxford Working Paper*.

Radzicki M.J. 2010. “System Dynamics and Its Contribution to Economics and Economic Modeling”. In *Encyclopedia of Complexity and Systems Science*, edited by R. Meyers, 727-737. New York: Springer.

Rebs, T., M. Brandenburg, and S. Seuring. “System Dynamics Modeling for Sustainable Supply Chain Management: A Literature Review and Systems Thinking Approach”. *Journal of Cleaner Production* 208:1265-1280.

Rosen, S., A. Hong, L Rayson, W. Bland, and J. Richkus. 2022. “A Simulation Framework for Studying Foreign Reliance on Regional Supply Chains at the Industry Level”. In *2022 Annual Modeling and Simulation Conference,* July 18-21, San Diego State University, San Diego, CA.

Shepherd, S.P. 2014. “A review of system dynamics models applied in transportation”. *Transportmetrica B: Transport Dynamics*, 2 (2):83-105.

Swinerd, C. and K. R. McNaught. 2012. “Design Classes for Hybrid Simulations Involving Agent-Based and System Dynamics Models”. In *Simulation Modelling Practice and Theory* 25(2012):118–133.

Tan, W. 2021. “Global Shipping Industry Disrupted Again, This Time by Floods in Europe and China”. Retrieved from *CNBC*; https://www.cnbc.com/2021/07/27/floods-in-europe-and-china-disrupt-global-shipping-supply-chains.html, accessed March 18, 2023.

U.S. Bureau of Economic Analysis. 2022. Gross Domestic Product [GDP], retrieved from Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/GDP, March 15, 2022.

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