WHAT WILL AUTONOMOUS TRUCKING DO TO U.S. TRADE FLOWS? APPLICATION OF THE RANDOM-UTILITY-BASED MULTI-REGIONAL INPUT-OUTPUT MODEL

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ABSTRACT
This study anticipates changes in U.S. highway and rail trade patterns following widespread availability of self-driving or autonomous trucks (Atrucks). It uses a random-utility-based multiregional input-output (RUBMRIO) model, driven by foreign export demands, to simulate changes in freight flows among 3109 U.S. counties and 117 export zones, via a nested-logit model for shipment or input origin and mode, including the shipper's choice between autonomous trucks and conventional or human-driven trucks (Htrucks). Different value of travel time and cost scenarios are explored, to provide a sense of variation in the uncertain future of ground-based trade flows.

Using the U.S. Freight Analysis Framework or FAF[4] data for travel times and costs and assuming that Atrucks lower trucking costs by 25% (per ton-mile delivered), domestic truck flow values are predicted to rise 2%, while rail flow values fall 16.1%. Due to predictions of change trip tables (shipment origins), rail flow volumes are actually predicted to rise for trip distances under 250 miles or greater than 1,550 miles in distance, with truck volumes rising for other distances. Introduction of Atrucks enables longer truck trade, but the low price of railway remains competitive for trade distance over 1,550 miles. Htrucks continue to dominate in shorter-distance freight movements, while Atrucks dominate at distances over 550 miles. Seven and eleven commodity sectors by truck see an increase in domestic flows and export flows, respectively. However, total ton-miles traveled by the 20 commodity groups falls, as long-distance railway use becomes relatively less attractive.

Key words: autonomous trucks, spatial input-output model, nationwide trade flow patterns, integrated transportation-land use modeling

MOTIVATION

Self-driving, fully-automated or autonomous vehicles (AVs) are an emerging transportation technology that may transform both passenger and freight transport decisions. Semi-automated trucks may enable automated driving under supervision and limited circumstances, such as driving long distances on an interstate. Fully automated self-driving trucks or "Atrucks" are those that can leave the truck terminal and travel to a destination without human intervention or presence in the truck cab (Goodwill, 2017). Atrucks may be equipped with other automated functions, like drop-offs and pick-ups, but most experts expect an attendant on board, doing other types of work, sleeping as needed, and ensuring thoughtful deliveries and pickups. Such multi-tasking of vehicle attendants will allow for extended use of commercial trucks (e.g., every day, almost 24 hours a day) and greater labor productivity, resulting in lower per-mile and per-ton-mile freight delivery costs.

In the United States, trucks carry 1,996 billion ton-miles in 2014, which is 37.7% of total ton-miles transported in that year (BTS, 2017). Investment in and use of Atrucks will affect not only national and regional economies (Clements and Kockelman 2017), but trade patterns, production levels, and goods pricing. Commercial trucks consume about 20% of the nation's transportation fuel, and self-driving technologies are predicted to reduce those diesel fuel bills by 4-7% (Liu and Kockelman 2017; Barth et al., 2004; Shladover et al., 2006).

Atrucks can reduce some environmental impacts, lower crash rates, and increase efficiency in warehousing operations, line-haul transportation, and last-mile deliveries. Platooned convoys should enable following truck drivers to avoid certain restrictions on service hours, enabling longer driving distances. Uranga (2017) predicts greater use of Atrucks before passenger vehicle automation, thanks to the more obvious economic benefits of self-driving trucks (which start with higher price tags, making the automation investments less of a cost burden). Of course, driver job loss is also a concern, and the International Transport Forum (O'Brien, 2017) predicts that up to 70% of all U.S. truck-driving jobs could be lost by 2030 (due to vehicle automation). But trucks may still require driver presence, due to loading dock restrictions, unusual problems on the road, and more complex operating systems.

While there is active investigative interest on the travel and traffic effects of self-driving cars, research into the travel and traffic impacts of Atrucks is dearly lacking. This paper anticipates Atrucks' trade pattern and production impacts across the U.S., and begins with a review of relevant works. It then discusses the random-utility-based multi-regional input-output (RUBMRIO) model methodology for tracking trade across zones or regions, describes a sub-nested mode choice model for Atrucks (versus Htrucks), and the results of various trade-scenario simulations across U.S. regions, highways, railways, and industries.

RELEVANT LITERATURE

Two papers currently investigate U.S. passenger-travel shifts, due to AV use (LaMondia et al., 2016; Perrine et al., 2017). Related topics include fuel consumption, congestion impacts, shared-fleet operations, dynamic ride-sharing, energy use, emissions, and roadside investments (see, e.g., Fagnant and Kockelman, 2014; Chen et al., 2016; International Transport Forum 2015; Land Transport Authority, 2017; Kockelman et al., 2016). LaMondia et al. (2016) forecasted U.S. mode shares for person-trips over 50 miles (one-way) from the state of Michigan, following the introduction of AVs. They predicted that 25% demand of airline passenger trips under 500 miles will shift to autonomous vehicles.. Perrine and Kockelman (2017) anticipated destination and mode-choice shifts in long-distance U.S. person-travel, including a major loss (48%) of airline revenue, using 4,566 National Use Microdata Area zones (NUMAs). The anticipate, long-term effects of AV access on long-distance personal travel are striking.

Some companies have written about the potential benefits of Atrucks. A DHL report (Kückelhaus, 2014) notes that Atrucks could lower their freight costs by 40% per vehicle- or ton-mile. Convoy systems would allow long-distance drives with large quantities of goods, through which Atrucks could reduce fuel use by 10 to 15% (Clements and Kockelman, 2017). Crash counts may fall by 50 percent or more (Kockelman and Li, 2016), along with various insurance costs. However, changing freight travel and land-use patterns due to Atrucks have been neglected. This is a new area of Atrucks that needs to be explored.

Trade Modeling

Input-Output (IO) analysis, originally proposed by Leontief (1941), uses matrix algebra to characterize inter-industry interactions within a single region, as households and government agencies spend money on goods, which are produced by mixing inputs from other industries, and so on. Demand is met by production adjustments, based on expenditure linkages across industries. Isard's (1960) spatial IO model allows for spatial disaggregation using fixed shares.. More recent extensions exploit random utility theory and entropy-maximization properties, as evident in the MEPLAN (Echenique et al., 1990), DELTA (Simmonds and Still, 1998), TRANUS (De la Barra et al., 1984), PECAS (Hunt and Abraham, 2003) and KIM models (Kim et al., 2002). These models also allow a land-use transportation feedback cycle, with freight and person (labor and consumer) flows responding to changes in network routes and travel costs.

The open-source RUBMRIO model is a similar extension, with applications to the state of Texas and U.S. counties. Kockelman et al. (2005) described the RUBMRIO's application to Texas's 254 counties, across 18 social-economic sectors and two modes of transport, meeting foreign export demands at 31 key ports. Huang and Kockelman (2010) developed a dynamic RUBMRIO model to equilibrate production and trade, labor markets and transportation networks simultaneously for Texas' counties over time (better recognizing starting distributions of labor and employment). Kim et al. (2002) used such a model for estimating interregional commodity flows and transportation network flows to evaluate the indirect impacts of an unexpected event (an earthquake) on nine U.S. states, represented by 36 zones.

Guzman and Vassallo (2013) used a RUBMRIO-style approach to evaluate the application of a distance-based charge to heavy-goods vehicles across Spain's motorways. Maoh et al. (2008) used the RUBMRIO model to simulate weather impacts on Canada's transportation system and economy. Du and Kockelman (2012) calibrated the RUBMRIO model to simulate U.S. trade patterns of 20 commodities among 3,109 counties, with its nested-logit model for input origin and truck-versus-rail mode choices. They noted how transportation cost changes (from generically more efficient or less efficient travel technologies, for example) were important, especially for central U.S. counties.

This study builds off of the Du and Kockelman (2012) work by adding the Atruck option into a sub-nest for mode choice (allowing for strong correlation in the Atruck vs. Htruck choice). The application's 20 socio-economic sectors, technology costs, and other assumptions are described below.

DATA SETS

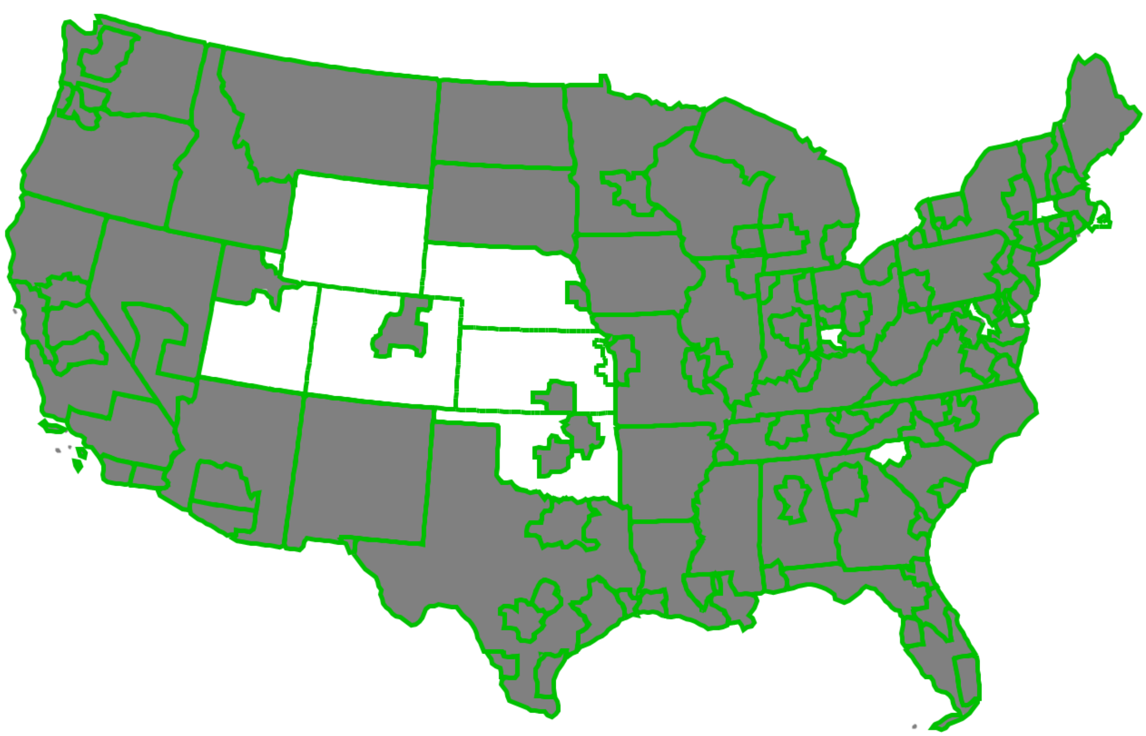
Data sets used for RUBMRIO model include the disaggregated freight zonal data from the U.S. Commodity Flow Survey (CFS), trade flow data from the U.S. DOT's Freight Analysis

Framework (FAF) version 4, industry-by-industry transaction table and regional purchase coefficients (in year 2008) from IMPLAN, and railway and highway network data from Caliper's TransCAD 7.0.

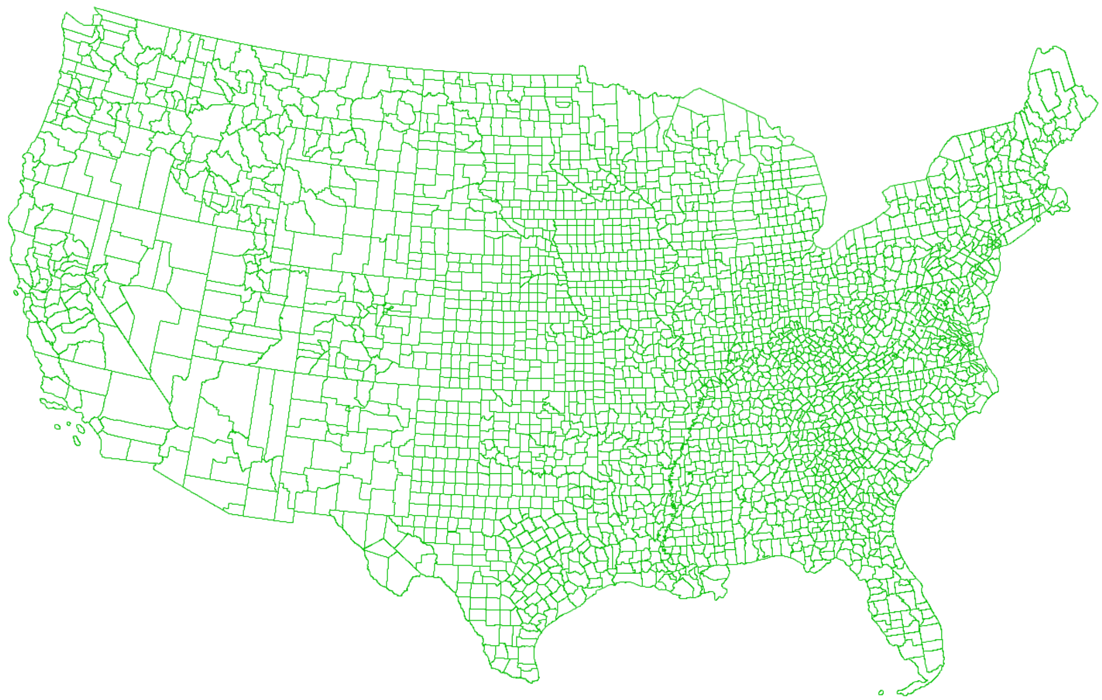
Freight Data

FAF^4 integrates trade data from a variety of industry sources, with emphasis on the Census Bureau's 2012 CFS and international trade data (Fullenbaum and Grillo, 2016). It provides estimates of U.S. trade flows (in tons, ton-miles, and dollar value) by industry, across 7 modes (truck, rail, water, air, pipeline, and others), and between all 132 FAF zones. FAF^4's origin-destination-commodity-mode annual freight flows matrix was used to predict domestic and export trade flows by zone. Among the nation's 132 FAF^4 zones, 117 Export FAF zones are used here as FAF^4 shows foreign export flow exiting U.S. from 117 zones, as shown in gray in Figure 1(a).

FAF^4 trade-flow data were then disaggregated into county-level matrices using the 2012 CFS boundary data which identifies the counties that belong to each of the FAF^4 zones. Ten metro areas were also added for the CFS in year 2012, and 3109 contiguous counties remain, after excluding the distant states of Hawaii and Alaska. Figure 1(b) shows the resulting 3109 counties. Interzonal travel times and costs by rail, Atruck and Htruck were all computed using TransCAD software, for the 3109×3109 FAF^4 county matrix based using shortest highway and railway paths. All intra-county travel distances were assumed to be the radii of circles having that county's same area.



(a) Continental United States' FAF^4 117 Export Zones



(b) Continental United States' 3109 Domestic Freight Counties

Figure 1 U.S. Domestic and Export Zones for Trade Modeling.

Economic Interaction Data

The model's embedded IO matrices' technical coefficients and regional purchase coefficients (RPCs) were obtained through IMPLAN's transaction tables, as derived from U.S. inter-industry accounts. Technical coefficients reflect production technology or opportunities (i.e., how dollars of input in one industry sector are used to create dollars of product in another sector) and are core parameters in any IO model. RPCs represent the share of local demand that is supplied by domestic producers. RPC values across U.S. counties are assumed constant here, since variations are unknown. However, counties closer to international borders are more likely to "leak" sales (as exports) than those located centrally, everything else constant. And production processes or technologies can vary across counties (and within industries, across specific manufacturers and product types, of course). This application assumes that all U.S. counties have access to the same production technologies, or technical coefficients table.

IMPLAN's 440-sector transaction table was collapsed into 18 industry sectors, plus Household and Government sectors to represent the U.S. economy in this trade-modeling exercise. Since FAF[4] uses the same 43 two-digit Standard Classification of Transported Goods (SCTG) classes (BTS, 2017) as the 2007 U.S. Commodity Flow Survey (CFS), IMPLAN's 440 sectors were bridged to a corresponding SCTG code based on the 2007 North American Industry Classification System or NAICS (Census Bureau, 2017). SCTG code 99 (for other good types) is not tracked here. See economic sectors for RUBMRIO model application table from Du and Kockelman (2012).

METHODOLOGY

In random utility choice theory, error terms enable unobserved heterogeneity in the decision-making process. Here, the RUBMRIO multinomial logit model has three branches, for origin choice, rail versus truck mode choice, and autonomous vs human-driven truck choice, as shown in Figure 2.

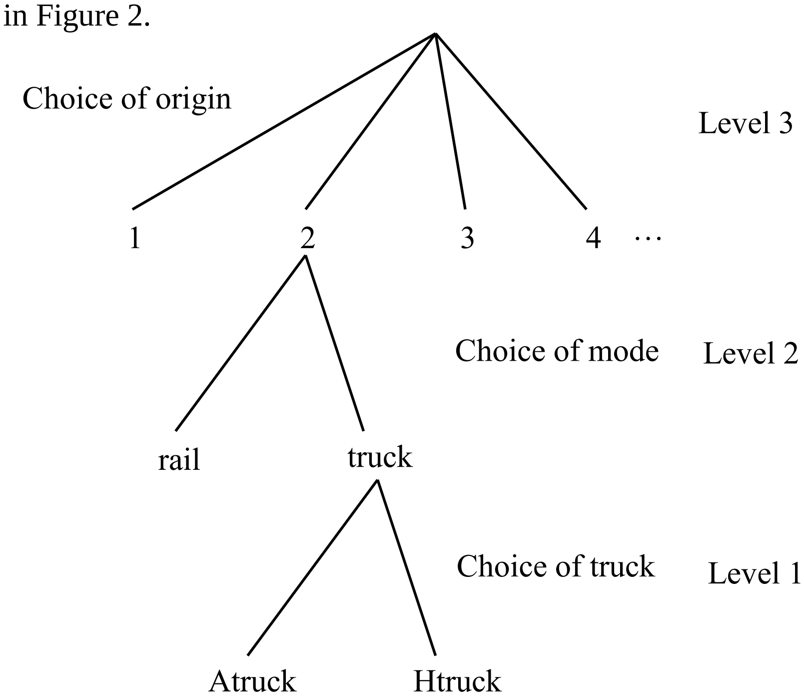


Figure 2 Random Utility Structure for Shipment Origin, Mode, and Truck-type Choices.

Equation (1) provides the three mode-choice utilities, conditioned on knowing a shipment's origin (i), destination (j), and industry or commodity type (m):

$$\begin{aligned}
U^m_{ij,\ rail} &= \tilde{V}^m_{ij,\ rail} + \tilde{V}^m_{ij} + \varepsilon^m_{ij,\ rail} + \varepsilon^m_{ij} \\
U^m_{ij,\ truck,\ Atruck} &= \tilde{V}^m_{ij,\ truck,\ Atruck} + \tilde{V}^m_{ij,\ truck} + \tilde{V}^m_{ij} + \varepsilon^m_{ij,\ truck,Atruck} + \varepsilon^m_{ij,\ truck} + \varepsilon^m_{ij} \\
U^m_{ij,\ truck,\ Htruck} &= \tilde{V}^m_{ij,\ truck,\ Htruck} + \tilde{V}^m_{ij,\ truck} + \tilde{V}^m_{ij} + \varepsilon^m_{ij,\ truck,Htruck} + \varepsilon^m_{ij,\ truck} + \varepsilon^m_{ij}
\end{aligned} \tag{1}$$

where

$\tilde{V}^m_{ij}$ = systematic utility of selecting origin i for acquisition of commodity m,

$\tilde{V}^m_{ij,\ rail}$, $\tilde{V}^m_{ij,\ truck}$ = systematic utilities associated with selecting origin i and rail mode/any truck type for movement of commodity m,

$\tilde{V}^m_{ij,\ truck,\ Atruck}$,$\tilde{V}^m_{ij,\ truck,\ Htruck}$ = systematic utilities associated with selecting origin i and Atruck/Htruck for movement of commodity m,

ε^m_{ij}, $\varepsilon^m_{ij,\ rail}$, $\varepsilon^m_{ij,\ truck}$, $\varepsilon^m_{ij,\ truck,Htruck}$, $\varepsilon^m_{ij,\ truck,Atruck}$ = random error terms associated with shipment origin, rail mode, truck mode, human-driven truck and self-driving truck choice respectively.

Origin Choice (Level 3)

Relying on nested logit formulae provided in Ben-Akiva and Lerman (1978), the probability of commodity-type m inputs coming to zone j from zone i (i.e., the choice likelihood [or input share] of zone i as an origin for this good's demand in zone j) is given by:

$$P_{ij}^{m}=\frac{\exp(V_{ij}^{m})}{\sum_{i}\exp(V_{ij}^{m})} \quad (2)$$

where

$$V_{ij}^{m}=-p_{i}^{m}+\gamma^{m}\ln(pop_{i})+\lambda^{m}\theta_{ij,mode}^{m}\Gamma_{ij,mode}^{m} \quad (3)$$

is the system utility using origin i for commodity m, and

$$\Gamma_{\mathrm{ij,mode}}^{\mathrm{m}}=\ln\left(\exp\left(\frac{V_{ij,\,rail}^{m}}{\theta_{ij,mode}^{m}}\right)+\exp\left(\frac{V_{ij,truck}^{m}}{\theta_{ij,mode}^{m}}\right)\right) \quad (4)$$

is the logsum of mode choice, with scale parameter $\theta_{ij,mode}^{m}$=1.2.

Mode Choice (Level 2)

Since the mode choice nested logit's random error terms are assumed to follow an iid Gumbel distribution, and setting the initial dispersion to scaling factor to 1, the probability of commodity m being transported by each of the two major modes (rail and truck), between any given ij pair, are as follows:

$$P_{rail|ij}^{m}=\frac{\exp\left(\frac{V_{ij,\,rail}^{m}}{\theta_{ij,mode}^{m}}\right)}{\exp\left(\frac{V_{ij,\,rail}^{m}}{\theta_{ij,mode}^{m}}\right)+\exp\left(\frac{V_{ij,truck}^{m}}{\theta_{ij,mode}^{m}}\right)}$$
$$P_{truck|ij}^{m}=\frac{\exp\left(\frac{V_{ij,truck}^{m}}{\theta_{ij,mode}^{m}}\right)}{\exp\left(\frac{V_{ij,\,rail}^{m}}{\theta_{ij,mode}^{m}}\right)+\exp\left(\frac{V_{ij,truck}^{m}}{\theta_{ij,mode}^{m}}\right)} \quad (5)$$

where

$$V_{ij,\,rail}^{m}=\beta_{0,\,rail}^{m}+\beta_{r,time}^{m}\times time_{ij,\,rail}+\beta_{r,cost}^{m}\times cost_{ij,\,rail}$$
$$\text{and } V_{ij,\,truck}^{m}=0+\theta_{ij,truck}^{m}\Gamma_{ij,truck}^{m} \quad (6)$$

are the general modes' systematic utilities and

$$\Gamma_{truck}^{m}=\ln\left(\exp\left(\frac{V_{ij,\,truck,Atruck}^{m}}{\theta_{ij,truck}^{m}}\right)+\exp\left(\frac{V_{ij,\,truck,Htruck}^{m}}{\theta_{ij,truck}^{m}}\right)\right) \quad (7)$$

is the logsum for the truck-mode choice, with scale parameter $\theta_{ij,truck}^{m}$ = 1.4 for base case. Travel time is a common component for the Atruck and Htruck utilities, since this work does not assume one is faster. Here, the truck mode serves as the base mode, so only the rail mode has an alternative specific constant (ASC).

Truck Choice (Level 1)

The probability of freight flow commodity m from zone i to zone j using mode Atruck and Htruck respectively in nest truck is given by:

$$P^m_{Atruck|ij,truck} = P^m_{truck|ij} \times P^m_{Atruck|truck} = \frac{\exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)}{\exp\left(\frac{V^m_{ij,\ rail}}{\theta^m_{ij,mode}}\right) + \exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)} \times \frac{\exp\left(\frac{V^m_{ij,\ truck,Atruck}}{\theta^m_{ij,truck}}\right)}{\exp\left(\frac{V^m_{ij,\ truck,Atruck}}{\theta^m_{ij,truck}}\right) + \exp\left(\frac{V^m_{ij,\ truck,Htruck}}{\theta^m_{ij,truck}}\right)} \tag{8}$$

$$P^m_{Htruck|ij,truck} = P^m_{truck|ij} \times P^m_{Atruck|truck} = \frac{\exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)}{\exp\left(\frac{V^m_{ij,\ rail}}{\theta^m_{ij,mode}}\right) + \exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)} \times \frac{\exp\left(\frac{V^m_{ij,\ truck,Htruck}}{\theta^m_{ij,truck}}\right)}{\exp\left(\frac{V^m_{ij,\ truck,Atruck}}{\theta^m_{ij,truck}}\right) + \exp\left(\frac{V^m_{ij,\ truck,Htruck}}{\theta^m_{ij,truck}}\right)}$$

where

$$V^m_{ij,\ truck,Atruck} = \beta^m_{0,\ Atruck} + \beta^m_{t,time} \times time_{ij,truck} + \beta^m_{t,cost} \times cost_{ij,Atruck}$$
$$V^m_{ij,\ truck,\ Htruck} = 0 + \beta^m_{t,time} \times time_{ij,truck} + \beta^m_{t,cost} \times cost_{ij,Htruck} \tag{9}$$

are the system utilities of moving commodity *m* from zone *i* to zone *j* using Atruck and/or Htruck modes (in the truck nest).

RUBMRIO Model Specification

An equilibrium trade-flow solution (where all producers obtain the inputs they need, and all export demands are met) can be achieved in RUBMRIO via Figure 3's iterative equation sequence. Zhao and Kockelman (2004) proved solution uniqueness. Flow-weighted averages of shipments' travel costs create input costs, which merge together to create output costs, as commodities (and labor) flow through the production and trade system. Once the solutions have stabilities (with domestic flow value changing by less than 1% between iterations), final disutilities of travel and trade provide mode shares by OD pair and commodity or industry sector.

This iterative process' calculations required about 2.25 hours using an Atruck-modified version of Kockelman et al.'s C++ open-source program (available at http://www.caee.utexas.edu/prof/kockelman/RUBMRIO_Website/homepage.htm).

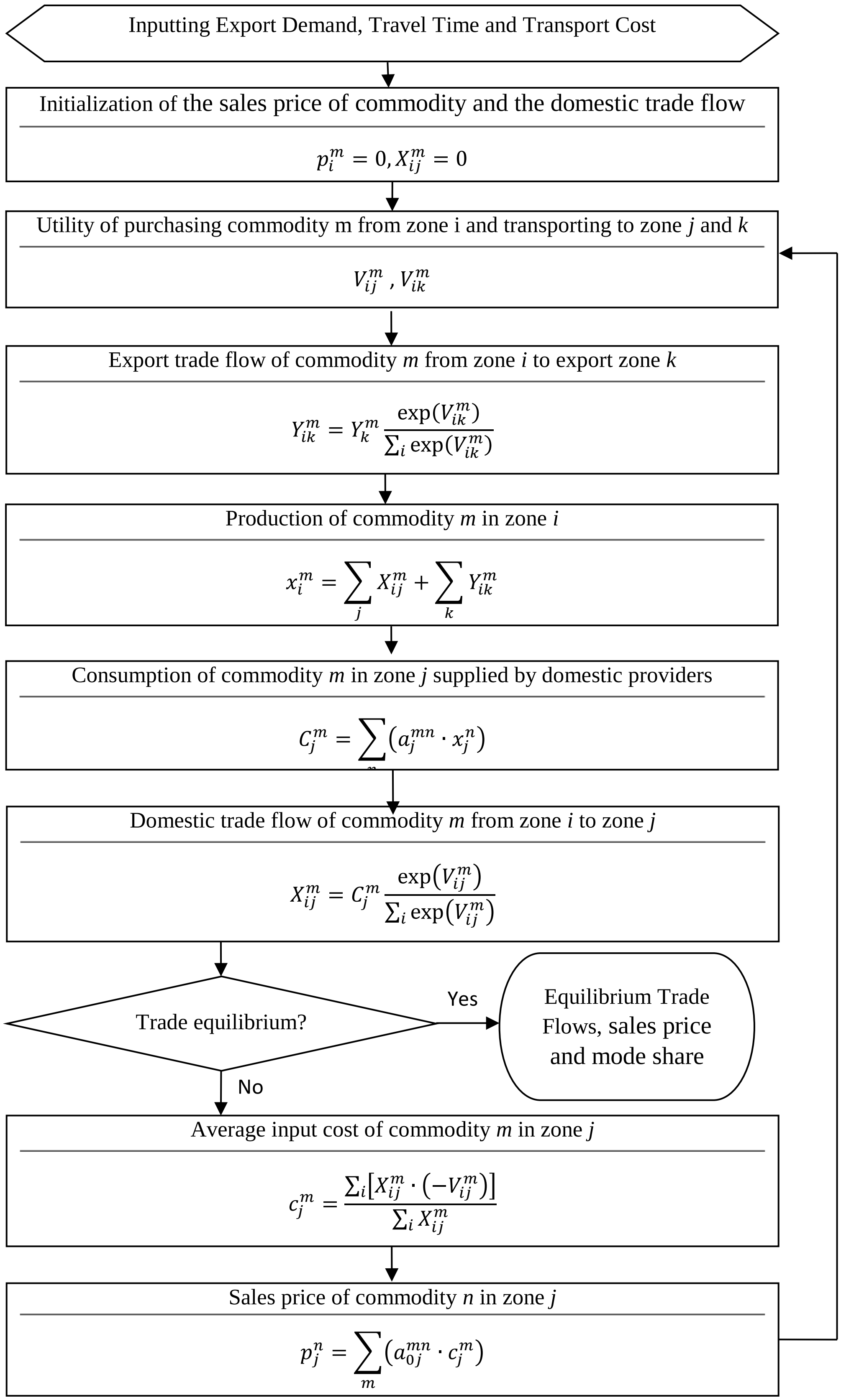

Inputting Export Demand, Travel Time and Transport Cost
Initialization of the sales price of commodity and the domestic trade flow
$p_i^m = 0, X_{ij}^m = 0$
Utility of purchasing commodity m from zone i and transporting to zone *j* and *k*
V_{ij}^m , V_{ik}^m
Export trade flow of commodity *m* from zone *i* to export zone *k*
$Y_{ik}^m = Y_k^m \frac{\exp(V_{ik}^m)}{\sum_i \exp(V_{ik}^m)}$
Production of commodity *m* in zone *i*
$x_i^m = \sum_j X_{ij}^m + \sum_k Y_{ik}^m$
Consumption of commodity *m* in zone *j* supplied by domestic providers
$C_j^m = \sum_m \left(a_j^{mn} \cdot x_j^n\right)$
Domestic trade flow of commodity *m* from zone *i* to zone *j*
$X_{ij}^m = C_j^m \frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)}$
Trade equilibrium?
Yes
Equilibrium Trade Flows, sales price and mode share
No
Average input cost of commodity *m* in zone *j*
$c_j^m = \frac{\sum_i \left[X_{ij}^m \cdot \left(-V_{ij}^m\right)\right]}{\sum_i X_{ij}^m}$
Sales price of commodity *n* in zone *j*
$p_j^n = \sum_m \left(a_{0j}^{mn} \cdot c_j^m\right)$

Figure 3 RUBMRIO Solution Algorithm (Adapted from Du & Kockelman [2012], Figure 2).

RUBMRIO's utility functions for domestic and export trade-flow splits (across shipment origin alternatives) depend on the cost of acquiring input type m from zone i, as well as zone i's "size" (measured as population here). Since there are three mode alternatives for these shipments, with the two truck modes sub-nested, the competing travel costs can be shown as logsums (the expected maximum utility or minimum cost of acquiring that input from different origin zones). After substituting those logsums into Figure 3's trade-flow equations, one has equations (10) and (11), where V_{ij}^{m} and V_{ik}^{m} are the utilities of purchasing one unit of industrial m's goods from region i for use as inputs to zone j's production process, or for export via zone k, respectively.

$$V_{ij}^{m}=-p_{i}^{m}+\gamma^{m}\ln(pop_{i})+\lambda^{m}\times\theta_{ij,mode}^{m}\times\ln\left(\begin{array}{c}\exp\left(\frac{\beta_{0,\,rail}^{m}+\beta_{r,time}^{m}\times time_{ij,\,rail}+\beta_{r,cost}^{m}\times cost_{ij,\,rail}}{\theta_{ij,mode}^{m}}\right)\\+\exp\left(\frac{\theta_{ij,truck}^{m}}{\theta_{ij,mode}^{m}}\times\ln\left(\begin{array}{c}\exp\left(\frac{\beta_{0,\,Atruck}^{m}+\beta_{t,time}^{m}\times time_{ij,truck}+\beta_{t,cost}^{m}\times cost_{ij,Atruck}}{\theta_{ij,truck}^{m}}\right)\\+\exp\left(\frac{\beta_{t,time}^{m}\times time_{ij,truck}+\beta_{t,cost}^{m}\times cost_{ij,Htruck}}{\theta_{ij,truck}^{m}}\right)\end{array}\right)\right)\end{array}\right) \quad (10)$$

$$V_{ik}^{m}=-p_{i}^{m}+\gamma^{m}\ln(pop_{i})+\lambda^{m}\times\theta_{ik,mode}^{m}\times\ln\left(\begin{array}{c}\exp\left(\frac{\beta_{0,\,rail}^{m}+\beta_{r,time}^{m}\times time_{ik,\,rail}+\beta_{r,cost}^{m}\times cost_{ik,\,rail}}{\theta_{ik,mode}^{m}}\right)\\+\exp\left(\frac{\theta_{ik,truck}^{m}}{\theta_{ik,mode}^{m}}\times\ln\left(\begin{array}{c}\exp\left(\frac{\beta_{0,\,Atruck}^{m}+\beta_{t,time}^{m}\times time_{ik,truck}+\beta_{t,cost}^{m}\times cost_{ik,Atruck}}{\theta_{ik,truck}^{m}}\right)\\+\exp\left(\frac{\beta_{t,time}^{m}\times time_{ik,truck}+\beta_{t,cost}^{m}\times cost_{ik,Htruck}}{\theta_{ik,truck}^{m}}\right)\end{array}\right)\right)\end{array}\right) \quad (11)$$

Parameter assumptions for γ^{m}, λ^{m} and β^{m} are based on Du and Kockelman's (2012) work, which has two levels of random utility structure – for origin and mode choices. Here, the rail's ASCs were set equal to the negative of the ASCs used for truck in their research, since a second type of truck mode was added as Atrucks. And the Atruck ASCs were assumed to be -0.1, because Atrucks is assumed to have higher preference related to safety compared with Htruck with the same operation cost. After assembling all these inputs, a series of different network and Atruck cost scenarios can be examined, using the RUBMRIO solution algorithms.

SIMULATION RESULTS

Figure 3's RUBMRIO equations were used to estimate U.S. trade flows between the nation's 3109 contiguous counties, as well as to 117 FAF[4] export zones, across 20 industries and 3 travel modes. \$10.7 trillion in trade flows were generated to meet the year 2015 export demand of \$1.15 trillion, as obtained from FAF[4] (with 24%, 18%, 17%, and 16% of those exports headed to Canada, Mexico, Europe and East Asia, respectively). The inter-county (domestic) flows account for 71.3% of FAF[4]'s domestic \$15.0 trillion trade flow. It is not 100% because the nation has another \$2.5 trillion in import flows (according to FAF[4], coming from other countries), which are not tracked here.

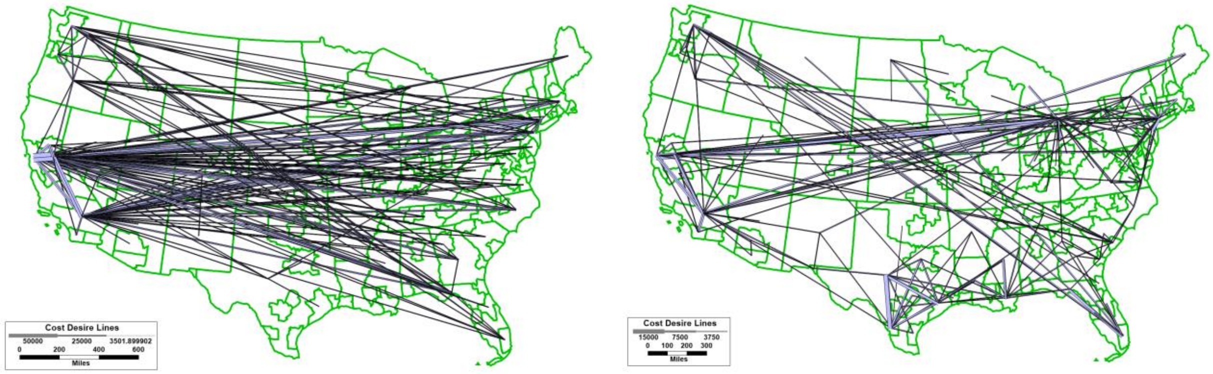
The base-case scenario assumes Htruck travel costs of \$1.73 per Htruck-mile and railcar costs of \$0.6 per container-mile (with different commodities filling containers differently, in terms of dollars per container). Table 1 compares RUBMRIO trade flow results to those in the FAF[4] database, after aggregating the 3109 trade zones into the 129 FAF zones, and counting the number of OD pairs that deliver the first 10 percent of trade flows (in dollar terms, rather than ton-miles or dollar-miles, for example), then the next set of OD pairs, and so forth (summing to

129 x 129 [domestic flows] zones pairs or 129 x 117 [export flows] zone pairs each). For example, the smallest-value domestic shipments that move $1.07 trillion, which is 10% of total domestic flow $10.7 trillion, come from 9604 FAF-zone pairs, according to the model results. In some contrast, FAF^4 values suggest that there are over 12,000 zone pairs involved in that first (smallest-shipment-size) set of flows. This comparison suggests that the base case RUBMRIO model equations and assumptions deliver reasonable trade-flow estimates, of FAF^4 volumes. However, RUBMRIO tends to “spread out” the trades across more OD pairs (with fewer small-size shipments) than FAF^4 data suggest. In other words, RUBMRIO shows less concentration of trade dollars or shipment sizes in the biggest OD trading patterns, for both domestic and export flows. There is obviously much more to U.S. trade than an origin’s population and its relative location on railways and highways, versus competing shipment sources. It is interesting how close RUBMRIO can come to replicating many trade patterns with a short set of equations (Figure 3 plus equations 10 and 11).

Table 1 Cumulative Distribution of RUBMRIO and FAF^4 Trade Flows

	Domestic Flows		Export Flows	
	RUBMRIO	FAF^4	RUBMRIO	FAF^4
0%-10%	9604	12,646	13,251	13,971
10%-20%	2738	2064	870	552
20%-30%	1579	935	410	257
30%-40%	1005	479	234	146
40%-50%	662	262	137	81
50%-60%	433	134	85	40
60%-70%	283	64	53	26
70%-80%	188	36	31	14
80%-90%	108	16	16	4
90%-100%	41	5	6	2

To look at trade patterns spatially, Figure 4 shows domestic trade flows above $5 billion and export trade flows about $1 billion. Many major domestic flows exist between western states, like California and Washington, to various eastern regions/FAF zones. In some contrast, major export flows (within the continental U.S., to access a port) also exist between coastal cities and their adjacent regions (often adjacent states). Moreover, exports from California ports appear to come largely from the Great Lakes region instead of from the Eastern Seaboard, thanks to a heavy export of Michigan-manufactured automobiles and trucks.



(a) Domestic Flows (Million $) (b)Export Flows (Million $)

Figure 4 Base Case Domestic and Export Trade Flows, between FAF^4 zones.

Sensitivity Analysis

Since great uncertainty still exists about the relative costs of acquiring and deploying Atrucks, multiple scenarios were tested here, with different parameter assumptions. Atruck operating costs are expected to be much lower than Htruck costs, overall, thanks to a reduction in operator/attendant burden from the driving task and Atrucks' greater utilization, as their attendants rest/sleep or perform other duties (and are not subject to strict hours of service regulations, since they cannot cause a fatal crash, for example). Wages and benefits may fall, or simply shift from administrative and service workers that used to be officed (e.g., those managing carrier logistics, customer service calls, or shipper billing) to workers that now travel between states on-board a moving office (and help with pickups and deliveries, as those arise).

Scenario 1 serves as a reference, high-technology (Atrucks in operation) case for the following discussion of nine different Atruck scenarios. Base case is the mode share before Atrucks implementation. After the introduction of Atrucks, the mode share of trucks increases compared to rail, but the total ton-mile and dollar mile decreases. Compared to Scenarios 1 through 3, the cost of Htruck use is assumed to be 20% higher (in Scenarios 4 through 6) or lower (Scenarios 7 through 9), while Atruck costs are assumed to be 75%, 50%, and 25% of Htruck costs (per ton-mile, container-mile or commodity-mile), respectively, resulting in 9 (3 x 3) separate scenarios. Table 2 presents basic mode split results for FAF^4 and these 9 scenarios. Interestingly, Atruck splits (either by dollar-miles carried or ton-miles transported) are very stable across the 9 scenarios, at around 90 percent and 85 percent, regardless of the relative price variation.

Sensitivity analysis is also applied for Atruck ASCs and scaling parameters for the nested logit model. With slight changes, the more attractive that one makes Atrucks, relative to Htrucks, the more dollar-miles and ton-miles will be carried by trucks. For the test of scaling parameter, if increased substitution is assumed between alternatives in the truck nest or the mode nest, the truck split will increase slightly.

Table 2 Sensitivity Analysis

(a) Operation Cost Test Results

Scenario	Cost of Htruck	Cost of Atruck	10^9 dollar-miles				10^9 Ton- miles			
			Rail	%	Truck	%	Rail	%	Truck	%
Base	-	-	1.87	10.5%	15.90	89.5%	6.89	13.83%	42.93	86.2%

1*	100%	75%	1.45	8.9%	14.77	91.0%	6.07	13.33%	39.46	86.7%
2	100%	50%	1.44	9.3%	14.12	90.8%	6.10	13.98%	37.52	86.0%
3	100%	25%	1.43	9.7%	13.38	90.3%	6.16	14.87%	35.26	85.1%
4	80%	75%	1.46	9.2%	14.40	90.8%	6.15	13.83%	38.31	86.2%
5	80%	50%	1.45	9.5%	13.84	90.5%	6.20	14.47%	36.64	85.5%
6	80%	25%	1.44	9.8%	13.25	90.2%	6.23	15.17%	34.85	84.8%
7	120%	75%	1.47	8.9%	14.99	91.1%	6.07	13.10%	40.26	86.9%
8	120%	50%	1.42	9.0%	14.40	91.0%	6.12	13.76%	38.35	86.2%
9	120%	25%	1.41	9.4%	13.52	90.6%	6.16	14.57%	36.11	85.4%

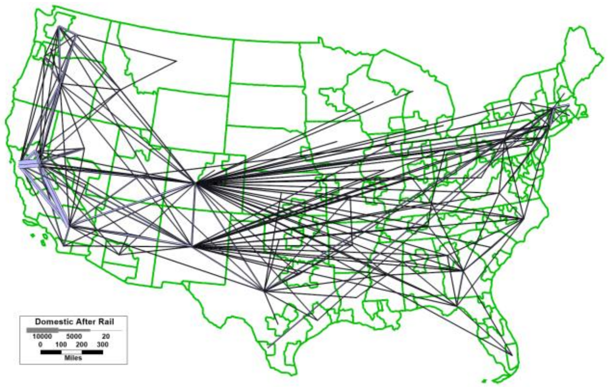
(b) Atruck ASCs Test

Scenario	ASC for Atruck	10^9 dollar-miles				10^9 Ton- miles			
		Rail	%	Truck	%	Rail	%	Truck	%
1*	-0.1	1.45	8.9%	14.77	91.1%	6.07	13.3%	39.46	86.7%
2	-0.3	1.45	8.9%	14.81	91.1%	6.08	13.3%	39.59	86.7%
3	0.1	1.46	9.2%	14.40	90.8%	6.15	13.8%	38.32	86.2%

(c) Scaling Parameters Test

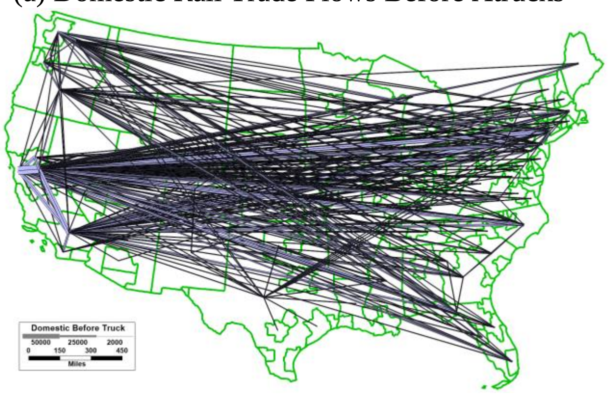
Scenario	$\theta^m_{ij,mode}$	$\theta^m_{ij,truck}$	10^9 dollar-miles				10^9 Ton- miles			
			Rail	%	Truck	%	Rail	%	Truck	%
1*	1.2	1.4	1.45	8.9%	14.77	91.0%	6.07	13.3%	39.46	86.7%
2	1.2	1.3	1.54	9.2%	15.13	90.8%	5.70	12.2%	41.10	87.8%
3	1.1	1.4	1.50	9.6%	14.15	90.4%	6.52	14.8%	37.77	85.3%

Figure 5 illustrates estimated changes in flow patterns for trucks and railroads before and after the introduction of Atrucks (where truck flows are the sum of Atruck and Htruck flows). The measurement scale is adjusted to reflect only the most common OD pairs and major flow volumes (since much more is carried by truck [than by rail] in the U.S. and for domestic [rather than export] purposes). For domestic trade flows, rail trade patterns suggest a dramatic shift toward continuing various trans-continental rail flows, following the introduction of Atrucks, from an end-point concentration in central Colorado. This is probably because Atrucks have replaced some of the mid- or long-distance flows from central Colorado so that rail trade goes directly from west locations to east locations. Truck flows are predicted to lose many interactions between the western U.S. and Floridian and northeastern regions, but experience greater interactions among northwestern regions. Export trade flows is much lighter than domestic flows, in general, and their connections among southern, northwestern and northeastern U.S. regions appear enhanced by rail ties, following introduction of Atrucks, while trucks appear to lose overall trade flows between the nation’s northwest and southeast regions.

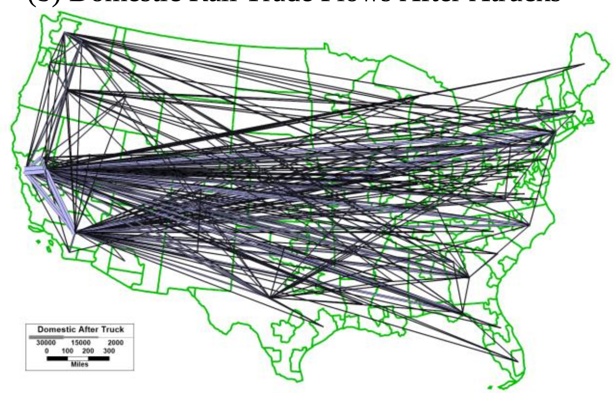


(a) Domestic Rail Trade Flows Before Atrucks

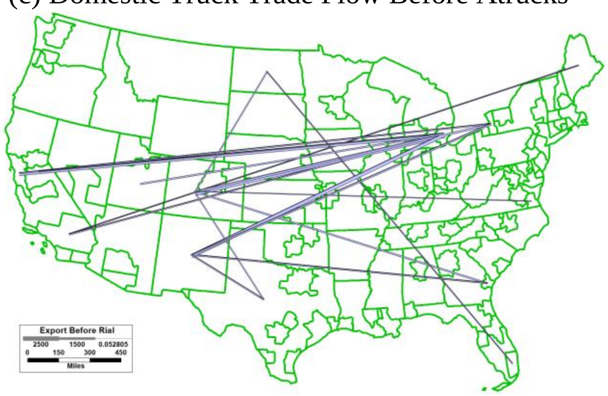
(b) Domestic Rail Trade Flows After Atrucks



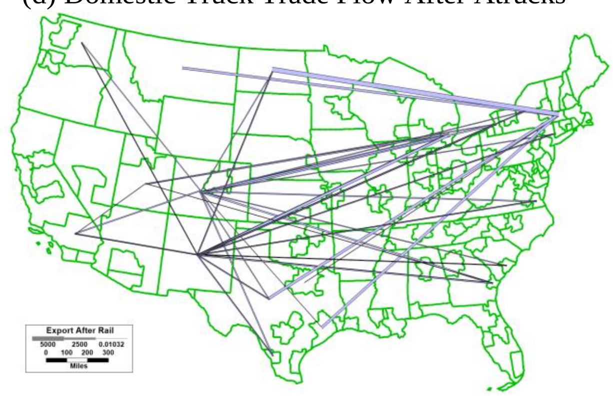
(c) Domestic Truck Trade Flow Before Atrucks



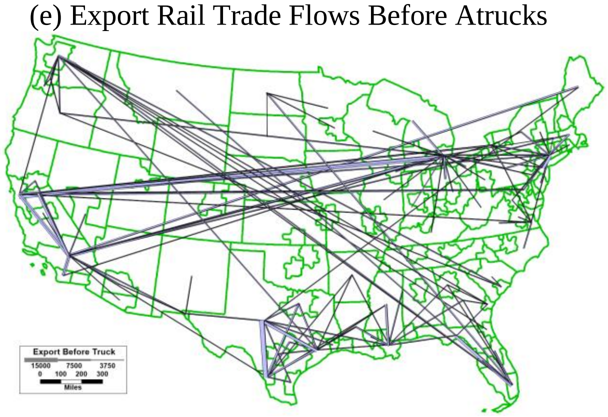
(d) Domestic Truck Trade Flow After Atrucks



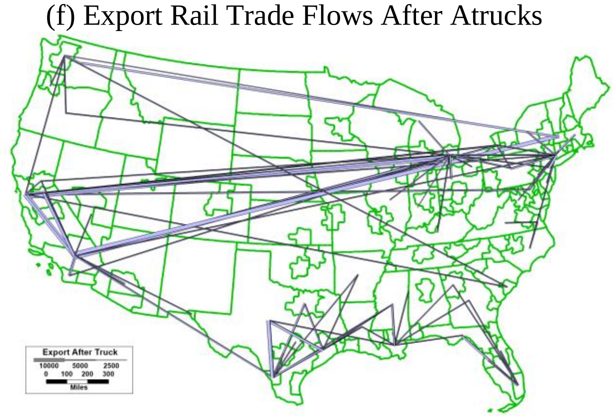
(e) Export Rail Trade Flows Before Atrucks



(f) Export Rail Trade Flows After Atrucks



(g) Export Truck Trade Flows Before Atrucks

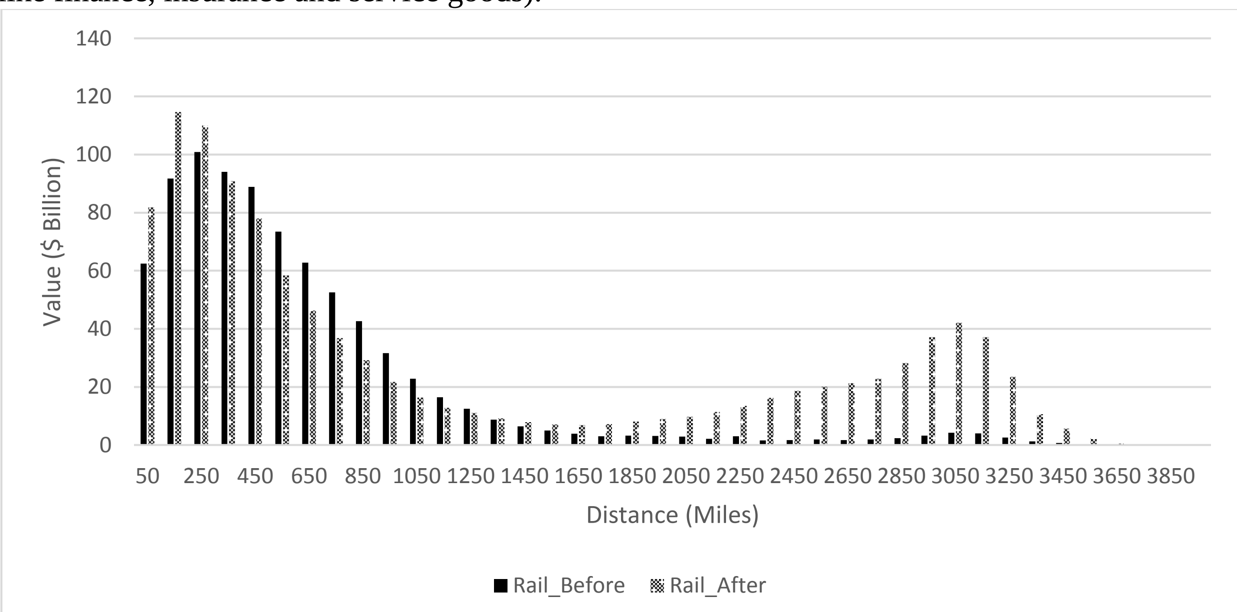


(f) Export Truck Trade Flows After Atrucks

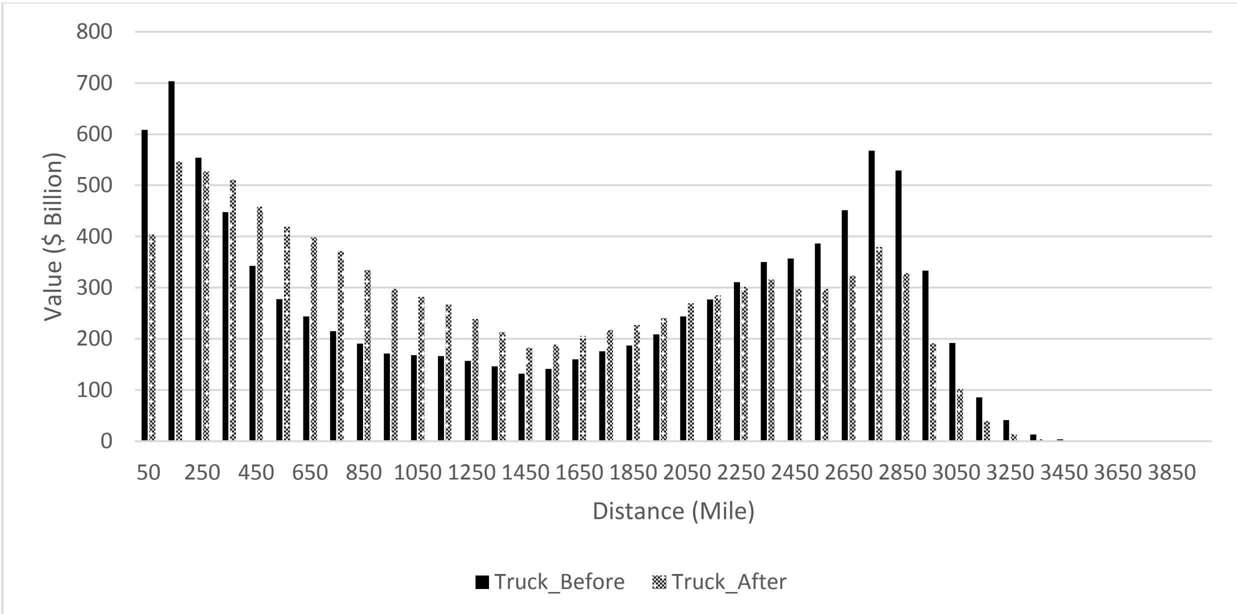
361 **Figure 5 Principal U.S. Trade Flow Patterns Before and After Atrucks ($ Million).**

Trip-length distributions are another meaningful way to view Atrucks' effects on travel patterns. Figure 6 shows such distributions for domestic rail shipments, (total) truck shipments, and Atruck versus Htruck shipments. Figure 6(a) shows that rail flows are predicted to rise at short distances (under 250 miles between counties) and very long distances (over 1550 miles), while trucks see flow increases on longer trips: between 350 miles and 2150 miles. This is likely because Atrucks are quite competitive for mid- and long-distance trade. However, when input access distances exceed 2000 miles, railway's lower costs prove very competitive, for many commodities (e.g., those that are less time-sensitive, low value per ton, and/or perishable).

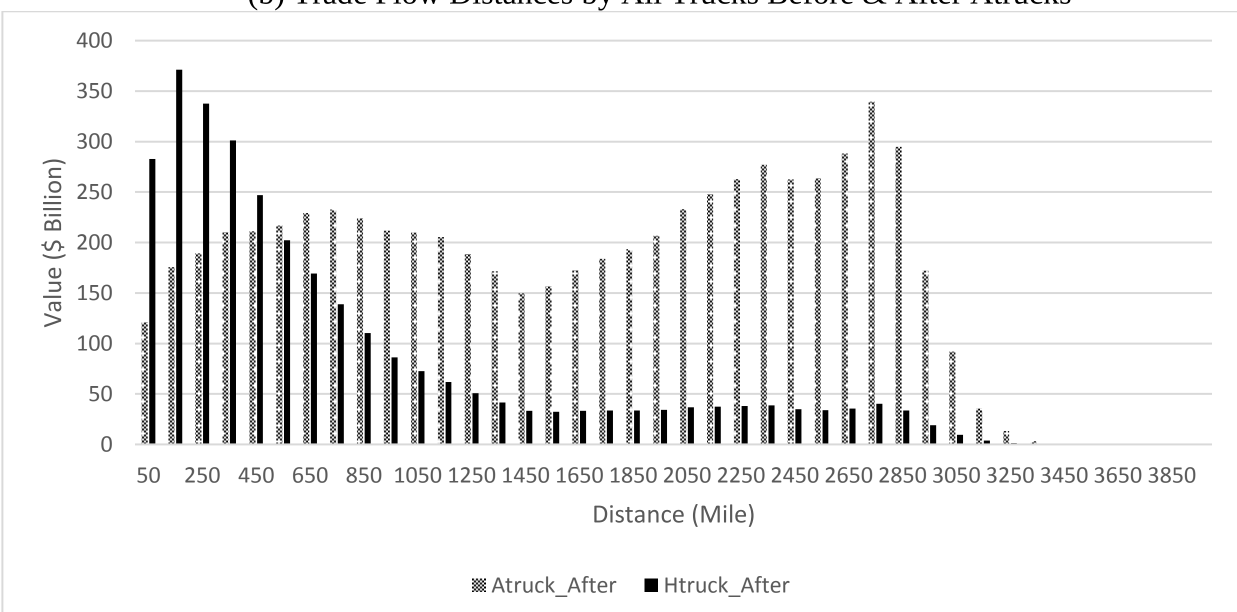
Figure 6(c) illustrates mode splits between Atrucks and Htrucks, across domestic trade-flow distances. Htrucks appear to still dominate up to about 300 miles of distance, and Atrucks clearly dominate after about 750 miles of travel distance. Interestingly, truck movements appear to peak at just 150 miles of (inter-county) travel distance, for domestic shipments, while Atruck flow values do not peak until 2,750 miles of travel distance. 2,750 miles is essentially the distance separating the nation's two largest regions: New York City and Los Angeles (as well as Miami to Los Angeles, for example), making this an important OD pair for many commodities (like finance, insurance and service goods).



(a) Trade Flow Distances by Rail Before & After Atrucks



(b) Trade Flow Distances by All Trucks Before & After Atrucks



(c) Trade Flow Distances by HTrucks & Atrucks (After Introduction of ATrucks)

Figure 6 Trip Length Distributions for U.S. Rail and Trucks Flows, Before and After Atrucks. (Note: x-axis values are distance mid-points for those bins.)

Table 3 shows commodity flow changes by mode, following the introduction of Atrucks, under the Base Case vs. reference Scenario 1. Domestic truck flows are forecast to decrease 8% by ton-mile and rail flow values fall by 12.6%. Machinery, miscellaneous, durable and non-durable manufacturing trade flows (between U.S. counties) are predicted to experience a large decrease (greater than 70%) as a result of Atruck implementation. This boost trend in ton-mile also happens to agriculture, forestry, fishing, hunting, chemicals, plastics and primary metal manufacturing, which showed a rise of greater than 60%. This is probably because Atrucks becomes a way better than train to transport these commodities to further destinations in time.

With the availability of Atrucks, food, beverage, tobacco product, computer, electronic product and electrical equipment manufacturing by trucks increase by approximately 30%. However, rail flow of these products increases more than double. Although the advent of Atrucks increases the demand, railway remains to be an effective and efficient way for transporting these commodities. Seven sectors see a decrease in total (domestic) value shipped, while 13 sectors gain an increase.

In terms of export flows, predicted truck flow values witness increases arranging from 9.8% to 95.7%, except for durable and non-durable manufacturing, which decreases by 90.9%. This might be the same reason as discussed for domestic flow. Total rail flow of commodities headed for U.S. export zones rises by 75.7% while total truck flow decreases by 1.5%. Interestingly, total export flows see rising trend for all types of commodities.

Table 3 Change in U.S. Trade Flow Ton-miles Before and After Atrucks

Million ton-miles	Domestic Truck			Domestic Rail			Domestic Total		
Sector	Before	After	%	Before	After	%	Before	After	%
1	27.89	45.20	62.1%	0.004	0.002	-40.8%	27.89	45.20	62.1%
2	1,237.8	1,516.8	22.5%	757.7	931.7	23.0%	1,996	2,448	22.7%
3	4,652.7	4,993.0	7.3%	2,874.6	3,948.2	37.3%	7,527	8,941	18.8%
4	131.36	170.11	29.5%	8.11	26.66	228.8%	139.47	196.76	41.1%
5	58.51	109.37	86.9%	4.98	1.17	-76.6%	63.49	110.54	74.1%
6	43.19	69.77	61.6%	4.94	1.53	-69.1%	48.13	71.30	48.1%
7	59.92	99.30	65.7%	8.82	5.57	-36.9%	68.74	104.87	52.6%
8	200.87	225.46	12.2%	9.88	0.19	-98.1%	210.75	225.64	7.1%
9	8.61	15.49	79.8%	0.09	0.25	188.0%	8.70	15.74	80.9%
10	8.12	10.89	34.1%	0.05	0.20	262.9%	8.18	11.09	35.6%
11	22.96	29.69	29.3%	2.34	2.01	-14.3%	25.30	31.69	25.3%
12	262.70	43.43	-83.5%	405.65	759.98	87.3%	668.35	803.41	20.2%
13	10.99	18.98	72.7%	0.13	0.16	23.3%	11.12	19.14	72.1%
14	164.19	143.04	-12.9%	12.24	1.36	-88.9%	176.43	144.40	-18.2%
15	2,498.5	2,226.5	-10.9%	191.01	20.63	-89.2%	2,690	2,247	-16.4%
16	496.17	441.67	-11.0%	36.40	2.90	-92.0%	532.6	444.6	-16.5%
17	13,918	12,388	-11.0%	1,021.3	55.1	-94.6%	14,939	12,443	-16.7%
18	16,701	14,701	-12.0%	1,239.1	80.4	-93.5%	17,940	14,781	-17.6%
19	330.63	292.18	-11.6%	24.44	1.57	-93.6%	355.1	293.8	-17.3%
20	1,250.1	1,107.6	-11.4%	92.62	10.16	-89.0%	1,342.7	1,117.7	-16.8%
SUM	42,084	38,647	-8.2%	6,694.5	5,849.8	-12.6%	48,778	44,497	-8.8%
Thousand ton-miles	Export Truck			Export Rail			Export Total		
Sector	Before	After	%	Before	After	%	Before	After	%
1	136.5	230.9	69.2%	0.0100	0.0003	-96.8%	136.5	230.9	69.2%
2	69,583	82,890	19.1%	42,297	51,492	21.7%	111880	134382	20.1%
4	110,132	137,754	25.1%	6,546	23,343	256.6%	116678	161097	38.1%
5	18,718	34,371	83.6%	1,830.6	372.4	-79.7%	20548	34744	69.1%
6	24,069	35,906	49.2%	2,847.0	706.6	-75.2%	26916	36612	36.0%
7	5,343	8,848	65.6%	826.11	449.08	-45.6%	6169	9297	50.7%
8	11,419	12,537	9.8%	529.54	9.91	-98.1%	11949	12547	5.0%
9	5,166	10,112	95.7%	43.99	0.37	-99.1%	5210	10112	94.1%

10	7,378	9,672	31.1%	38.77	0.11	-99.7%	7417	9672	30.4%
11	31,291	44,488	42.2%	13,475	3,223	-76.1%	44766	47711	6.6%
12	119,506	10,863	-90.9%	141,356	289,143	104.5%	260862	300007	15.0%
13	10,684	19,365	81.2%	119.1	7.4	-93.7%	10803	19372	79.3%
SUM	413,426	407,037	-1.5%	209,909	368,747	75.7%	623335	775784	24.5%

CONCLUSIONS

This study used the RUBMIO trade model to anticipate the shifts in U.S. trade patterns due to the introduction of a Atrucks. Lower-cost trucking operations will impact choice of mode as well as input origins, affecting production and flow decisions for domestic and export trades. Here, 20 commodity types are tracked using the 2012 CFS and FAF^4 data sets. Sensitivity analysis allows for variations in predictions, given the great uncertainty that accompanies shippers' future cost-assessments, adoption rates, and use of Atrucks. Such predictions should prove helpful to counties and regions, buyers and suppliers, investors and carriers, as they prepare for advanced automation in our transportation systems.

This study is an initial attempt to reflect self-driving trucks in long-distance freight systems. It relies on U.S. highway and railway networks as well as FAF^4 trade data. Extensions of this work may wish to reflect other modes, like airlines, waterways, and pipelines, as well as multi-modal and inter-modal flows, local supply-chains, urban logistics, and local production capabilities and port capacities. In terms of the RUBMRIO model's specification, reflecting the dynamic evolution of population and employment patterns (as in Huang and Kockelman [2010]), commuting and shopping trips, with intra-regional and inter-regional congestion, as well as seasonal variations in certain shipments (like agriculture and coal) may prove very helpful. Further extensions on random utility models employed here can come through different nesting structures, as well as operator awake hours, routing, and delivery scheduling.

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