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 current U.S. Freight Analysis Framework (FAF^4) data for travel times and costs - and assuming that Atrucks lower trucking costs by 25% (per ton-mile delivered), truck flow values in ton-miles are predicted to rise 11%, due to automation's lowering of trucking costs, while rail flow values fall 4.8%. Rail flows are predicted to rise 6.6% for trip distances between 1,000 and 1,500 miles, with truck volumes rising for other distances. Introduction of Atrucks favors longer truck trades, but rail's low price remains competitive for trade distances over 3,000 miles. Htrucks continue to dominate in shorter-distance freight movements, while Atrucks dominate at distances over 500 miles. Eleven and twelve commodity sectors see an increase in trucking's domestic flows and export flows, respectively. And total ton-miles across all 13 commodity groups rise slightly by 3.1%, as automation lowers overall shipping costs.

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 year 2014, trucks carried 1,996 billion ton-miles of freight around the U.S., or 37.7% of the nation's total ton-miles transported 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. long-distance-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 (47%) 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) noted 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. Atrucks cost-savings impacts on freight momement and industry siting and sizing decisions have been neglected. This new topic area of Atrucks is explored here.

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 13 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's (2012) work by adding the Atruck option into a sub-nest for mode choice, allowing for strong correlation in the Atruck vs. Htruck choice (since these are two very similar modes). 13 aggregate "industries" or socio-economic sectors are used here, since all nested logit model parameters are calibrated from FAF[4] data, which rely on SCTG commodity classes. Corresponding NAICS and IMPLAN codes are shown in Table 1, which is adapted from Du and Kockelman's (2012) work. The application's 13 sectors, technology costs, and other assumptions are described below.

TABLE 1 Description of Economic Sectors in RUBMRIO Model

Sector	Description	IMPLAN Code	NAICS Code	SCTG Code
1	Agriculture, Forestry, Fishing and Hunting	1~19	11	1
2	Mining	20~30	21	10~15
3	Construction	34~40	23	--
4	Food, Beverage and Tobacco Product Manufacturing	41~74	311, 312	2~9
5	Petroleum and Coal Product Manufacturing	115~119	324	16~19
6	Chemicals, Plastics and Rubber Product Manufacturing	120~152	325, 326	20~24
7	Primary Metal Manufacturing	170~180	331	32
8	Fabricated Metal Manufacturing	181~202	332	33
9	Machinery Manufacturing	203~233	333	34
10	Computer, Electronic Product and Electrical Equipment Manufacturing	234~275	334, 335	35, 38
11	Transportation Equipment Manufacturing	276~294	336	36, 37
12	Other Durable & Non-Durable Manufacturing	75~114, 153~169, 295~304	313~316, 321~323, 327, 337	25~31, 39
13	Miscellaneous Manufacturing	305~318	339	40, 41, 43

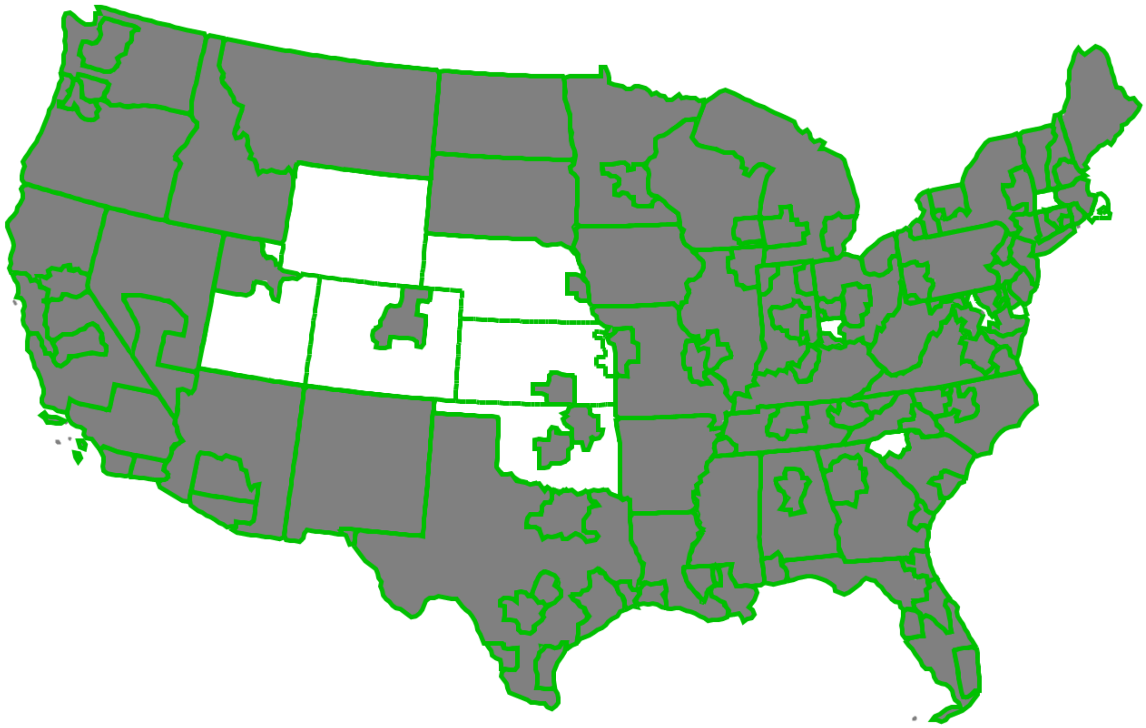
DATA SETS

Data sets used here 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 tables and regional purchase coefficients (in year 2008) from IMPLAN, and railway and highway network data from Caliper's TransCAD 7.0.

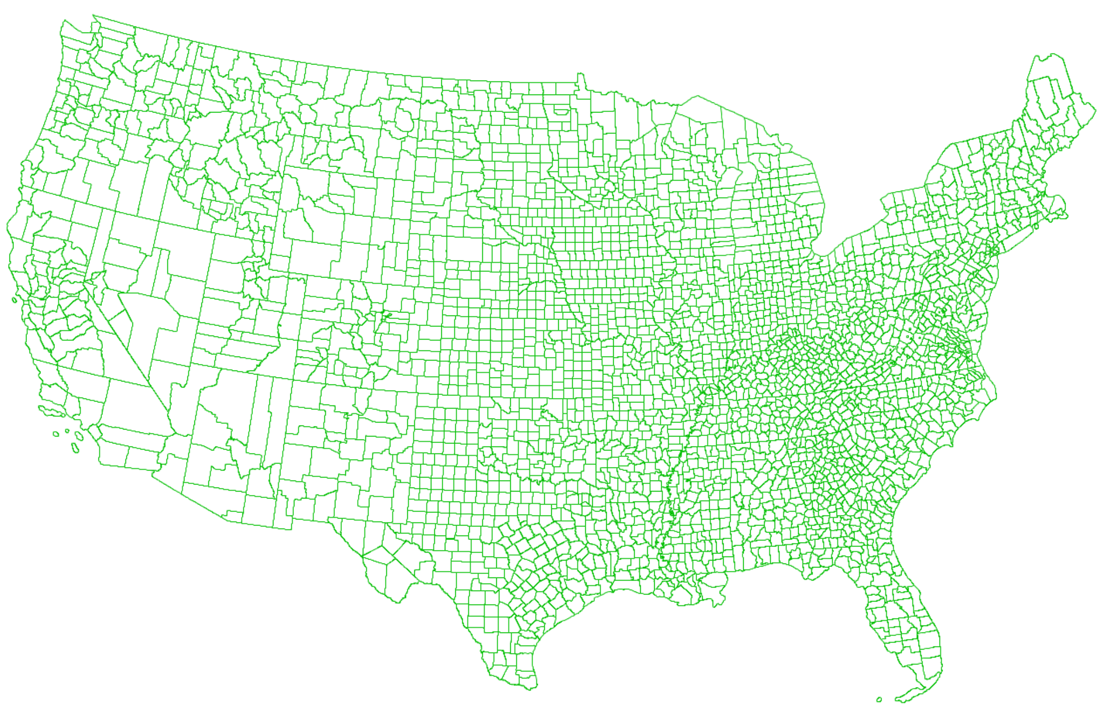
Freight Data

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 FAF^4's 132 aggregate zones. FAF^4's origin-destination-commodity-mode annual freight flows matrices were used to predict domestic and export trade flows by zone FAF^4 data show foreign export flows exiting the U.S. from 117 of these 132 zones, as shown in gray in Figure 1(a).So these same 117 zones serve as both production and export zones in this paper's trade modeling system.

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



(a) Continental United States' FAF^4 132 Zones, with 117 Export Zones (shown in grey)



(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 13 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.

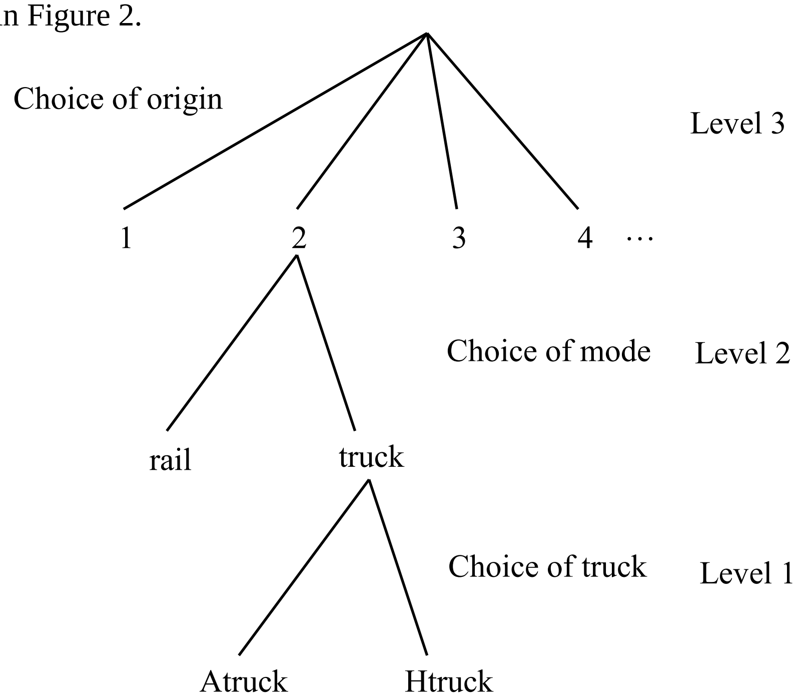


FIGURE 2 Random utility structure for shipment origin, mode, and truck-type choices.

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

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

where
$\widetilde{V}^m_{ij}$ = systematic utility of selecting origin *i* for acquisition of commodity *m*,
$\widetilde{V}^m_{ij,\,rail}$, $\widetilde{V}^m_{ij,\,truck}$ = systematic utilities associated with selecting origin *i* and rail mode/any truck type for movement of commodity *m*,
$\widetilde{V}^m_{ij,\,truck,\,Atruck}$,$\widetilde{V}^m_{ij,\,truck,\,Htruck}$ = systematic utilities associated with selecting origin *i* and Atruck/Htruck for movement of commodity *m*, and
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:

$$P^m_{ij} = \frac{\exp(V^m_{ij})}{\sum_i \exp(V^m_{ij})} \tag{2}$$

where

$$V^m_{ij} = -p^m_i + \gamma^m \ln(pop_i) + \lambda^m \theta^m_{ij,mode} \Gamma^m_{ij,mode} \tag{3}$$

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

$$\Gamma^{\mathrm{m}}_{ij,mode} = \ln\left(\exp\left(\frac{V^m_{ij,\,rail}}{\theta^m_{ij,mode}}\right) + \exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right) \right)$$

(4)

is the logsum of mode choice, with scale parameter $\theta^m_{ij,mode}$=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:

$$\begin{aligned} P^m_{rail|ij} &= \frac{\exp\left(\frac{V^m_{ij,\,rail}}{\theta^m_{ij,mode}}\right)}{\exp\left(\frac{V^m_{ij,\,rail}}{\theta^m_{ij,mode}}\right) + \exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)} \\ P^m_{truck|ij} &= \frac{\exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)}{\exp\left(\frac{V^m_{ij,\,rail}}{\theta^m_{ij,mode}}\right) + \exp\left(\frac{V^m_{ij,truck}}{\theta^m_{ij,mode}}\right)} \end{aligned} \tag{5}$$

where

$$V^{m}_{ij,\ rail}=\beta^{m}_{0,\ rail}+\beta^{m}_{r,time}\times time_{ij,\ rail}+\beta^{m}_{r,cost}\times cost_{ij,\ rail}$$
and $V^{m}_{ij,\ truck}=0+\theta^{m}_{ij,truck}\Gamma^{m}_{ij,truck}$ (6)

are the general modes' systematic utilities and

$$\Gamma^{m}_{truck}=\ln\left(\exp\left(\frac{V^{m}_{ij,\ truck,Atruck}}{\theta^{m}_{ij,truck}}\right)+\exp\left(\frac{V^{m}_{ij,\ truck,Htruck}}{\theta^{m}_{ij,truck}}\right)\right) \quad (7)$$

is the logsum for the truck-mode choice, with scale parameter $\theta^{m}_{ij,truck}$ = 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. In fact, Atrucks may complete long trips faster than Htrucks, since Atruck operators can sleep while the vehicle is en route. 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:

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

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

where

$$V^{m}_{ij,\ truck,Atruck}=\beta^{m}_{0,\ Atruck}+\beta^{m}_{t,time}\times time_{ij,truck}+\beta^{m}_{t,cost}\times cost_{ij,Atruck}$$
$$V^{m}_{ij,\ truck,\ Htruck}=0+\beta^{m}_{t,time}\times time_{ij,truck}+\beta^{m}_{t,cost}\times cost_{ij,Htruck} \quad (9)$$

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 this solution's 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).

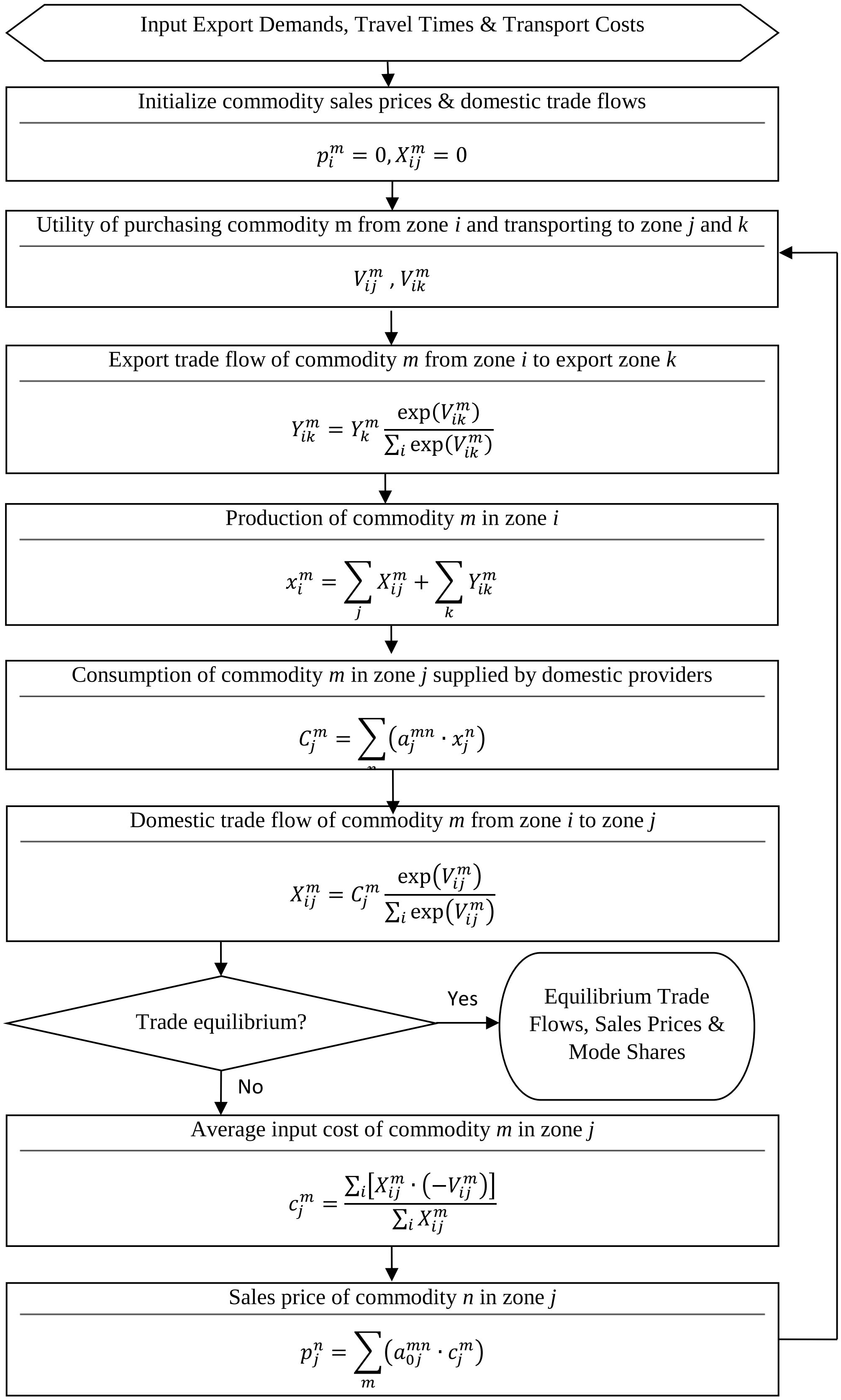


FIGURE 3 RUBMRIO solution algorithm (Adapted from Du & Kockelman [2012], Figure 2).

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 (which reflect 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. Moreover, the Atruck ASCs were assumed to be -0.1, because Atrucks should be somewhat preferred, after travel-cost and time considerations, thanks to safety and communications benefits. After assembling all these inputs, shown in Table 2, a series of different network and Atruck cost scenarios can be examined, using the RUBMRIO solution algorithms.

TABLE 2 Parameter Estimates for Origin, Mode and Truck Choice Equations

Sector	Origin Choice Parameters		Mode Choice Parameters			Truck Choice Parameter			VOTT ($/hr)
	$\theta_{ij}^{m}=1$		$\theta_{ij,mode}^{m}=1.2$			$\theta_{ij,truck}^{m}=1.4$			
	γ^m	λ^m	$\beta_{0,\ rail}^{m}$	$\beta_{r,time}^{m}$	$\beta_{r,cost}^{m}$	$\beta_{0,\ Atruck}^{m}$	$\beta_{t,time}^{m}$	$\beta_{t,cost}^{m}$	
1	0.05	0.90	-3.38	-4.81	-4.85	-5.61	-5.66	-0.10	24.18
2	0.41	7.66	-1.11	-1.03	-2.01	-1.20	-2.34	-0.10	2.12
4	0.86	-2.86	-3.36	2.17	0.56	2.53	0.65	-0.10	6.15
5	0.10	2.02	-1.00	-1.87	-4.09	-2.18	-4.77	-0.10	52.46
6	0.79	1.60	-0.85	-1.21	-1.34	-1.41	-1.57	-0.10	26.61
7	0.75	3.38	-0.86	-0.99	-1.54	-1.15	-1.79	-0.10	37.31
8	0.90	0.35	-1.91	-0.57	-0.89	-0.67	-1.04	-0.10	37.17
9	0.78	0.68	2.17	-10.20	-8.38	-11.90	-9.77	-0.10	19.71
10	1.00	0.19	0.95	-7.20	-4.99	-8.40	-5.82	-0.10	16.64

11	1.02	-1.68	2.08	-7.31	-6.32	-8.53	-7.38	-0.10	20.77
12	0.89	2.18	-3.32	1.85	0.69	2.16	0.81	-0.10	8.96
13	0.92	1.61	-1.70	-2.28	-2.35	-2.66	-2.74	-0.10	24.76

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 13 industries and 3 travel modes. $8.3trillion in trade flows were generated to meet the year 2015 export demand of $1.04 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 model's total flow predictions account for 91.3% of FAF^4's total $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 travel costs of $1.85 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 3 compares RUBMRIO trade flow results to those in the FAF^4 database, after aggregating the model's 3109 trade zones into the nation's 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 model's smallest-value domestic shipments come from 13,896 FAF-zone pairs, for $0.85 trillion, or the first 10% of the total ($8.5 trillion) in domestic flows. FAF^4-based values (for highly aggregate regions/zones) suggest something similar: over 12,000 FAF-zone pairs are involved in that first 10% (smallest-shipment-size) set of flows.

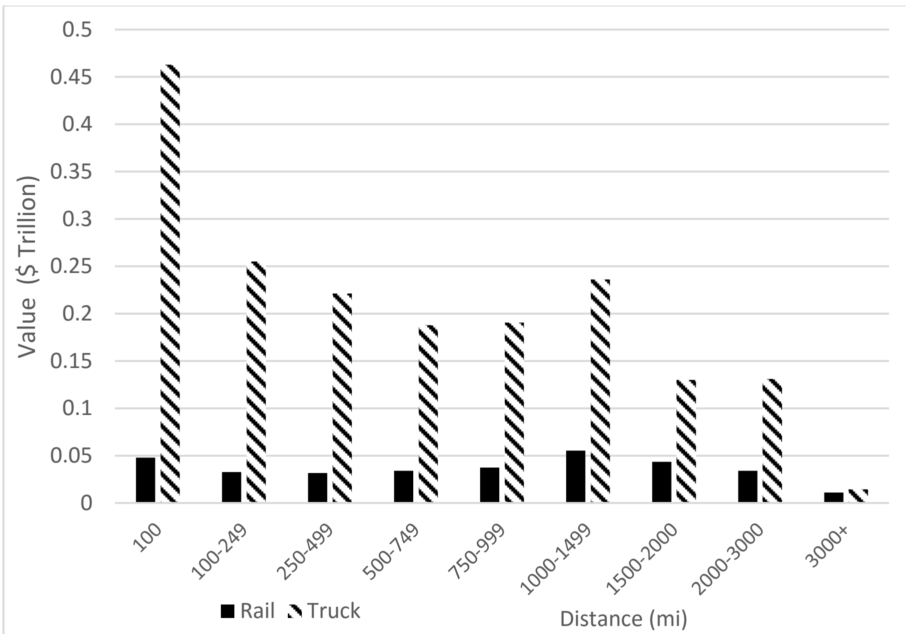
Table 3's comparison suggests that the base case RUBMRIO model equations and assumptions deliver reasonable trade-flow estimates of FAF^4 volumes. However, RUBMRIO tends to "spread out" the trades across more OD pairs (with fewer small-size shipments) than FAF^4 data suggest. In other words, RUBMRIO predictions suggest 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 concise and transparent set of equations (Figure 3 plus equations 10 and 11).

TABLE 3 Cumulative Distribution of RUBMRIO and FAF^4 Trade Flows

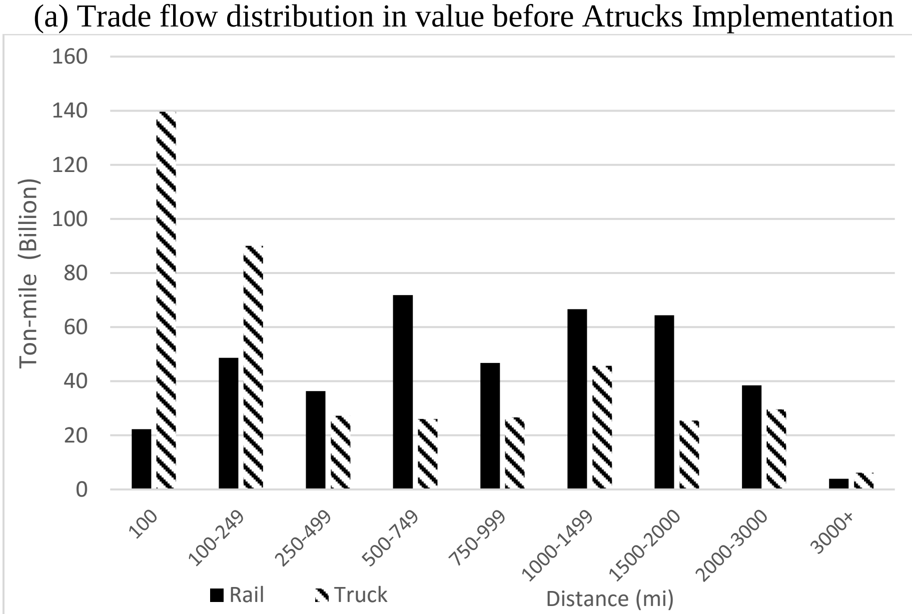
	Domestic Flows		Export Flows	
	RUBMRIO	FAF^4	RUBMRIO	FAF^4
0%-10%	13,896	12,646	14,217	13,971
10%-20%	1,354	2064	617	552
20%-30%	621	935	267	257
30%-40%	324	479	149	146
40%-50%	183	262	97	81
50%-60%	118	134	65	40
60%-70%	82	64	37	26
70%-80%	49	36	19	14

80%-90%	12	16	9	4
90%-100%	2	5	3	2

Figure 4 shows RUBMBRIO's base case trip distribution by trade values and ton-miles, and appears reasonable compared to FAF statistics (Strocko et al., 2014). However, truck trade-value flows are much greater than rail's values across all distances. In ton-mile trading, truck dominates among lower-distance flows, while rail dominates at longer distances.



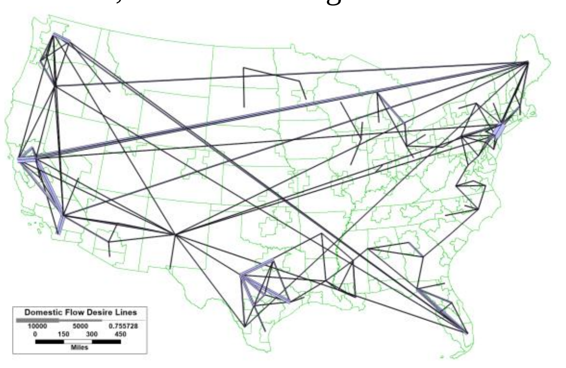
(a) Trade flow distribution in value before Atrucks Implementation



(b) Trade flow distribution in ton-mile before Atrucks Implementation

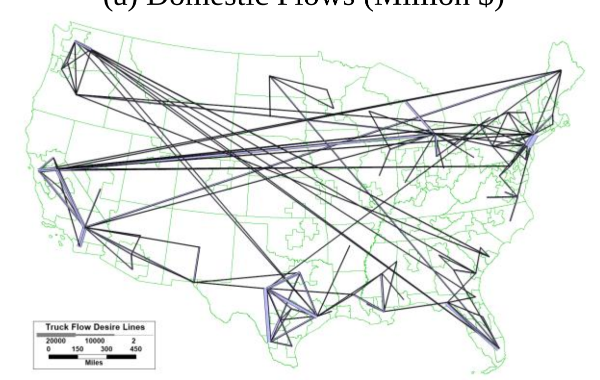
FIGURE 4 Trade distributions (by $ value & ton-miles) for base case (Business as Usual) scenario

For a spatial perspective of these results, Figure 5 shows domestic trade flows and export trade flows pattern, without showing lines for value less than 5%. 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. Truck flows show more intra-state trips with shortest distances, like trips within Texas, Florida and New York, while more longer rail flows tend to cross the nation.

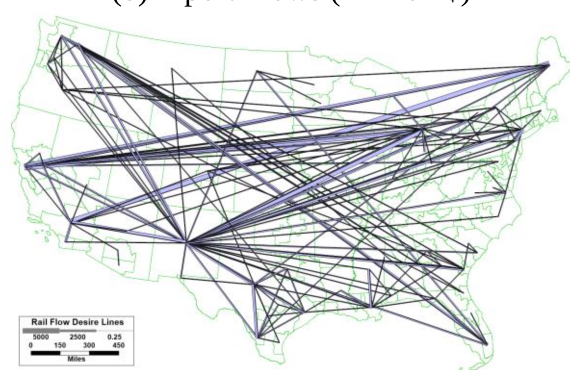


(a) Domestic Flows (Million $)

(b)Export Flows (Million $)



(c) Truck Flows (Million $)



(d) Rail Flows (Million $)

FIGURE 5 Base case domestic and export trade flows (per year), 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 4 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, 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.

TABLE 4 Sensitivity Analysis

(a) Operation Cost Test Results

Scenario	Cost of Htruck	Cost of Atruck	$ Trillion				Billion dollar-miles				Billion ton-miles			
			Rail	%	Truck	%	Rail	%	Truck	%	Rail	%	Truck	%
Base	-	-	0.33	15.3	1.83	84.7	631	43.5	820	56.5	399	49.0	416	51.0
1*	100%	75%	0.21	9.6	1.95	90.4	417	28.4	1,051	71.6	371	44.9	455	55.1
2	100%	50%	0.24	11.2	1.91	88.8	505	33.7	995	66.3	380	45.2	461	54.8
3	100%	25%	0.22	10.4	1.91	89.6	432	27.9	1,114	72.1	374	43.1	494	56.9
4	80%	75%	0.24	10.9	1.92	89.1	494	33.0	1,003	67.0	383	43.8	493	56.2
5	80%	50%	0.25	11.5	1.90	88.5	518	33.6	1,022	66.4	387	43.2	509	56.8
6	80%	25%	0.22	10.1	1.92	89.9	425	26.9	1,154	73.1	379	41.1	543	58.9
7	120%	75%	0.26	11.9	1.90	88.1	595	41.2	848	58.8	384	48.8	402	51.2
8	120%	50%	0.23	10.9	1.91	89.1	459	30.2	1,059	69.8	373	45.0	455	55.0
9	120%	25%	0.23	10.9	1.91	89.1	489	29.7	1,159	70.3	393	44.7	485	55.3

(b) Atruck ASCs Test

Scenario	ASC for Atruck	$ Trillion				Billion Dollar-miles				Billion Ton- miles			
		Rail	%	Truck	%	Rail	%	Truck	%	Rail	%	Truck	%
1*	-0.1	0.24	11.2	1.91	88.8	505	33.7	995	66.3	380	45.2	461	54.8
2	-0.3	0.24	11.4	1.91	88.6	505	33.7	994	66.3	380	45.2	461	54.8
3	0.1	0.24	11.3	1.91	88.7	505	33.7	995	66.3	380	45.1	462	54.9

(c) Scaling Parameters Test

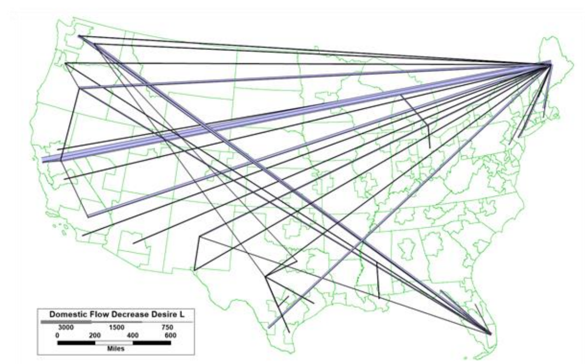
Scenario	$\theta^{m}_{ij,mode}$	$\theta^{m}_{ij,truck}$	$ Trillion				Billion Dollar-miles				Billion Ton-miles			
			Rail	%	Truck	%	Rail	%	Truck	%	Rail	%	Truck	%
1*	1.2	1.4	0.24	11.2	1.91	88.8	505	33.7	995	66.3	380	45.2	461	54.8

2	1.2	1.3	0.21	9.9	1.92	90.1	426	26.4	1,187	73.6	385	39.0	603	61.0
3	1.1	1.4	0.22	10.3	1.92	89.7	459	29.8	1,081	70.2	379	41.5	535	58.5

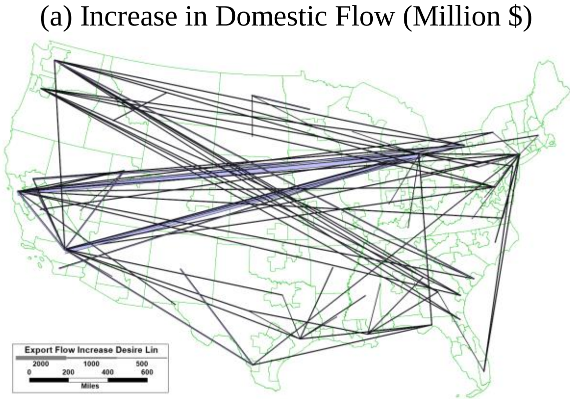
Figure 6 illustrates estimated changes in flow patterns for trucks and railroads before and after the introduction of Atrucks (where truck flows are the sum of Atruck and Htruck flows), with spider maps of rising versus falling flows shown separately. The measurement scale is adjusted to reflect only major flow values (million dollars between OD pairs greater than 5% of total flow value) since much more value is carried by truck [than by rail] in the U.S. and for domestic [rather than export] purposes). Results suggest that increases in domestic flow types occur most heavily along the nation's western coast (through California) and between California and New York. Export flows have their greatest increases between the Great Lakes region (including Michigan and Illinois) and California. Both domestic and export flows are estimated to fall from trucking automation options along the nation's northeastern areas and between Florida and Washington.

As shown in Figure 6, truck flows are also predicted to lose many interactions between the western U.S. and Florida and northeastern states, while experiencing greater interactions between Northwestern (Washington and Oregon) and Eastern (Georgia and South Carolina), and also between the Great Lakes region (including Michigan and Illinois) and California. This is probably due to Atrucks being better able to meet freight demand in Florida and northeastern areas by obtaining more inputs from the nation's northwestern areas. Rail flows are estimate to rise only in and around New Mexico, while noticeably elsewhere (e.g., in Texas and from San Francisco and Arizona to the Great Lakes and northeastern areas, respectively).

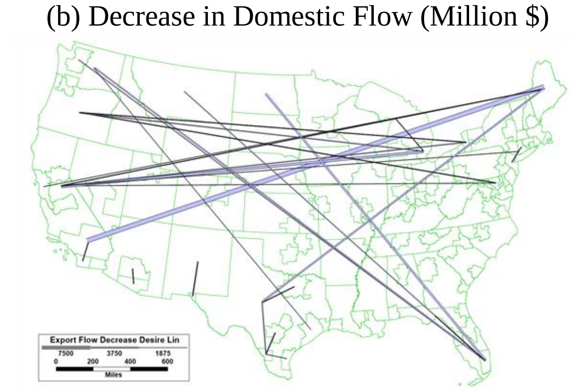
(a) Increase in Domestic Flow (Million $)



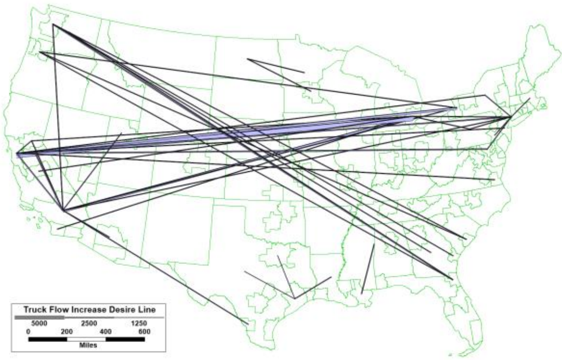
(b) Decrease in Domestic Flow (Million $)



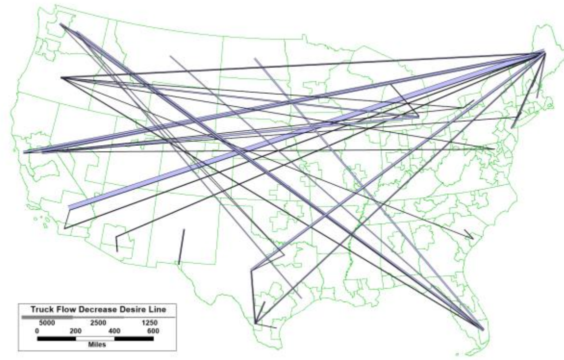
(c) Increase in Export Flow (Million $)



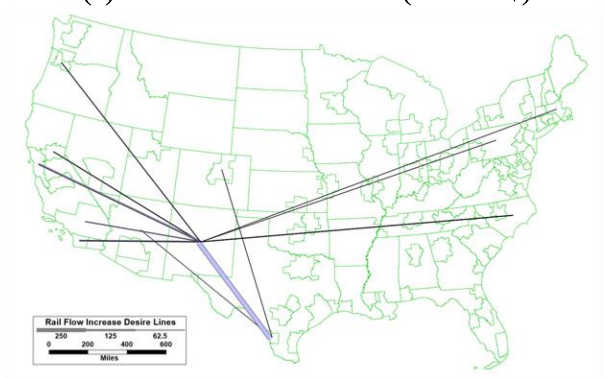
(d) Decrease in Export Flow (Million $)



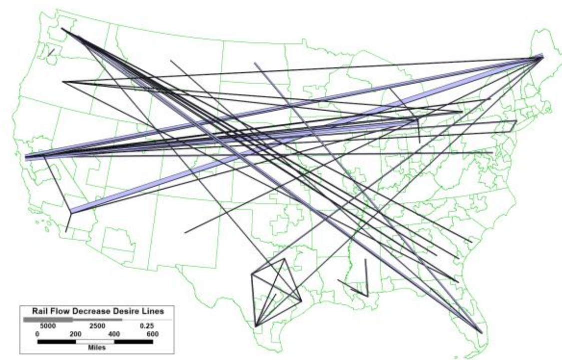
(e) Increase in Truck Flow (Million $)



(f) Decrease in Truck Flow (Million $)



(g) Increase in Rail Flow (Million $)



(f) Decrease in Rail Flow (Million $)

FIGURE 6 Principal U.S. trade flow patterns before and after Atrucks ($ Million per year).

Table 5 shows estimates of flow changes across major U.S. cities. Most (like Sacramento, Washington DC, Indianapolis, and Nashville) experience increases in trucking flows, both into and out of the city. However, Miami, Detroit, Salt Lake City and Houston are estimated to experience roughly a 10% decrease in their current outbound truck flows (with the exception of El Paso, Texas), alongside increases in their pass-through trucking volumes (due to the travel-cost benefits that automation brings the trucking mode). All major cities are predicted to see lower rail flows (inbound and outbound), with San Jose CA and Washington DC experiencing more than 70% reductions in outbound rail flows, and a similar situation happens for rail flows into Jacksonville FL and Washington DC.

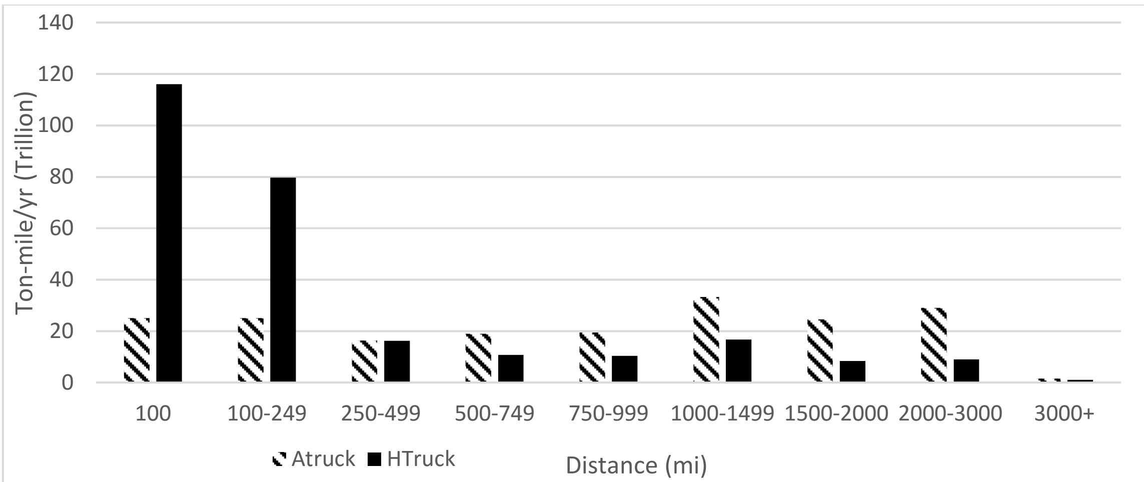
TABLE 5 Automated Trucking's Impact on Trade Flows Originating from or Destined for Major U.S. Cities

State	City	Truck Flow (change in $)		Rail Flow (change in $)	
		Out	In	Out	In
AZ	Phoenix	0%	-3%	-35%	-42%
CA	Los Angeles	4%	-1%	-37%	-45%
CA	Sacramento	22%	15%	-40%	-35%
CA	San Diego	10%	5%	-25%	-26%
CA	San Jose	19%	2%	-72%	-42%
CO	Denver	14%	9%	-6%	-15%
DC	Washington	38%	34%	-77%	-74%
FL	Miami	-21%	-3%	-67%	-53%

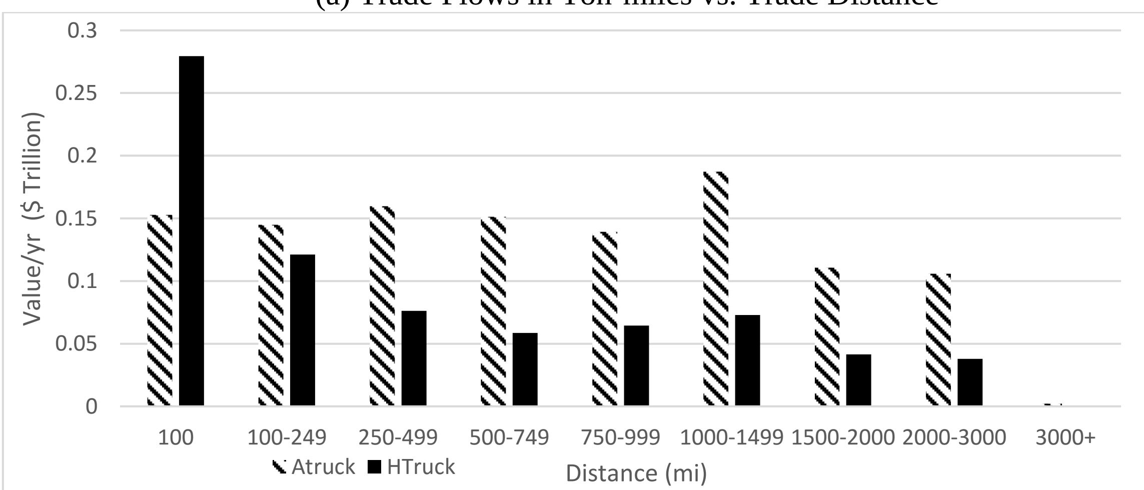
FL	Orlando	5%	5%	-43%	-39%
FL	Jacksonville	5%	19%	-44%	-73%
GA	Atlanta	11%	10%	-40%	-44%
IL	Chicago	7%	5%	-46%	-41%
IN	Indianapolis	18%	16%	-42%	-34%
KY	Louisville	15%	9%	-40%	-49%
MA	Boston	5%	10%	-48%	-38%
MD	Baltimore	8%	9%	-41%	-52%
MI	Detroit	-12%	6%	-43%	-50%
MN	Minneapolis	17%	13%	-44%	-36%
MO	Kansas City	17%	17%	-50%	-42%
NC	Charlotte	14%	13%	-42%	-36%
NJ	New York	1%	4%	-39%	-37%
NJ	Philadelphia	8%	9%	-40%	-34%
NV	Las Vegas	8%	4%	-34%	-39%
OH	Columbus	14%	13%	-41%	-34%
OK	Oklahoma City	12%	9%	-43%	-39%
OR	Portland	17%	4%	-53%	-39%
TN	Memphis	16%	7%	-45%	-50%
TN	Nashville	22%	19%	-41%	-34%
TX	Austin	0%	-7%	-39%	-38%
TX	Dallas	-2%	-3%	-41%	-41%
TX	Houston	-11%	-1%	-42%	-44%
TX	San Antonio	-6%	-8%	-40%	-41%
TX	El Paso	9%	5%	-44%	-41%
UT	Salt Lake City	-11%	-1%	-46%	-50%
WA	Seattle	3%	-4%	-52%	-39%

Trip-length distributions are another meaningful way to view Atrucks' effects on travel patterns. Figure 7 shows such distributions for total rail shipments, total truck shipments, and Atruck versus Htruck shipments. Figures 7(a) and 6(b) illustrate mode splits between Atrucks and Htrucks, across domestic trade-flow distances. Htrucks appear to still dominate up to about 250 miles of distance, while Atrucks appear to clearly dominate after about 500 miles of travel distance. Htruck flows fall as distance increases, while Atruck flows are quite robust across all distances. Atruck trade volumes appear to peak at 1000 to 1500 miles, which is approximately the distance from Seattle, Washington to Los Angeles, California, or from Dallas, Texas to San Francisco, or from New York to Miami. These are major OD pairs for many commodities (like finance, insurance and service goods).

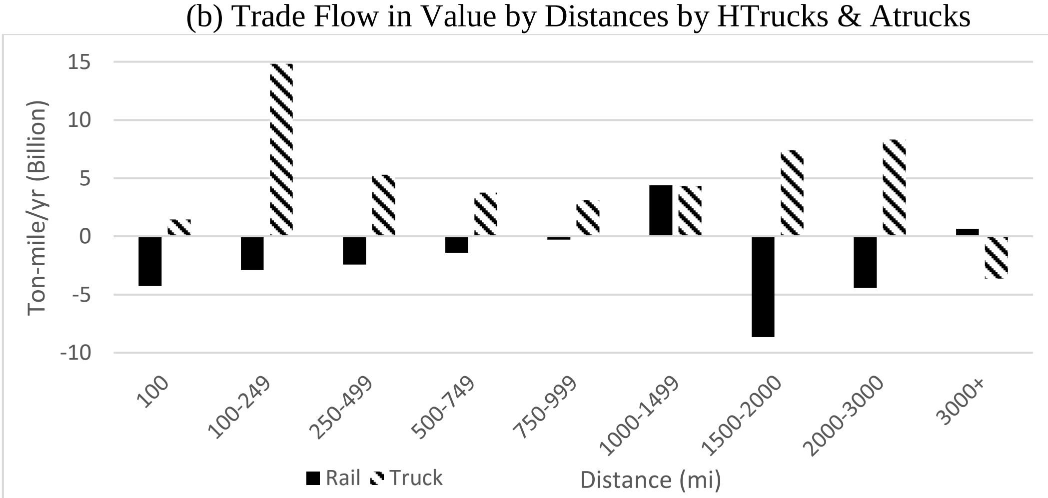
Figures 7(c) and 7(d) show how ton-mile truck flows are predicted to rise for all trip distances, excepting those over 3,000 miles. Trade increments by truck peaks at 100-249 miles, indicating that trade flows are also predicted to transport more within counties. It is interesting to see that the trade value decreases for both truck and rail at smaller distance, showing that trade flows are moving towards longer distances. Rail flow values appear to drop at distances up to 3,000 mi, with a slight increase for very long rail distances - over 3,000 miles. This is likely because Atrucks are quite competitive for mid- and long-distance trade. However, when input access distances exceed 3000 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). There is also a 6.6% increase of rail flow of ton-mile at 1,000 to 1,499 miles. This is probably due to the specific demand of a certain commodity for some interstate OD pairs.



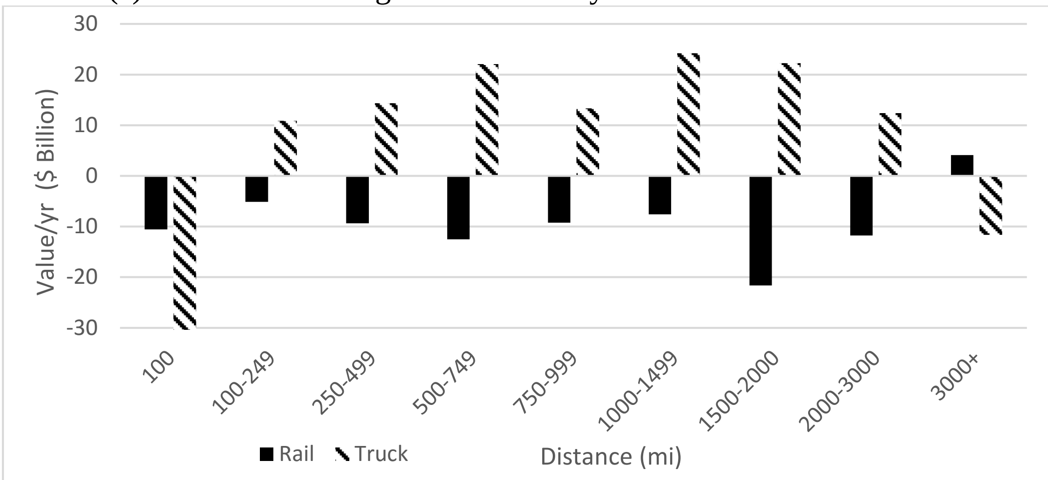
(a) Trade Flows in Ton-miles vs. Trade Distance



(b) Trade Flow in Value by Distances by HTrucks & Atrucks



(c) Trade Flow Change in Ton-mile by Distances Before & After Atrucks



(d) Trade Flow Change in Value by Distances Before & After Atrucks

FIGURE 7 Trip length distributions for U.S. rail and trucks flows, before and after Atrucks.

Table 6 shows commodity flow changes by mode, following the introduction of Atrucks, under the Base Case vs. reference Scenario 2. Introduction of automated trucking or "Atrucks" is expected to increase both total domestic flows and total export ton-mile and value flows, by 2% to 4% respectively. Domestic truck flows (in ton-miles) are forecast to rise 11% (versus a BAU/no-new-technology scenario) and rail flow values fall by 24%. Transportation equipment manufacturing and durable and non-durable manufacturing trade flows (between U.S. counties) are predicted to fall, while construction, food, beverage, tobacco products, primary and fabricated metal manufacturing are all predicted to see a small increase in their trade flows, as a result of automated trucking. Agriculture, forestry, fishing, hunting, chemicals, plastics, petroleum and coal products show some of the biggest relative increases (greater than 10%), presumably because Atrucks making trucking relative more useful in these domains. As expected, railway becomes a *relatively* less effective or efficient way to transport such commodities. Ten sectors see a decrease in total (domestic) value shipped by rail while only three sectors are predicted to rise. Although machinery manufacturing, computers, other electronic products and electrical equipment manufacturing transported by rail rise by more than 500% following automated trucking's introduction, this increment is still much less than the increases transported by truck.

Finally, export truck flows are estimated to rise, from range of 5% to 47%, excepting only durable and non-durable manufacturing trades, which are forecast to shift almost all to rail. Total rail flows of 328 billion ton-miles/year headed for U.S. export zones remains stable, while total truck flows are expected to rise by 11%. Total ton-miles (sum of Truck and Rail or sum of Domestic and Export) increase by 3.1%. As readers can see, RUBMRIO's system of trading equations (Figure 3) deliver a wide array of meaningful predictions, the complexity of which would not be quantifiable without such programs.

Table 6 Change in U.S. Trade Flow Ton-miles Before and After Atrucks

Million ton-miles	Domestic Truck	Domestic Rail	Truck	Domestic

Sector	Before	After	%	Before	After	%	Before	After	%	Before	After	%
1	4,103	5,004	22	7	3	-54	4,203	5,126	22	4,110	5,007	22
2	64,544	76,257	18	14,530	10,442	-28	71,482	84,572	18	79,075	86,699	10
3	149,723	155,453	4	32,655	30,037	-8	156,662	162,741	4	182,379	185,490	2
4	3,382	3,956	17	1,944	1,518	-22	35,715	42,644	19	5,326	5,474	3
5	3,273	4,243	30	554	330	-40	9,170	11,937	30	3,827	4,573	19
6	6,423	8,013	25	1,583	987	-38	18,189	23,070	27	8,006	9,000	12
7	5,511	6,228	13	1,618	1,298	-20	8,157	9,255	13	7,129	7,526	6
8	39,130	50,775	30	10,716	1,006	-91	47,617	61,961	30	49,846	51,781	4
9	2,980	3,825	28	7	47	582	5,403	7,103	31	2,986	3,872	30
10	2,372	2,855	20	15	91	512	6,770	8,454	25	2,387	2,946	23
11	7,581	3,457	-54	3,392	5,630	66	30,145	36,587	21	10,973	9,087	-17
12	203	0.01	-100	425	183	-57	16,701	0.02	-100	628	183	-71
13	1,926	2,346	22	94	75	-19	6,470	8,088	25	2,019	2,422	20
SUM	291,150	322,412	11	67,540	51,647	-24	416,683	461,539	11	358,691	374,059	4
Million ton-miles	Export Truck			Export Rail			Rail			Export		
Sector	Before	After	%	Before	After	%	Before	After	%	Before	After	%
1	100	122	22	0.18	0.08	-55	7	3	-54	100	122	22
2	6,937	8,316	20	1,739	1,257	-28	16,269	11,700	-28	8,676	9,573	10
3	6,939	7,288	5	1,745	1,619	-7	34,400	31,656	-8	8,684	8,907	3
4	32,333	38,688	20	18,153	14,542	-20	20,097	16,060	-20	50,486	53,230	5
5	5,897	7,695	30	1,013	607	-40	1,567	937	-40	6,910	8,302	20
6	11,766	15,058	28	3,029	1,769	-42	4,613	2,757	-40	14,796	16,827	14
7	2,645	3,027	14	807	646	-20	2,425	1,943	-20	3,453	3,672	6
8	8,488	11,186	32	2,396	163	-93	13,113	1,170	-91	10,884	11,350	4
9	2,424	3,278	35	4.72	0.61	-87	12	47	309	2,429	3,279	35
10	4,398	5,599	27	29	0.46	-98	44	92	110	4,427	5,599	26
11	22,563	33,129	47	17,816	6,256	-65	21,208	11,886	-44	40,379	39,385	-2
12	16,498	0.01	-100	284,834	301,447	6	285,259	301,629	6	301,332	301,447	0
13	4,544	5,742	26	226	96	-58	319	171	-46	4,769	5,838	22
SUM	125,533	139,127	11	331,793	328,404	-1	399,333	380,051	-5	457,326	467,531	2

CONCLUSIONS

This study uses the RUBMIO trade model to anticipate the shifts in U.S. trade patterns due to the introduction of Atrucks. Lower-cost trucking operations will impact choice of mode and input origins, affecting production and flow decisions for domestic and export trades across states, nations, and continents. Here, 13 commodity types were 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 early attempt to reflect self-driving trucks in long-distance freight systems 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.

AUTHOR CONTRIBUTION

The authors confirm the contribution to the paper as follows: study conception and design: Y. Huang and K. Kockelman.; Data analysis and interpretation of results: Y. Huang; Draft manuscript preparation: Y. Huang, and K. Kockelman. All authors reviewed the results and approved the final version of the manuscript.

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