IMPACTS OF AUTOMATED TRUCKS ON U.S. FREIGHT MOVEMENTS: APPLICATION AND ENHANCEMENT OF THE RANDOM-UTILITY-BASED MULTIREGIONAL INPUT-OUTPUT MODEL

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Abstract

Fully automated trucks (ATrucks) will impact the US freight flow patterns, due to time and cost savings compared to human-driven trucks (HTrucks). This paper advances the random-utility-multiregional input-output (RUBMRIO) model to have explicit mode's commodity-pricing impacts and predicts impacts of ATrucks on freight mode and origin choices across 20 commodity sectors across US. Assuming ATrucks' operating cost to be 60% of that for HTrucks, results suggest that time and cost savings from the use of ATrucks not only accommodate the need to acquire high-value goods from more closer locations but also facilitates the transportation of goods with the same value from farther away. HTrucks' shares diminish as distance rises with ATrucks' mode share in transported value fairly stable at 50% across all distance, however, rail's share is minimal for shorter distances but rises to approximately 20% for trips longer than 250 miles. Overnight time savings lead to an increase in the total value and ton-miles of goods transported by ATrucks, peaking at an increase of 11% for trips between 500 and 750 miles. Based on the sensitivity analysis of varying ATrucks' operating cost, ATrucks transport three times the ton-miles of HTrucks when there is an 80% reduction of the operating cost, while they still transport double the HTruck ton-miles when they have 40% increased cost due to time savings.

Key Words: automated trucks; spatial input-output model; nationwide trade flow patterns; integrated transportation-land use modeling

1. Introduction

The implementation of autonomous trucking will bring sweeping changes to the world of freight transport. Semi-automated trucks, which function under supervised automated driving conditions, are already being tested globally as part of pilot programs on interstate highways or designated areas by trucking companies such as TuSimple, Aurora, and Kodiak Robotics. In the foreseeable future, fully automated self-driving trucks (referred to as ATrucks in this paper), may autonomously depart from truck terminals or warehouses, navigating to their intended destinations without requiring human intervention. Notably, TuSimple made headlines in 2023 by completing a fully autonomous truck run on open public roads (TuSimple, 2023), while Kodiak Robotics has outlined plans to commence full driverless operations in 2024 (Delandro, 2023).

Trucks transported 2.43 trillion ton-miles of freight across the United States in 2020, constituting 46.2% of the nation's total ton-miles for that year (BTS, 2023). Furthermore, in 2021, 28% of the overall U.S. energy consumption was attributed to the transportation of people and goods, with 24.5% of transportation energy consumption stemming from commercial and freight trucks (U.S. Department of Energy, 2024). The use of ATrucks, along with platooned convoys, are expected to reduce lower crash rates, increase line-haul transportation efficiency and mitigate negative environmental impacts (Clements and Kockelman, 2017; Barth et al., 2004). The extensive adoption of ATrucks may occur before the automation of passenger vehicles, driven by apparent economic advantages that could result in a notable reduction of diesel fuel costs, potentially up to 7% (Liu and Kockelman, 2017; Shladover et al., 2006; Uranga, 2017).

In ATrucks, no onboard drivers are required although remote operators might be necessary to perform vehicle control tasks. While an attendant might still be present onboard for paperwork or coordination duties (Yankelevich, et al., 2018), this setup allows for extended utilization of commercial trucks, potentially operating every hour of every day (if effectively coordinated), leading to increased labor productivity. Consequently, the removal of onboard drivers is expected to yield reduced freight transportation costs, whether measured on a per-mile or per-ton-mile basis. The resulting changes in both time and cost for freight transportation brought by ATrucks have implications not only for national and regional economies but also for trade patterns, production levels, and goods pricing.

While significant attention is directed towards advancing the automation technology of ATrucks on highways (e.g., Lee et al., 2021; Calvert et al., 2019) and envisioning ATruck implementations (e.g., Slowik and Sharpe, 2018; Bhoopalam et al., 2023), there remains a gap in research examining the time and cost impacts of ATrucks on national freight travel. This study utilizes Freight Analysis Framework 5 (FAF5) data to estimate the mode and origin choices of freight carriers. The model parameters derived from these estimations are then integrated into the random-utility-based multi-regional input-output (RUBMRIO) model (refer to Cascetta et al., 2008; Ruiz and Kockelman, 2006; Bachmann, 2016) to investigate how patterns of freight flow may change based on the impacts of automation technology on truck cost and operation. Ruiz and Kockelman (2006) applied RUBMRIO model for 18 economic sectors across Texas' 254 counties, to assess project impacts on trade, production, and worker locations. Cascetta et al. (2008) calibrated RUBMRIO parameters to anticipate freight demand impacts across long-term scenarios in Italy. Bachmann (2016) applied the RUBMRIO model to Canada, and concluded that Canada's important trade relationship with US made it susceptible to negative economic impacts caused by decreases in global transportation costs. Huang and Kockelman (2020) used the RUBMRIO model to estimate US trade flows based on Year 2012 FAF4 data. If ATrucks lower trucking costs by 25% (per ton-mile delivered), the model predicts an 11% increase in truck flow volumes, and 4.8% fall in rail flows. But those studies did not separate the impacts of individual mode on commodity pricing, and had just one overall impact represented as the mode choice logsum.

This paper is based on previous RUBMRIO model from Huang and Kockelman (2020), which used year 2012 (FAF4) data. This paper contributes by bringing the model data sources to the most recent FAF5 data, enhancing model structure to accommodate explicit mode's commodity-pricing impacts with weighted shipping costs, and updating sub-model parameters to reflect more current shipping behavior. ATrucks' per-mile operating cost is assumed to be 60% of that for human-driven trucks (HTruck), factoring in the benefits of increased safety, a lower wage bill for truck drivers, and a higher initial cost (e.g., purchase of tractor) to introduce ATrucks. Sensitivity analysis is also added to explore the impacts of various ATruck's per-mile operating cost compared to HTrucks.

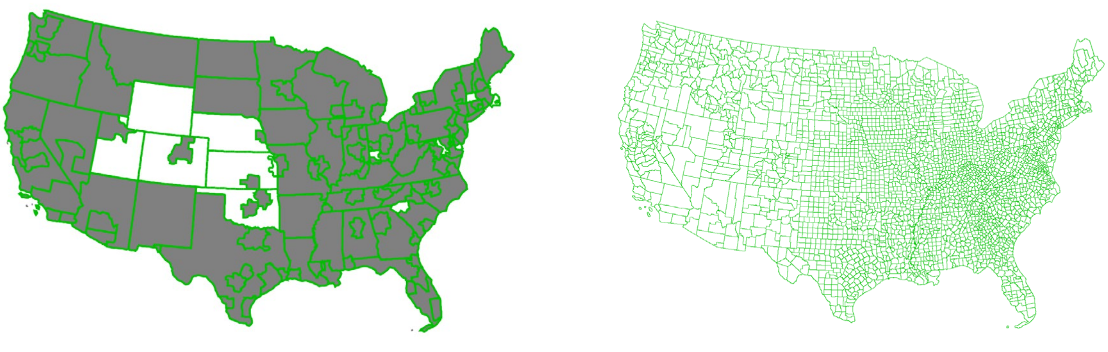
The remainder of this paper proceeds through each component of the freight models, showing the datasets that are used, how each part of the RUBMRIO model is estimated and parameterized, and offering insight into significant trends that will affect nationwide freight trade flows. This paper then concludes with a summary of results and actions for further development.

2. Data Sets

This section introduces the prepared datasets for the freight model, as well as the model estimations. The estimated models used in the RUBMRIO model will be specified in the following section.

2.1. Freight Analysis Framework (FAF5) Data

FAF5 integrates trade information from diverse industry sources, with a primary focus on the Census Bureau's 2017 Commodity Flow Survey (CFS) and international trade data (Census Bureau, 2021). The platform provides estimates of US trade flows, measured in tonnage, ton-miles and dollar value, segmented by industry and distributed between the 129 aggregate zones within the US across eight transportation modes (truck, rail, water, air, multiple modes and mail, pipeline, non-domestic, and others). Utilizing FAF5's origin-destination-commodity-mode matrices, this study employs these annual freight flow matrices to project domestic and export trade flows by zone. Analysis of FAF5 data reveals that foreign export flows depart the US from 117 of the 129 zones, as depicted in gray in Figure 1(a). Consequently, these same 117 zones function as both production and export zones within the trade modeling system presented in this paper.



(a) (b)

Figure 1. Continental US Domestic and Export Zones for Trade Modeling, (a) FAF5 129 Zones, with 117 Export Zones (shown in gray) and (b) 3109 Domestic Freight Counties.

The FAF5 zones were further broken down into county-level matrices utilizing the 2017 Commodity Flow Survey (CFS) boundary data, which identifies the counties associated with each FAF5 zone. In the year 2017, ten metropolitan areas were incorporated into the CFS data, resulting in a total of 3,109 contiguous counties (depicted in Figure 1(b)) after excluding the geographically distant states of Hawaii and Alaska. Travel times and costs between zones were calculated for the 3,109 × 3,109 county matrix, considering interzonal transportation by rail, ATruck, and HTruck, based on the shortest highway and railway paths in terms of free-flow travel time. All travel distances within a county were assumed to be the radii of circles with the same area as that county.

2.2. Economic Interaction Data

The technical coefficients and regional purchase coefficients (RPCs) within the model's embedded input-output (IO) matrices were obtained from IMPLAN's transaction tables, derived from US inter-industry accounts. Technical coefficients reflect production technology or opportunities, detailing how dollars of input in one industry sector are utilized to generate dollars of product in another sector. These coefficients are fundamental parameters in any IO model. RPCs represent the share of local demand that is supplied by domestic producers. In this context, RPC values are assumed to be constant across US counties due to unknown variations. 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 US counties have access to the same production technologies or technical coefficients table. Furthermore, IMPLAN's 440-sector transaction table was consolidated into 20 industry sectors, along with Household and Government sectors, to represent the US economy in this trade-modeling exercise.

3. Model Parameters

3.1. Freight Mode Choice

The freight mode choice model serves as a key component in the RUBMRIO model, as it distributes the freight flow for an origin-destination (OD) pair by mode. The freight mode choice model was estimated by leveraging data assembled from different sources. FAF5 freight flow data provides freight flow records, with skims supported by FAF4, rJourney (Outwater and Bradley, 2018), and county-level population data. Considering the significant disparity in the magnitudes of transported values for different commodities, a unique mode choice model was estimated for each commodity. FAF5 encompasses 42 distinct commodity types, which were further aggregated into 20 types that align with the input-output table (Table 1). Sector/Industry 3 is considered similar to sector 2, so they are estimated as the same category. Ton-miles of each commodity transported between OD pairs by modes are used as the weights for each freight flow record, and weights are further normalized and transformed using a log function to maintain a reasonable scale. Sectors 14 to 20 do not have specific Standard Classification of Transported Goods (SCTG) code, so their parameters are the average of all other sectors.

Table 1. Description of Economic Sectors in RUBMRIO Model

Sector	Description	IMPLAN Code	NAICS Code	SCTG Code	Value Transported in 2022 (billion)
1	Agriculture, Forestry, Fishing, and Hunting	1 to 19	11	1	98.1
2	Mining	20 to 30	21	10 to 15	3413.8

3	Construction	34 to 40	23		
4	Food, Beverage, and Tobacco Product Manufacturing	41 to 74	311, 312	2 to 9	3191.6
5	Petroleum and Coal Product Manufacturing	115 to 119	324	16 to 19	2177.6
6	Chemicals, Plastics, and Rubber Product Manufacturing	120 to 152	325, 326	20 to 24	824.9
7	Primary Metal Manufacturing	170 to 180	331	32	267.5
8	Fabricated Metal Manufacturing	181 to 202	332	33	131.5
9	Machinery Manufacturing	203 to 233	333	34	126.9
10	Computer, Electronic Product, and Electrical Equipment Manufacturing	234 to 275	334, 335	35, 38	104.1
11	Transportation Equipment Manufacturing	276 to 294	336	36, 37	210.3
12	Other Durable and Non-Durable Manufacturing	75 to 114, 153 to 169, 295 to 304	313 to 316, 321 to 323, 327, 337	25 to 31, 39	2476.9
13	Miscellaneous Manufacturing	305 to 318	339	40, 41, 43	518.1
14	Transportation, Communication and Utilities	31 to 33, 332 to 353	22, 48, 49, 51	--	--
15	Wholesale Trade	319	42	--	--
16	Retail Trade	320 to 331	44, 45	--	--
17	FIRE (Finance, Insurance and Real Estate)	354 to 366	52, 53	--	--
18	Services	367 to 440	54 to 56, 61, 62, 71, 72, 81, 92	--	--
19	Household	--	--	--	--
20	Government	--	--	--	--

For each model, four skim tables are used as variables in the utility function: truck travel time, truck cost, rail travel time, and rail cost. Truck travel time was derived from the 2010 rJourney data (Outwater and Bradley, 2018), which provides passenger travel times between National User Model Areas (NUMAs) across the US. NUMAs are zones utilized for the rJourney model that are comprised of counties or Census Public Use Microdata Areas (PUMAs). The origin and destination's population-weighted travel times at the NUMA level are aggregated into FAF zone level to offer an average passenger travel time between FAF zones. Since truck trips require more time than the highway travel time estimated for passenger vehicles, the following equation is used to transform highway travel time to truck travel time from zone i to zone j (Cambridge Systematics, 2002):

$$t_{ij,truck} = \frac{dist_{ij,truck}}{v_{truck}} + \left\lfloor \frac{dist_{ij,truck}}{v_{truck}} / h \right\rfloor * h' \quad (1)$$

where $dist_{ij,truck}$ is the highway distance in miles, v_{truck} is the average truck speed (assumed to be 45 miles per hour), h is daily working hours (assumed to be 10 hours), and h' is the additional hours needed for every 10 hour work shift (assumed to be 14 hours). The $\lfloor\ \rfloor$ operator rounds down the digit number to the nearest whole number.

Rail time from zone i to zone j is calculated based on the rail distance, with further adjustments from the equation in Texas's statewide analysis model (SAM) to show a fixed 30 hours' dwelling time h_{rail} and an average speed v_{rail} of 21.72 miles per hour on railways:

$$t_{ij,rail} = h_{rail} + \frac{dist_{ij,rail}}{v_{rail}} \quad (2)$$

In addition, travel times are transformed from hours into minutes with a log transformation further applied, to maintain a reasonable scale for both truck and rail.

Truck cost and rail cost from zone i to zone j ($s_{ij,truck}$ and $s_{ij,rail}$, respectively) are calculated based on travel distances. The American Transportation Research Institute (ATRI) gives an average truck cost for 2022 of $2.251 per mile, with drivers' wage accounting for 40% and fuel for 28% of that cost (ATRI, 2023). Rail cost was about $1.59 per mile on average in 2019 (Ashe, 2022). Truck and rail distances are calculated based on FAF5, by dividing total ton-mile by total tons transported to demonstrate the average distance per ton for each FAF's OD pair by commodity. The cost terms are used directly, without a log transformation, as this is easier to normalize to the unit of one dollar when using the equations in the RUBMRIO model.

With freight flow records and skim tables obtained, the model was estimated in the R computer language using the Apollo package (Hess and Palma, 2019). Generic time and cost coefficients now ensure just one value of travel time for each commodity type. Table 2 presents model results with generic time and cost coefficients for both truck and rail (β^m_{cost} and β^m_{time}, respectively), setting truck as the baseline ($\beta^m_0 = 0$). This gives the following utility function for truck and rail to transport commodity m from zone i to zone j:

$$V_{ij}^{m,truck} = \beta_0^m + \beta_{cost}^m \cdot s_{ij,truck} + \beta_{time}^m \cdot t_{ij,truck} \quad (3)$$

$$V_{ij}^{m,rail} = \beta_0^m + \beta_{cost}^m \cdot s_{ij,rail} + \beta_{time}^m \cdot t_{ij,rail} \quad (4)$$

Results show a disutility with increased travel times and costs, and trucks are preferred in general over rail. Most coefficients are significant at 0.05, except "Agriculture, Forestry, Fishing, and Hunting," "Primary Metal Manufacturing," and "Miscellaneous Manufacturing." This may be due to one or more commodities within the category showing a pattern distinct from the rest.

Table 2. Freight Model Choice Parameter Estimates using FAF5 Data

Sector	Parameters	Estimate	Std. Err.	t-stat	P-value
(1) Agriculture, Forestry, Fishing, and Hunting	β^1_{rail}	-6.671	7.867	-0.848	0.397
	β^1_{time}	-1.080	3.203	-0.337	0.736
	β^1_{cost}	-1.024	3.152	-0.325	0.745
(2) Mining and Construction	β^2_{rail}	0.283	0.102	2.769	0.006
	β^2_{time}	-0.562	0.037	-15.170	0.000
	β^2_{cost}	-0.208	0.044	-4.755	0.000
(4) Food, Beverage, and Tobacco Product Manufacturing	β^4_{rail}	-0.679	0.074	-9.228	0.000
	β^4_{time}	-0.451	0.029	-15.464	0.000
	β^4_{cost}	-0.219	0.027	-8.145	0.000
(5) Petroleum and Coal Product Manufacturing	β^5_{rail}	0.332	0.115	2.873	0.004
	β^5_{time}	-0.586	0.042	-14.027	0.000
	β^5_{cost}	-0.351	0.049	-7.098	0.000
(6) Chemicals, Plastics, and Rubber Product Manufacturing	β^6_{rail}	-0.306	0.076	-4.024	0.000
	β^6_{time}	-0.465	0.030	-15.398	0.000
	β^6_{cost}	-0.128	0.029	-4.463	0.000
(7) Primary Metal Manufacturing	β^7_{rail}	-1.356	0.160	-8.472	0.000

Sector	Parameters	Estimate	Std. Err.	t-stat	P-value
	β^{7}_{time}	-0.087	0.061	-1.432	0.152
	β^{7}_{cost}	-0.422	0.064	-6.610	0.000
(8) Fabricated Metal Manufacturing	β^{8}_{rail}	-1.231	0.168	-7.348	0.000
	β^{8}_{time}	-0.237	0.066	-3.566	0.000
	β^{8}_{cost}	-0.326	0.061	-5.344	0.000
(9) Machinery Manufacturing	β^{9}_{rail}	-1.541	0.184	-8.369	0.000
	β^{9}_{time}	-0.230	0.074	-3.106	0.002
	β^{9}_{cost}	-0.303	0.065	-4.655	0.000
(10) Computer, Electronic Product, and Electrical Equipment Manufacturing	β^{10}_{rail}	-1.394	0.142	-9.852	0.000
	β^{10}_{time}	-0.248	0.057	-4.356	0.000
	β^{10}_{cost}	-0.219	0.049	-4.443	0.000
(11) Transportation Equipment Manufacturing	β^{11}_{rail}	-1.270	0.118	-10.745	0.000
	β^{11}_{time}	-0.180	0.048	-3.777	0.000
	β^{11}_{cost}	-0.276	0.042	-6.596	0.000
(12) Other Durable and Non-Durable Manufacturing	β^{12}_{rail}	-0.981	0.065	-15.100	0.000
	β^{12}_{time}	-0.324	0.025	-12.720	0.000
	β^{12}_{cost}	-0.265	0.024	-11.110	0.000
(13) Miscellaneous Manufacturing	β^{13}_{rail}	-2.771	0.177	-15.676	0.000
	β^{13}_{time}	-0.064	0.069	-0.924	0.356
	β^{13}_{cost}	-0.480	0.060	-8.026	0.000

3.2. Freight Origin Choice

The freight origin choice model is also a key component in the RUBMRIO model, as it distributes freight flow across different potential origins. The freight origin choice model uses similar freight flow records as the mode choice model estimation but aggregates records by modes. We used two components for the utility in the origin choice model. One is the population, which is the most common size factor in location choice models, and the natural log of population ensures that choice probabilities scale properly. The second component is the logsum across mode alternatives, which is also standard, since logsums reflect the expected maximum utility of the competing modes that can serve that journey. The utility function to transport commodity m from i to j is as follows:

$$V_{ij}^{m} = \gamma^{m} \log\left(pop_{j}\right) + \delta^{m} \ln\left(\sum_{d \in D} \exp\left(V_{ij}^{md}\right)\right) \quad (5)$$

where γ^{m} and δ^{m} are parameters to be estimated for log of population and mode choice logsum, respectively, and $D = \{Truck, Rail\}$. The model was also estimated using the Apollo package in R software (Hess and Palma, 2019), with iterative coding for 132 different FAF zones as origins, while excluding any origins that are unavailable. "Unavailable" here indicates FAF OD pairs that do not have freight flow between them. Table 3 shows the model estimates.

Table 3. Freight Origin Choice Model Estimates

Sector	Parameters	Estimate	Std. Err.	t-stat
(1) Agriculture, Forestry, Fishing, and Hunting	γ^{1}	0.247	0.052	4.800
	δ^{1}	0.382	0.016	23.702
(2) Mining and Construction	γ^{2}	0.287	0.019	14.883

Sector	Parameters	Estimate	Std. Err.	t-stat
	δ^2	2.503	0.036	68.788
(4) Food, Beverage, and Tobacco Product Manufacturing	γ^4	0.504	0.010	48.738
	δ^4	1.842	0.016	116.724
(5) Petroleum and Coal Product Manufacturing	γ^5	0.314	0.026	12.167
	δ^5	2.395	0.039	61.141
(6) Chemicals, Plastics, and Rubber Product Manufacturing	γ^6	0.533	0.011	49.029
	δ^6	1.807	0.017	104.318
(7) Primary Metal Manufacturing	γ^7	0.449	0.022	20.835
	δ^7	2.393	0.055	43.243
(8) Fabricated Metal Manufacturing	γ^8	0.531	0.020	26.208
	δ^8	1.785	0.042	42.292
(9) Machinery Manufacturing	γ^9	0.524	0.019	26.898
	δ^9	1.291	0.031	41.230
(10) Computer, Electronic Product, and Electrical Equipment Manufacturing	γ^{10}	0.742	0.016	47.376
	δ^{10}	1.077	0.024	45.364
(11) Transportation Equipment Manufacturing	γ^{11}	0.574	0.016	36.781
	δ^{11}	2.001	0.034	59.185
(12) Other Durable and Non-Durable Manufacturing	γ^{12}	0.602	0.009	69.883
	δ^{12}	1.640	0.014	116.103
(13) Miscellaneous Manufacturing	γ^{13}	0.624	0.015	40.549
	δ^{13}	0.741	0.011	66.529

3.3 Truck Mode Choice

In order to reflect the impacts from automated trucks (ATrucks), ATrucks are added as an additional mode nested within the truck mode, and thus the utility of truck in the mode choice nest is the logsum of the truck-type choice model. Truck-type choice model borrows the cost and time coefficients from the upper nest for truck and rail. The alternative specific constants (ASCs) for ATrucks are set as −0.1 to recognize the initial high cost and the gradual adoption and preference for automation technology. The operating cost of ATrucks is taken to be 60% of that of HTrucks, based on the assumption of increased safety, a lower wage bill for truck drivers, and a higher initial cost. Figure 2 shows the nesting structure of the mode and origin choices. The detailed mode choice equations follow Huang and Kockelman (2020).

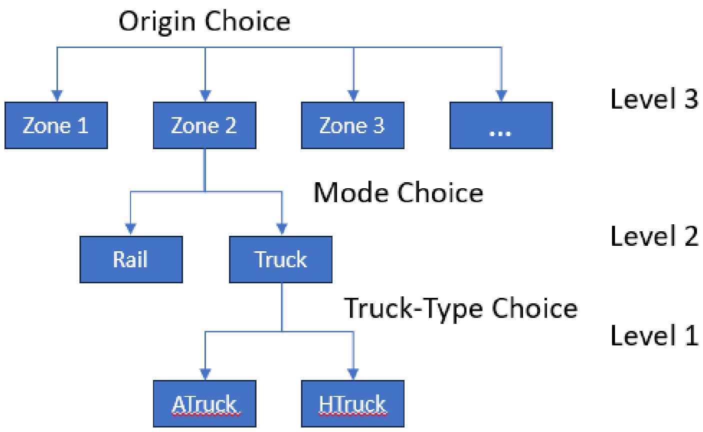


Figure 2. Origin, Mode, and Truck-Type Choice Structure

The parameters are shown in Table 4, based on the estimates from Table 2 and Table 3. The nesting coefficients are set as 1, 1/1.2 and 1/1.4 to reflect the nests from a joint structure to lower-level choices that have more correlations. With more data about the user preference of ATrucks, future work can dedicate more efforts in estimating a large three-level nesting model instead of the two models that are estimated separately in this paper.

Table 4. Parameter Estimates for Origin, Mode, and Truck-Type Choice Equations

Sector	Origin Choice Parameters		Mode Choice Parameters			Truck-Type Choice Parameter		
	θ_{ij}^{m}=1		$\theta_{ij,mode}^{m}$=1/1.2			$\theta_{ij,truck}^{m}$=1/1.4		
	γ^m	λ^m	$\beta_{1,\,rail}^{m}$	$\beta_{time,\,rail}^{m}$	$\beta_{cost,\,rail}^{m}$	$\beta_{1,\,Atruck}^{m}$	$\beta_{truck,time}^{m}$	$\beta_{truck,cost}^{m}$
1	0.25	0.38	-6.67	-1.08	-1.02	-0.10	-1.08	-1.02
2	0.29	2.50	0.28	-0.56	-0.21	-0.10	-0.56	-0.21
4	0.50	1.84	-0.68	-0.45	-0.22	-0.10	-0.45	-0.22
5	0.31	2.40	0.33	-0.59	-0.35	-0.10	-0.59	-0.35
6	0.53	1.81	-0.31	-0.47	-0.13	-0.10	-0.47	-0.13
7	0.45	2.39	-1.36	-0.09	-0.42	-0.10	-0.09	-0.42
8	0.53	1.79	-1.23	-0.24	-0.33	-0.10	-0.24	-0.33
9	0.52	1.29	-1.54	-0.23	-0.30	-0.10	-0.23	-0.30
10	0.74	1.08	-1.39	-0.25	-0.22	-0.10	-0.25	-0.22
11	0.57	2.00	-1.27	-0.18	-0.28	-0.10	-0.18	-0.28
12	0.60	1.64	-0.98	-0.32	-0.27	-0.10	-0.32	-0.27
13	0.62	0.74	-2.77	-0.06	-0.48	-0.10	-0.06	-0.48

4. Random-Utility-Based Multiregional Input-Output Model Specifications

This section introduces different components of the RUBMRIO model, including the disutility function, production function, and trade flows. The proof of the existence and the uniqueness of the RUBMRIO variant model is also shown.

4.1. Disutility Function

In the RUBMRIO model, both internal trade flows and external trade flows (from counties to export zones/customs districts) are based on the disutility of acquiring some commodity m from origin zone i and consuming it in zone j, shown in equation (6) (or exporting it to zone k, shown in equation (7)).

$$V_{ij}^{m} = -p_i^m + \gamma^m \log(pop) + \delta^m \ln\left(\sum_{d\in D} \exp\left(V_{ij}^{md}\right)\right) (6)$$

$$V_{ik}^{m} = -p_i^m + \gamma^m \log(pop) + \delta^m \ln\left(\sum_{d\in D} \exp\left(V_{ik}^{md}\right)\right) (7)$$

where $D = \{Truck, Rail\}$, with $V_{ij}^{m,truck}$ and $V_{ij}^{m,rail}$ defined in equations (3) and (4), p_i^m is the price of purchasing \$1 of commodity m in zone i (in units of utility), and γ^m and δ^m are estimated parameters based on origin and shipping-mode choice by zone and sector from section 2.

4.2. Production Function

The behavior of land and transport markets are highly affected by the components' market prices, including land rents and transport costs, which in turn affect production, consumption, and location decisions. The cost of producing one unit of commodity n in zone i is a function of the cost of inputs from other firms at other locations and the corresponding transport costs. The form of the overall manufacturing cost and ultimate sales price is shown in equation (8).

$$p_j^n = \sum_m \left(a_{0j}^{mn} \cdot c_j^m\right) \ \forall j, n \ (8)$$

where a_{0j}^{mn} is the technical coefficient for zone j, which defines the fractional amount of commodity m required to produce one unit of commodity n in zone j, and c_j^m is the weighted-average cost of input m in zone j. These technical coefficients, a_{0j}^{mn}, come from the original year 2008 IMPLAN transactions tables (Minnesota IMPLAN Group, 1997) for total purchases, both local and imported. IMPLAN (Impact Analysis for Planning) is a social accounting and impact analysis software, developed by the Minnesota IMPLAN Group. It is assumed that every commodity has the same value-weight ratio to sustain equation (8) since the technical coefficients are measured in value instead of quantity (see more discussions in Cascetta et al., 2008). The input costs, c_j^m, are a weighted average of input purchase price p_i^m for commodity m for all input zones i plus the associated generalized transport costs b_{ij}^{md} (from each zone i to zone j using mode d), as shown in equations (9) and (10). The weight factors are the interzonal trade flows by mode (X_{ij}^{md}). This is the key improvement from previous studies that they used a single logsum term in equation (9) to represent the expected mode choice utility, but here a weighted average for each mode b_{ij}^{md} (utility that considers origin population and mode choice) makes it explicit in mode's commodity-pricing impacts.

$$B_{ij}^{md} = p_i^m + b_{ij}^{md} \ \forall i, m \ (9)$$

$$c_j^m = \frac{\sum_i \sum_d \left(X_{ij}^{md} \cdot B_{ij}^{md}\right)}{\sum_i \sum_d X_{ij}^{md}} \ \forall j, m \ (10)$$

4.3. Trade Flows

Trade flows can be calculated when all the other values are given, including export demands, production costs, technical coefficients, and transport costs. Under an assumption of profit-maximizing/cost-minimizing behavior, with unobserved heterogeneity in alternatives, consumers (both final and intermediate) will buy from the producer(s) that can supply the lowest total price (including transport costs) of any input. Unobserved heterogeneity introduces the random element, which, under an assumption of iid Gumbel distribution, leads to the multinomial logit model for origin and mode choices. Two kinds of trade flow are estimated in the current RUBMRIO model; these are the interzonal trade flows by modes, X_{ij}^{md}, and the flows to export zones by modes, Y_{ik}^{md}, as shown here:

$$X_{ij}^{md} = C_j^m \frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)} \frac{\exp\left(V_{ij}^{md}\right)}{\sum_d \exp\left(V_{ij}^{md}\right)} \quad \forall i, j, m, d \ (11)$$

$$Y_{ik}^{md} = Y_k^m \frac{\exp(V_{ik}^m)}{\sum_i \exp(V_{ik}^m)} \frac{\exp\left(V_{ik}^{md}\right)}{\sum_d \exp\left(V_{ik}^{md}\right)} \quad \forall i, k, m, d \ (12)$$

where C_j^m is the total volume of *m* consumed in zone *j*, which can be calculated based on equation (13):

$$C_j^m = \sum_n \left(a_j^{mn} \cdot x_j^n\right) \ \forall j, m \ (13)$$

Here, a_j^{mn} is the technical coefficient matrix (following leakage considerations) for zone *j*, which defines the amount of commodity *m* required (from within the state) to produce one unit of commodity *n* in zone *j*. And x_i^m is the total production of commodity *n* in zone *i*, which is the sum of the trade flows leaving zone *i* to meet the demands of other producers and export zones.

$$x_i^m = \sum_j \sum_d X_{ij}^{md} + \sum_k \sum_d Y_{ik}^{md} \ \forall i, m \ (14)$$

Equations 6 through 14 constitute the majority of the RUBMRIO model; these equations are solved iteratively to achieve an equilibrium trade pattern. To resolve this set of equations (and achieve a convergent solution), the iterations begin by setting all prices to zero, solving for trade-flow probabilities, and generating an initial pattern of trade. This alters the price structure, and thus the trade pattern. We continue updating prices and patterns until convergence. Zhao and Kockelman's work (2002) describes this process.

4.4. Solution Existence and Uniqueness

This section presents the fixed-point RUBMRIO variant problem that incorporates the cost of modes in the average cost calculations for commodities, compared to the general form in Zhao and Kockelman (2004), which uses an average cost term as logsum.

Define P_{ij}^m as the probability that region *j* purchases input *m* from region *i* and P_{ij}^{md} as the probability of choosing mode *d* given that region *j* purchases input *m* from region *i*:

$$P_{ij}^m = \frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)} \ (15)$$

$$P_{ij}^{md} = \frac{\exp\left(V_{ij}^{md}\right)}{\sum_d \exp\left(V_{ij}^{md}\right)} \quad (16)$$

Then we can reformulate the average cost:

$$p_j^n = \sum_m a_{0j}^{mn} \cdot c_j^m = \sum_m a_{0j}^{mn} \cdot \frac{\sum_i \sum_d \left(X_{ij}^{md} \cdot B_{ij}^{md}\right)}{\sum_i \sum_d X_{ij}^{md}}$$

$$= \sum_m a_{0j}^{mn} \cdot \frac{\sum_i \sum_d \left[X_{ij}^{md} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]}{\sum_i \sum_d X_{ij}^{md}}$$

$$= \sum_m a_{0j}^{mn} \cdot \frac{\sum_i \sum_d \left[C_j^m \frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)} \frac{\exp\left(V_{ij}^{md}\right)}{\sum_d \exp\left(V_{ij}^{md}\right)} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]}{\sum_i \sum_d X_{ij}^{md}}$$

$$= \sum_m a_{0j}^{mn} \cdot \frac{C_j^m \sum_i \sum_d \left[\frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)} \frac{\exp\left(V_{ij}^{md}\right)}{\sum_d \exp\left(V_{ij}^{md}\right)} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]}{C_j^m}$$

$$= \sum_m a_{0j}^{mn} \cdot \sum_i \sum_d \left[\frac{\exp\left(V_{ij}^m\right)}{\sum_i \exp\left(V_{ij}^m\right)} \frac{\exp\left(V_{ij}^{md}\right)}{\sum_d \exp\left(V_{ij}^{md}\right)} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]$$

$$= \sum_m a_{0j}^{mn} \cdot \sum_i \sum_d \left[P_{ij}^m P_{ij}^{md} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]$$

We then denote:

$$\vec{p} = \{p_j^n\}$$

Therefore

$$f_j^n(\vec{p}) = \sum_m a_{0j}^{mn} \cdot \sum_i \sum_d \left[P_{ij}^m(\vec{p}) P_{ij}^{md} \cdot \left(p_i^m + b_{ij}^{md}\right)\right]$$

$$= \sum_m a_{0j}^{mn} \cdot \sum_i P_{ij}^m(\vec{p}) \cdot \left[p_i^m + \sum_d \left(P_{ij}^{md} \cdot b_{ij}^{md}\right)\right]$$

Therefore, we have a fixed-point problem as follows:

$$\vec{p} = \vec{f}(\vec{p}) \qquad (17)$$

Compared to Zhao and Kockelman (2004), this fixed-point problem variant replaces the generic transportation price (regardless of modes) with the probability-weighted transportation cost for different modes. The proof of existence and uniqueness of the solution to this fixed-point model follows Zhao and Kockelman (2004):

(1) Existence condition for the price solution

First, we impose a rather weak condition on the feasible set to ensure the existence of a solution. Let $K_p = \left\{p_{ij}^n | 0 \leq p_{ij}^n \leq p_{ij}^{n*}, \forall i, j, n\right\}$, where $\left\{\boldsymbol{p_{ij}^{n*}}\right\}$ are upper bounds that we assume can be determined a priori (in practice, one can usually choose very large numbers as upper bounds). Then K_p is a bounded and closed convex subset (therefore, a compact set) on the space R^{MJJ}. We can easily observe that if the prices are bounded, the function $\vec{f}$ also can be considered bounded, since it is a convex combination of prices (plus transportation costs) across space (i.e., $\sum_i P_{ij}^m = 1, \forall m$) and economic sectors (i.e., $\sum_m a_j^{mn} \leq 1, \forall n, j$). If one assumes that $\vec{f}$'s upper bounds are also $\{\boldsymbol{p}_{ij}^{n*}\}$, one essentially assumes that the upper bounds are large enough to accommodate the transportation prices' contributions to $\vec{f}$. Then, $\vec{f}$ is a mapping $K_p \to K_p$, and it is continuous. Following Brouwer's theorem (see Khamsi and Kirk, 2001), we then have the following condition:

The fixed-point problem (17) provides at least one solution if and only if there exist positive constants $\{\boldsymbol{p}_{ij}^{n*}\}$ such that the fixed-point problem (17) provides at least one feasible solution in the space $\boldsymbol{K_b}$.

(2) Uniqueness condition for the price solution

Sufficient conditions for the uniqueness of the solution of a fixed-point problem are given by Banach's theorem (see Border, 1985), which requires that the function be contractive over a complete set or the function be quasi-contractive (implying monotonicity) over a compact set. We consider that K_p is in a normed space, due to the mean-value theorem (see Khamsi and Kirk, 2001), if $\|\nabla \vec{f}(\vec{p})\| < 1$; then the fixed-point problem has a unique solution, and the sequence $\vec{p}^{(t+1)} = \vec{f}(\vec{p}^{(t)})$ converges on the unique solution $\vec{p} = \vec{f}(\vec{p})$, if $\vec{p}^{(o)} \in K_p$.

Now consider the general case of a dispersion parameter λ^m for the origin choice model:

$$P_{ij}^m = \frac{\exp\left(\lambda^m V_{ij}^m\right)}{\sum_i \exp\left(\lambda^m V_{ij}^m\right)} \quad (18)$$

Follow the same process in Zhao and Kockelman (2004), when the probabilities are determined by relative disutilities, which depend on prices:

$$\frac{\partial f_j^n(\vec{p})}{\partial p_i^m} = \frac{\partial}{\partial p_i^m}\left[\sum_m a_j^{mn} \sum_k P_{kj}^m(\vec{p}) \cdot \left(p_k^m + p_k^m + \sum_d \left(P_{ij}^{md} \cdot b_{ij}^{md}\right)\right)\right]$$

$$= a_j^{mn} \frac{\partial}{\partial p_i^m}\left[\sum_k P_{kj}^m(\vec{p}) \cdot \left(p_k^m + \sum_d \left(P_{ij}^{md} \cdot b_{ij}^{md}\right)\right)\right]$$

$$= a_j^{mn} \cdot P_{ij}^m \cdot \left\{1 - \lambda^m \left[\left(p_i^m + \sum_d \left(P_{ij}^{md} \cdot b_{ij}^{md}\right)\right) - c_j^m\right]\right\} \quad (19)$$

Letting $d_{ij}^d = \sum_d \left(P_{ij}^{md} \cdot b_{ij}^{md}\right)$, equation (19) can be written as:

$$\frac{\partial f_j^n(\vec{p})}{\partial p_i^m} = a_j^{mn} \cdot P_{ij}^m \cdot \left\{1 - \lambda^m\left[p_i^m + d_{ij}^d - c_j^m\right]\right\}$$

which is the same equation as (3.14) in the Zhao and Kockelman (2004) paper. This proof then merges with the proof in Zhao and Kockelman (2004) (equation 3.14 forward) to show that $\|\nabla \vec{f}(\vec{p})\| < 1$, and we reach the following restrictive uniqueness condition for price solution:

The fixed-point problem (17) results in at most one equilibrium price solution if the dispersion parameters $\{\boldsymbol{\lambda^m}\}$ are sufficiently small such that the inequality $\lambda^m < 1/\max_{1\leq i,j\leq J}\left(p_i^m + d_{ij}^m - c_j^m\right) \; \forall m$ holds.

5. Scenario Experiment and Analysis

The base case scenario of the model was set on year 2020, when only human-driven trucks (HTrucks) were available, while ATrucks are added as an additional mode nested within the truck mode. The base case scenario without ATrucks shows a total $1.06 trillion export demand and $11.1 trillion domestic demand, with trucks dominating the market, generally moving 95% of product value while rail moves the other 5%. When measured by transported ton-mile, trucks represent 91%, and rail represents 8%. Given that the model is primarily driven by export demand, this remains consistent in both the base case and the ATruck scenarios, with total domestic flow showing minimal differences across scenarios (less than a 0.1% variation). With the ATruck option added in the model, the flow and ton-mile transported shifted among the shipping distances. As indicated in Table 5, a substantial increase in domestic flows is observed between 500 miles and 1,500 miles after the introduction of ATrucks, accompanied by a decline between 1,500 miles and 3,000 miles. Mid-long-distance origins become more favorable choices compared to super long-haul origins, attributed to the overall reduced shipping cost that compensates for the necessity of obtaining high-value goods from more distant locations. However, the trend is different for ton-miles. Transported domestic and export ton-miles increased for all distances, which indicates an overall trend of shipments from longer distance origins, due to the low cost and shortened shipment time that make it easy for goods to be transported from farther away.

Table 5. Change in Flow ($) and Ton-miles after ATruck Introduction

Distances (miles)	<100	100-249	250-499	500-749	1000-1499	1500-2000	2000-3000	3000+
Domestic flow ($)	-0.1%	12.6%	11.8%	46.9%	54.4%	-16.8%	-53.2%	4.6%
Export flow ($)	8.2%	5.4%	-16.6%	6.8%	12.5%	2.5%	5.6%	9.4%
Domestic ton-miles	1.8%	12.7%	11.1%	66.6%	68.1%	38.2%	27.2%	6.6%
Export ton-miles	26.5%	15.0%	3.6%	30.5%	36.2%	23.6%	27.2%	27.0%

Figure 3 shows the percentage change in truck (sum of ATruck and HTruck) and rail mode choice for domestic and export flow in ton-miles after the introduction of ATrucks. The implementation of ATrucks leads to an overall increase in domestic and export truck ton-miles across all distances, with a notable surge observed in the 500 to 1,500-mile range. Export rail ton-miles experience a shift towards trucks, while domestic rail's share increases, particularly for trips shorter than 1,500 miles. This outcome is a result of a combined modeling effect arising from the overall reduced shipping cost facilitated by ATrucks and the weighted shipping cost, prompting the selection of closer origins for high-value goods in both truck and rail scenarios. For export shipments, there is a decrease for rail across all distances, which shifted to ATrucks.

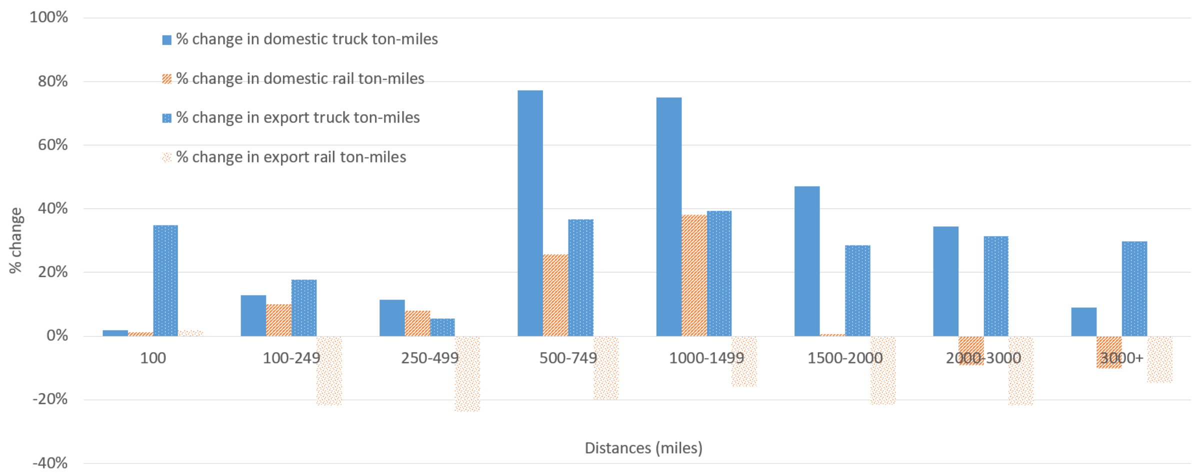


Figure 3. Change in Domestic and Export Ton-Miles by Mode after the Introduction of ATrucks

The introduction of ATrucks brings the shift in mode share. Figure 4 shows the mode split (in terms of transported value) among HTrucks, ATrucks, and rail in the ATruck scenario (with 60% of the operating cost of HTrucks). HTrucks' mode share diminishes as the distance increases, while ATrucks' share is fairly stable across all distances at about 50%. Rail's mode share is minimal for shorter distances but rises to approximately 20% for trips longer than 250 miles.

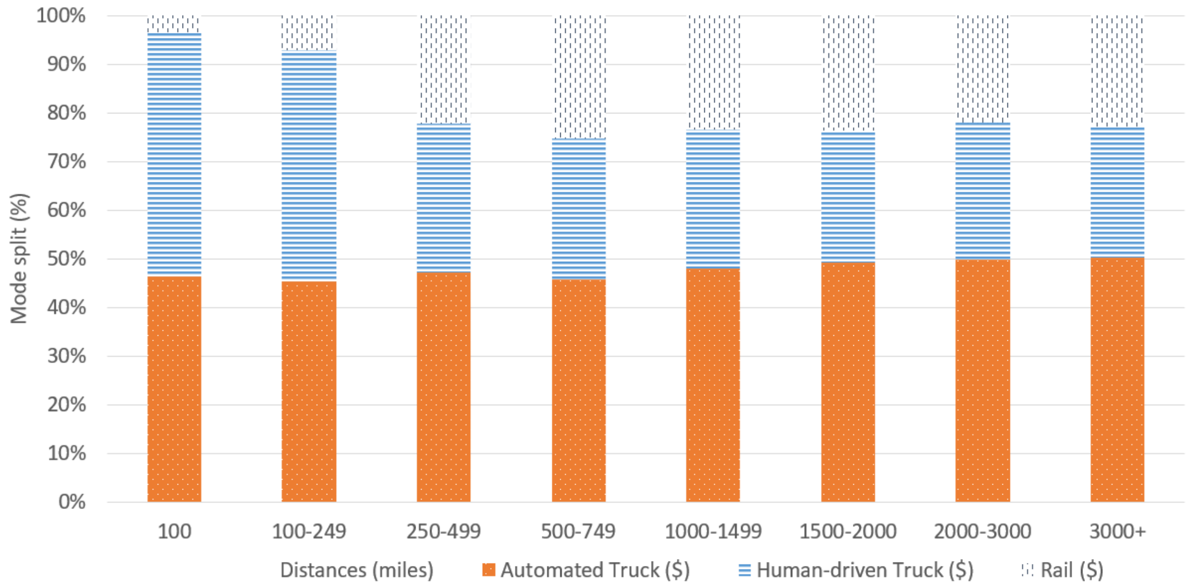


Figure 4. Mode Share with Introduction of ATrucks

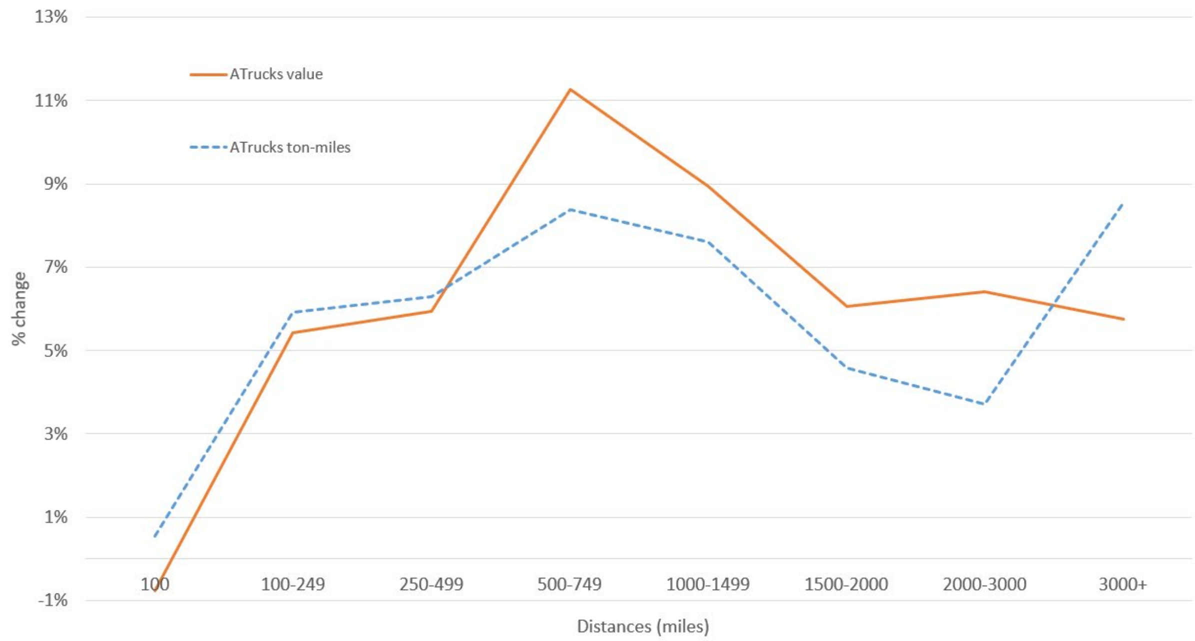


Figure 5. Change in Value and Ton-Miles Transported when ATrucks' Overnight Time Savings and Cost Savings Are Taken into Account (Compared to Cost Savings Only)

As mentioned, a major benefit of ATrucks is that, unlike HTrucks, whose drivers need to rest nightly, they can keep driving overnight. In the mode choice model estimates, an extra 14 hours of non-driving time is assumed for every 10 hours of an HTruck's on-road travel time. Figure 5 provides a comparison of two ATruck scenarios, one where ATrucks reduce cost by 40% and also eliminate overnight resting time, and another where ATrucks only reduce the cost without realizing any time savings. Figure 5 demonstrates that if the travel time saved by ATrucks is taken into consideration, they attract up to 11% more value and 8% more ton-miles. This increase diminishes as distances become longer, with ATrucks' transported value experiencing a 6% rise for trips exceeding 1,500 miles. However, the most substantial increase in ton-miles occurs within the distance range of 500 to 750 miles, where time savings begin to manifest over a single night, and for distances exceeding 3,000 miles, where the cumulative time saved becomes significant, as these longer trips used to span multiple days.

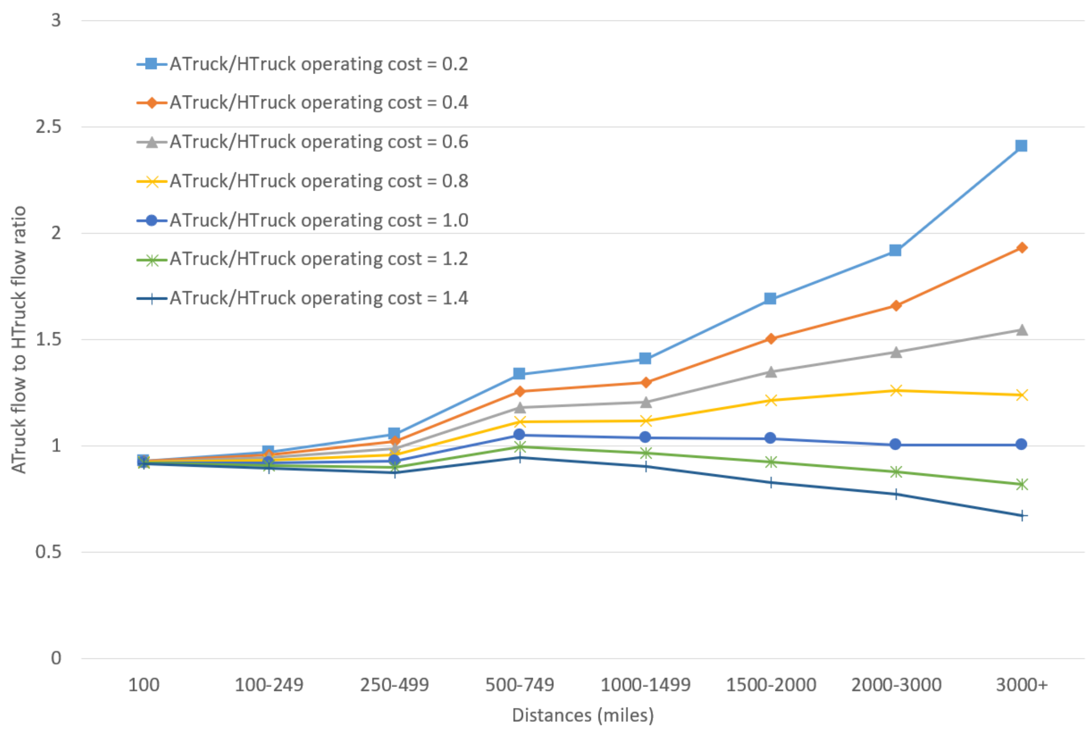


Figure 6. Sensitivity Analysis on Domestic ATruck Flow to HTruck Flow Ratio by Distances

Initially, the operating cost of ATrucks was assumed to be 60% of that of HTrucks. However, considering the potential need for more skilled operators and the higher initial training costs for operators to ensure safety benefits, a sensitivity analysis was performed to examine scenarios ranging from high initial costs for ATrucks until they become mature, fully functional, and widely applied. The relative cost of ATruck to HTruck was varied from 0.2 to 1.4 in this analysis, demonstrating a range from an 80% reduction in operating cost to a 40% increase compared to HTrucks, with a step of a 20% increase.

The ratio of value transported by ATruck to the value by Htruck is shown in Figure 6. At a distance of 100 miles, all scenarios show a value of about 0.95, primarily due to the setting in the utility function, where time and cost considerations are not significant for such short distances. As the origins become farther away, the time and cost benefits of ATrucks become more evident. For scenarios where ATrucks have the same operating cost as HTrucks (the line with round markers), the ratio increases with distance, reaching around 1 when the origins are 500 miles away or more. In cases where ATrucks have a lower cost, the ratio rises, favoring ATrucks up to a ratio of 2.5 (for shipping distances over 3,000 miles) when there is an 80% reduction in operating cost. Conversely, the ratio drops to 0.7 (for shipping distances over 3,000 miles) when the operating cost of ATruck is 40% higher than HTrucks.

Figure 7 shows the ATruck to Htruck ratio by value and ton-miles, for domestic and export flow respectively. All trends decrease with the rise of ATruck's operating cost. ATrucks have a higher ratio to HTrucks in terms of ton-miles, which also fall faster when operating cost increases. ATrucks transport three times the ton-miles of HTrucks when there is an 80% reduction of the operating cost, while they still transport double the HTruck ton-miles when they have 40% more cost. This is attributed to the time savings that ATrucks can provide, enabling faster transportation of goods to more distant customers.

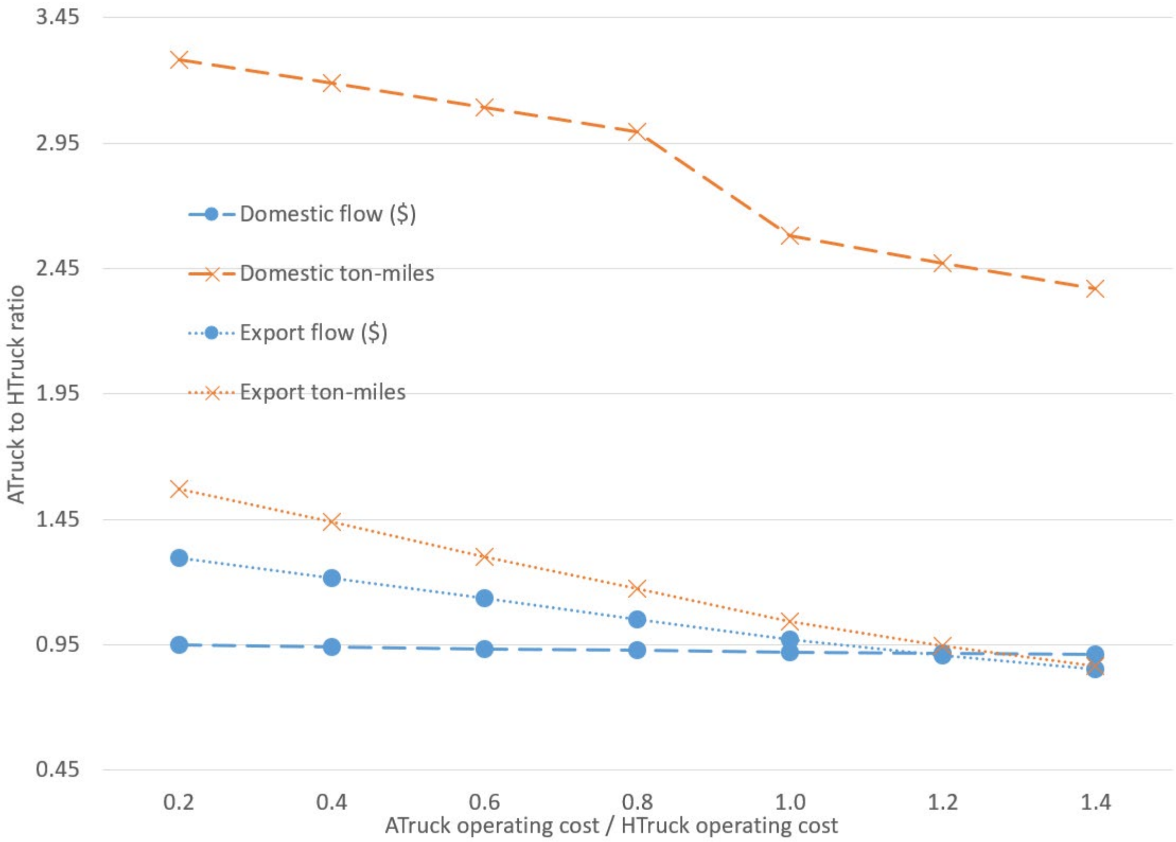


Figure 7. Sensitivity Analysis on Share of ATrucks (vs. HTrucks) by ATruck's Operating Cost

6. Conclusion

This paper anticipates the US trade flow before and after the introduction of automated trucks, leveraging the RUBMRIO model with estimated origin and mode choice parameters from FAF5 data. Automated trucks' per-mile operating cost is assumed as 60% of the cost of human-driven trucks, due to the elimination of drivers' wages, and the former are also assumed to save 14 hours by not stopping overnight. A sensitivity analysis was also conducted to see how varying ATrucks' cost savings can impact nationwide trade flows.

Model results show that ATrucks bring an overall increase in domestic and export truck ton-miles across all distances, especially in the 500 to 1,500-mile range. In terms of the value transported, a substantial increase in domestic flows is observed between 500 miles and 1,500 miles after the introduction of ATrucks, accompanied by a decline between 1,500 miles and 3,000 miles. The change in value and ton-miles show that time and cost savings from the use of ATrucks not only accommodate the need to acquire high-value goods from more closer locations but also facilitates the transportation of goods with the same value from farther away.

Compared to just cost savings, travel time saved by ATrucks can attract up to 11% more value and 8% more ton-miles. In terms of mode share between HTrucks and ATrucks, HTrucks have a slightly higher mode share in transported value for short-distance transportation. However, ATrucks are the preferred mode for origin-destination pairs separated by more than 250 miles. ATrucks transport three times the ton-miles of HTrucks when there is an 80% reduction of the operating cost, while they still transport double the HTruck ton-miles when they have 40% more cost.

Future work on freight predictions that account for ATrucks would extract the origin and destination information of different states to explore more detailed local domestic and export patterns. A sensitivity analysis that looks at ATrucks manned by attendants across a range of pay and job duty ranges can be conducted to see how the varying operating costs of ATrucks impacts mode choice.

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Data Availability

The data that support the findings of this study are available from the corresponding author, YH, upon reasonable request.

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