Industry Perceptions of Highly Automated Technologies for Trucks

Freight Mobility Research Institute Webinar Series

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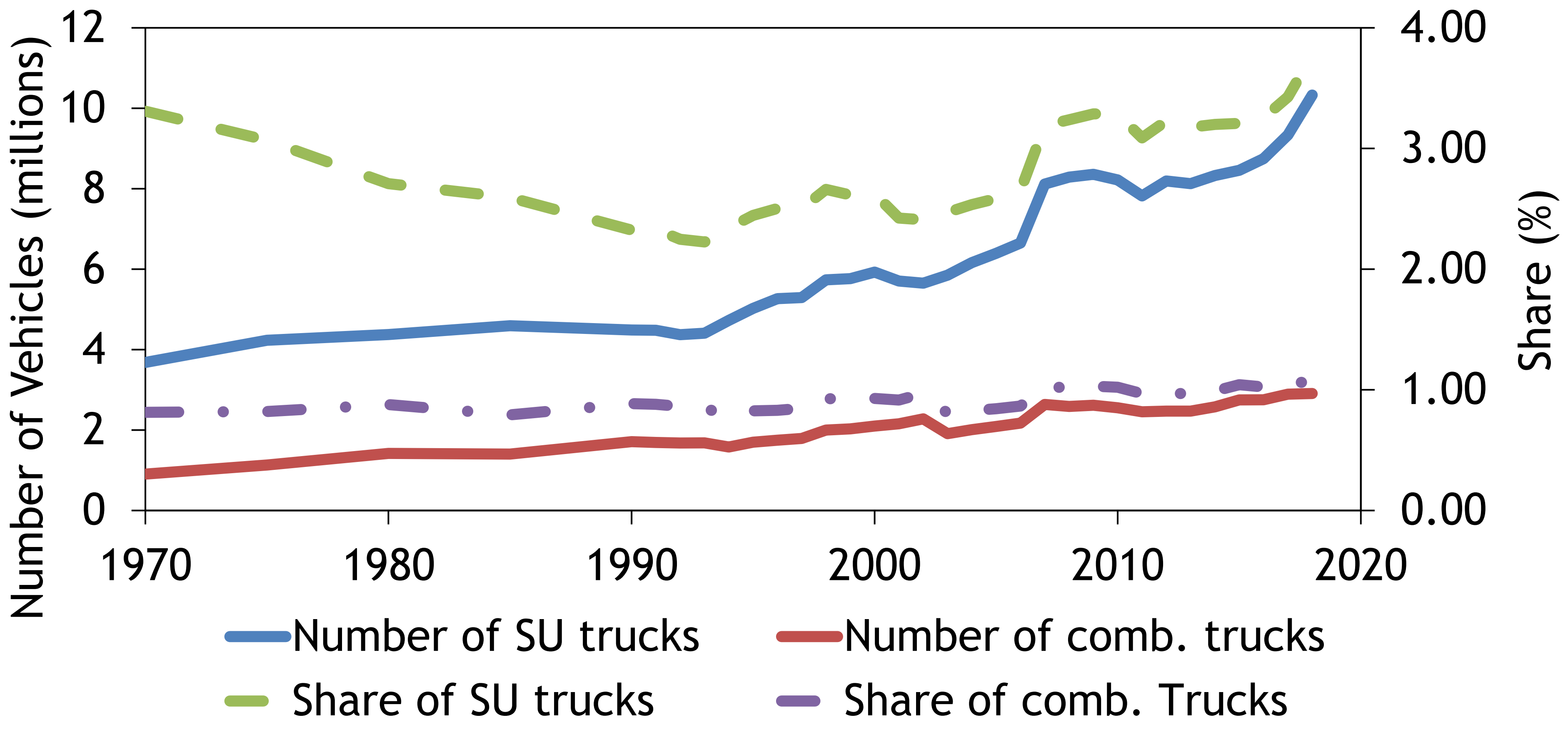
Content

- Introduction
- Survey design and results
- Modeling framework
- Results
- Ongoing efforts and future work

Introduction – Truck Fleet

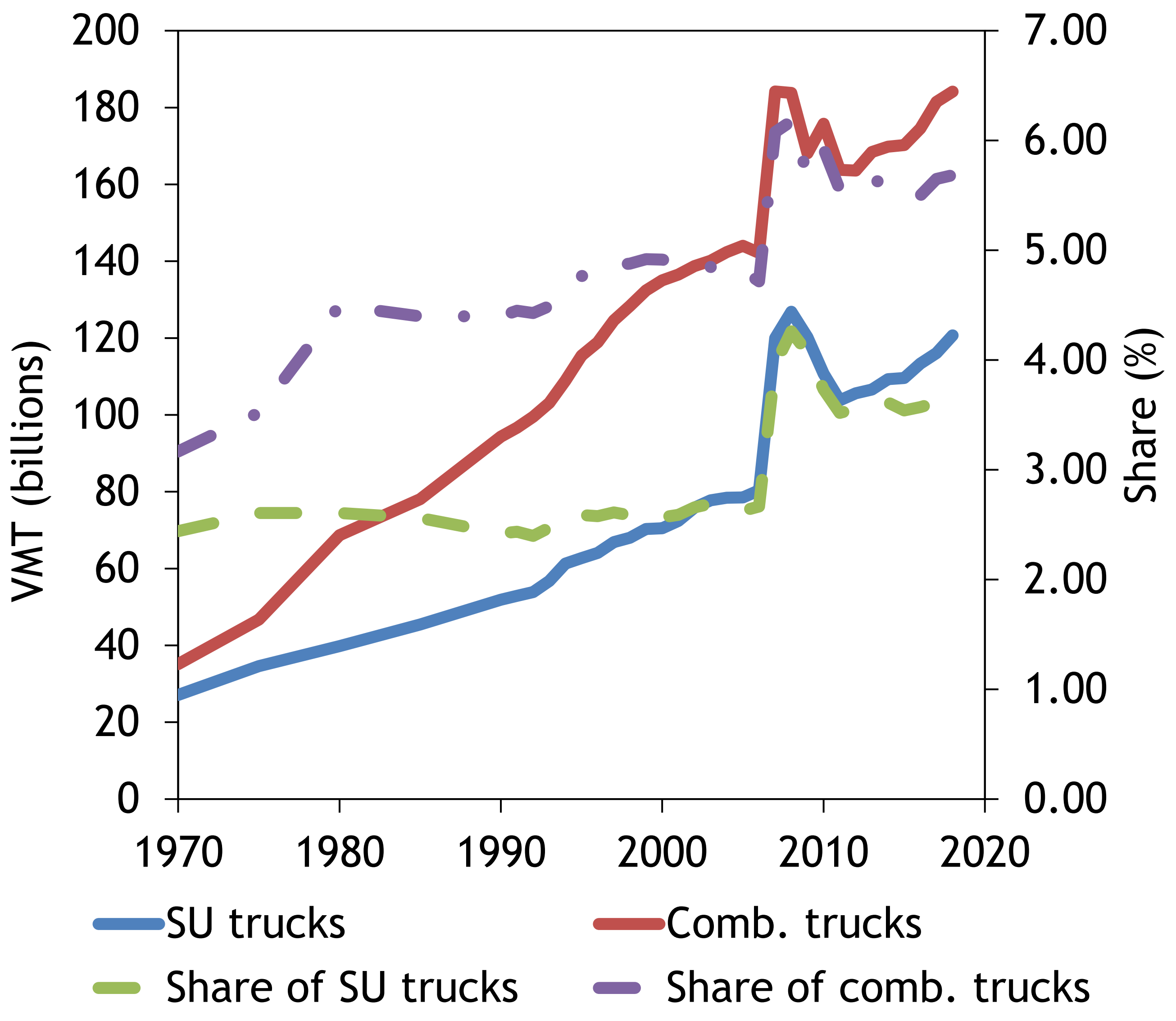
- There were more than 273 million on-road vehicles in the US in 2018
- Trucks account for about 4.8% of all vehicles
  - 2.9 millions (1.06%) combination trucks (this share (the purple curve) has not significantly changed over time)
  - 10.3 millions (3.77%) single unit trucks



Source: BTS

Introduction – Truck VMT

- However, the story is different when it comes to VMT!
- Total VMT in 2018: 3,240 (billion)
- Freight vehicles account for about 9.4% of total VMT (compare to 4.8% vehicle share)
  - Share of combination trucks: 5.68% (compare to 1.06% vehicle share). This share (the purple curve) has increased over time
  - Share of single unit trucks: 3.72%



Source: BTS

Introduction- Technology and Impact on Trucks

Multiple highly automated technologies for trucks are emerging.

- **Active Braking Systems**
  - Automatic emergency braking
  - Air disc brakes
  - Adaptive cruise control
- **Active Steering Systems**
  - Lane keep assist
  - Lane centering
  - Adaptive steering control
- **Active Warning Systems**
  - Lane departure
  - Forward collision
  - Blind spot detection
- **Camera Monitoring Systems**
  - In-cab facing driver training
  - Forward facing event recording
  - Side rear-view for mirrors

Source: ATRI

Motivation

- Share of future truck VMT could be higher
  - Considering less stress of driving and larger time windows
- Reduced transportation cost impact
  - Driver cost vs. technology cost
- Complexity of investment
  - Among small, medium and large companies
- Industry perceptions of highly automated trucks-critically important

Data

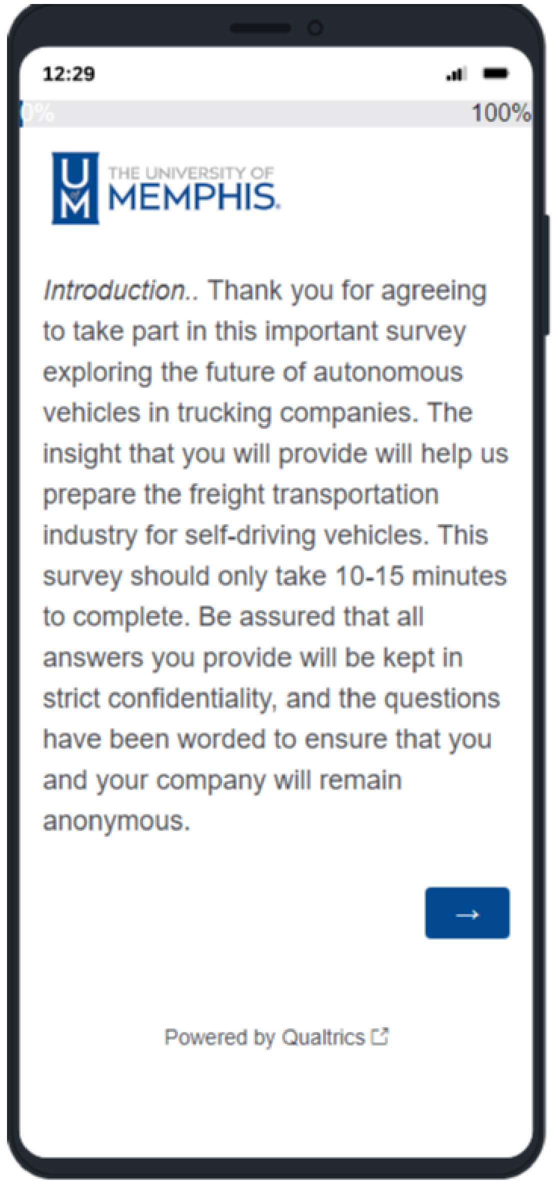
- National truck fleet ownership companies
  - Categorization based on employee size
  - Small (<50), medium (50-500) and large (>500)

- A stated preference survey (more next slide)

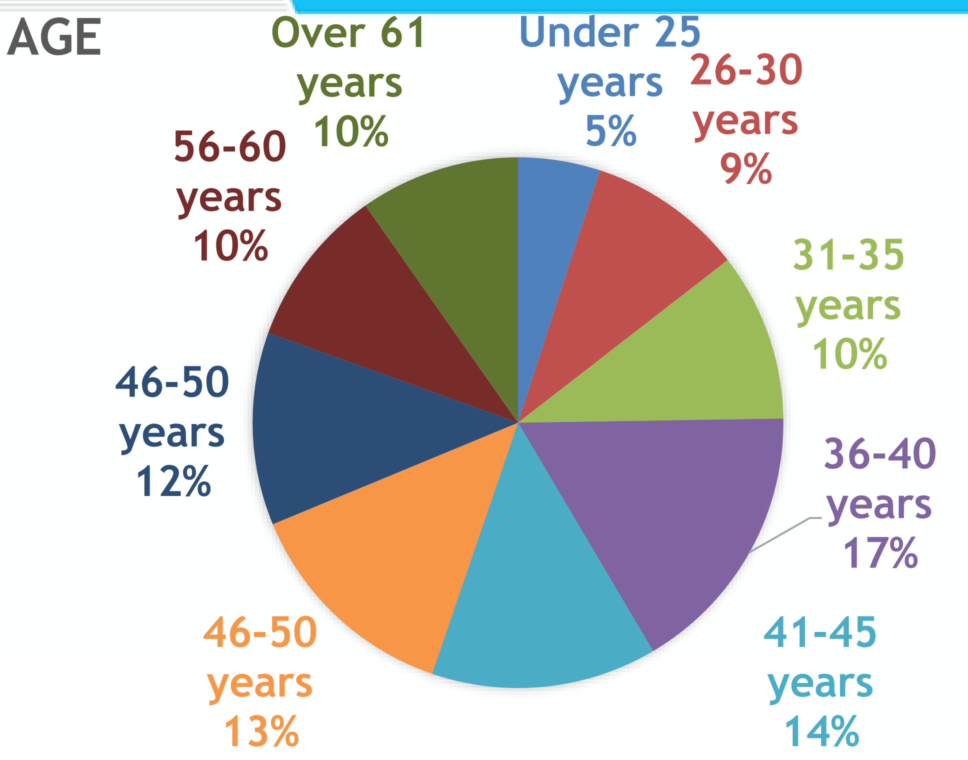
- Sample size consideration
  - Difficult to obtain sample size
  - Cochran’s and Yamane’s method – min. of 400 samples

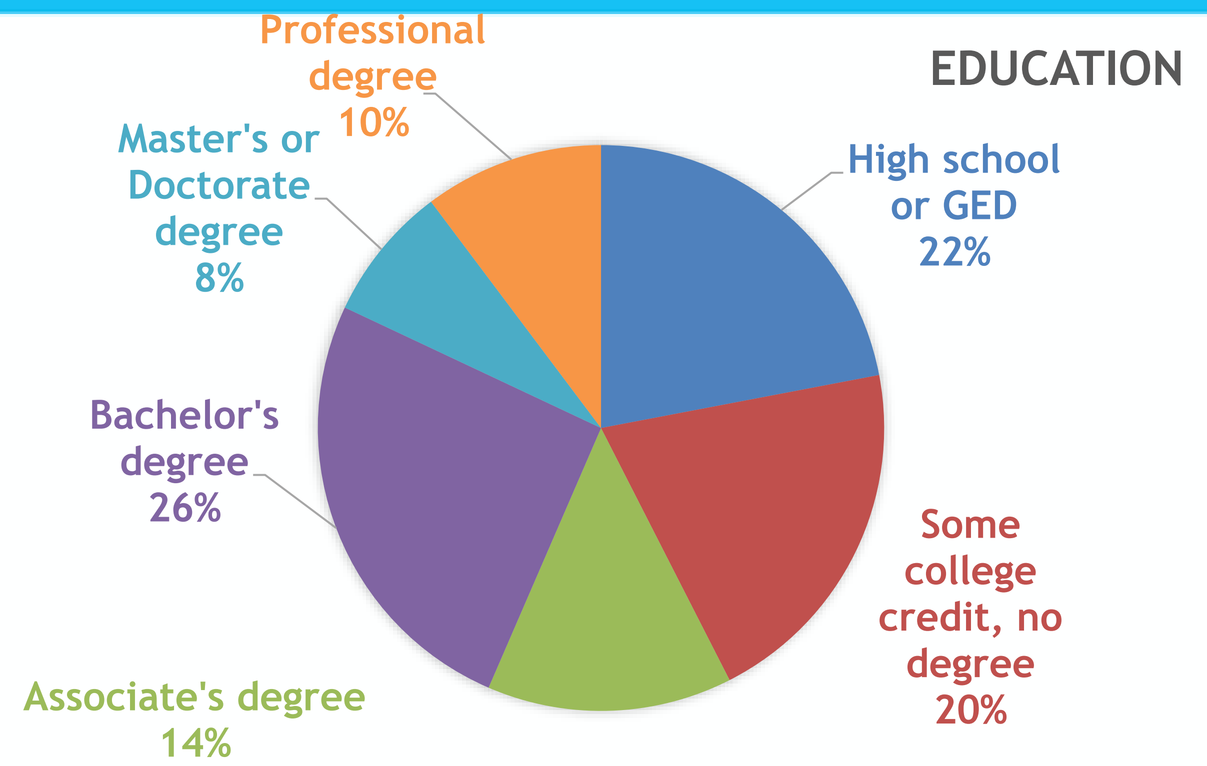
Survey Data Collection

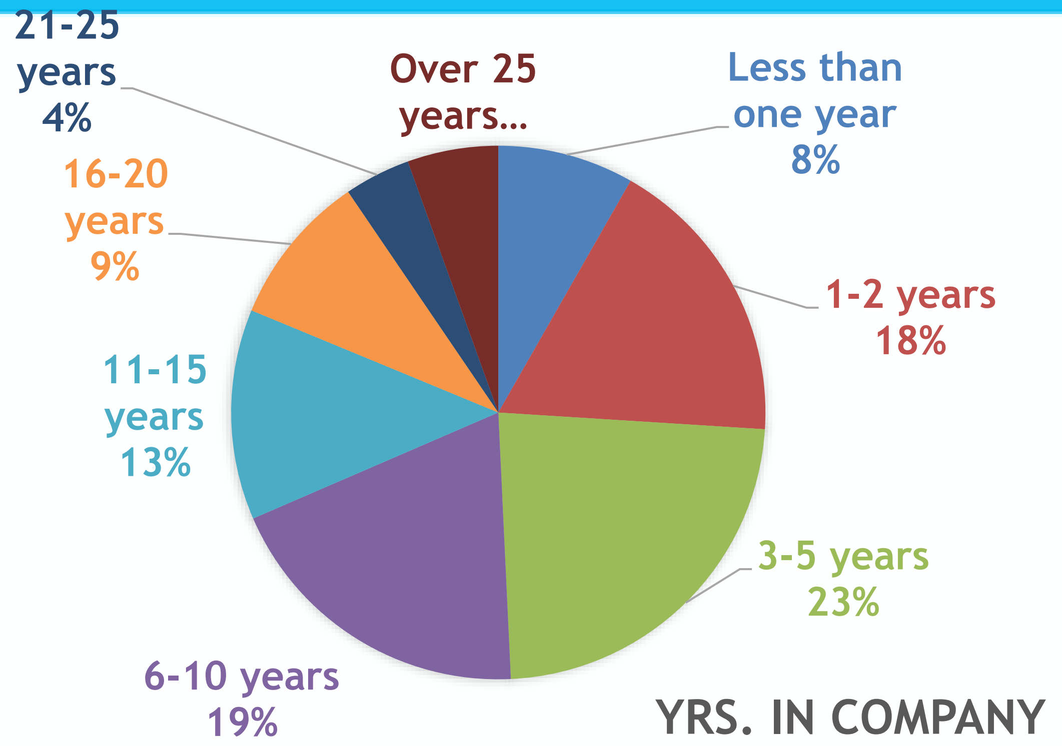
- On Qualtrics and paid for time
- Over a period of two weeks in July 2020
- Time for survey completion 10-15 min
- 60 questions
  - Respondents' socio-economic characteristics
  - Company characteristics
  - Preferences
- Administered for quality check and quick completion

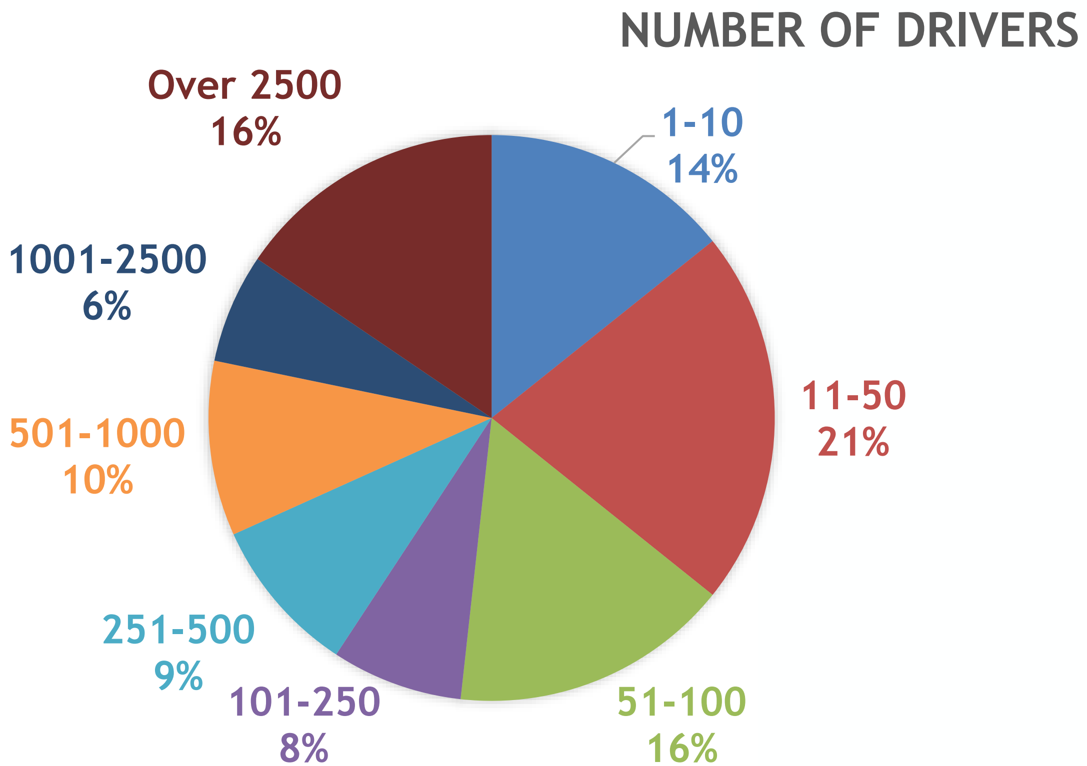


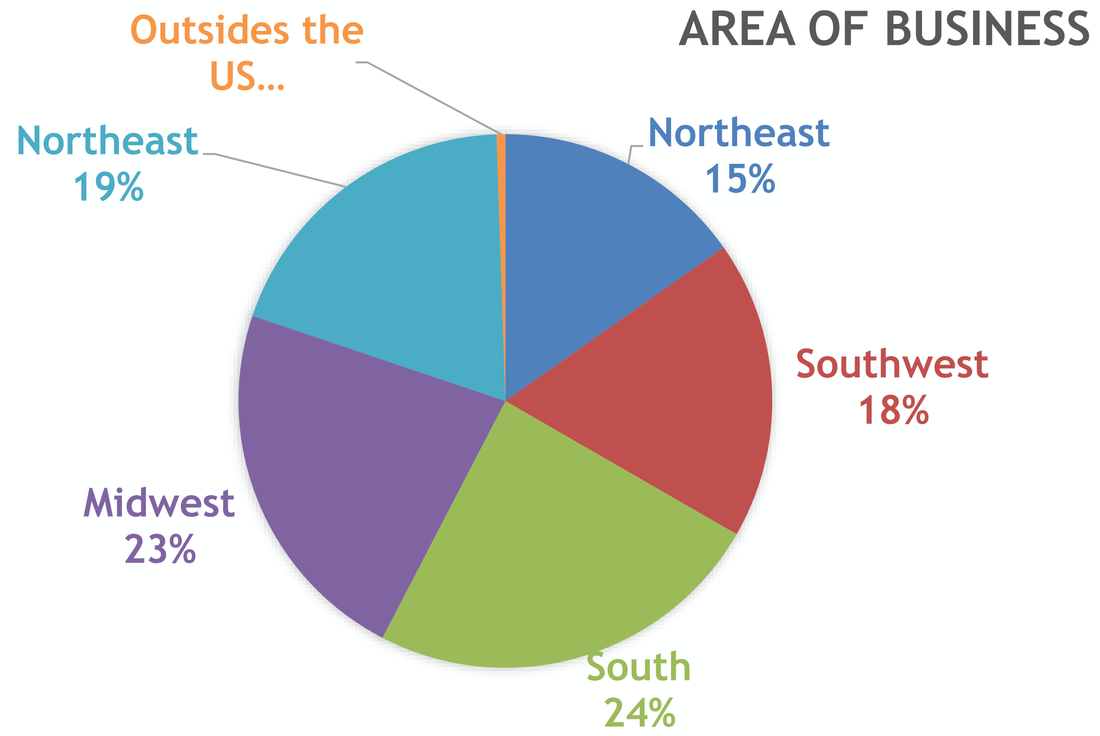
Survey Results (1)



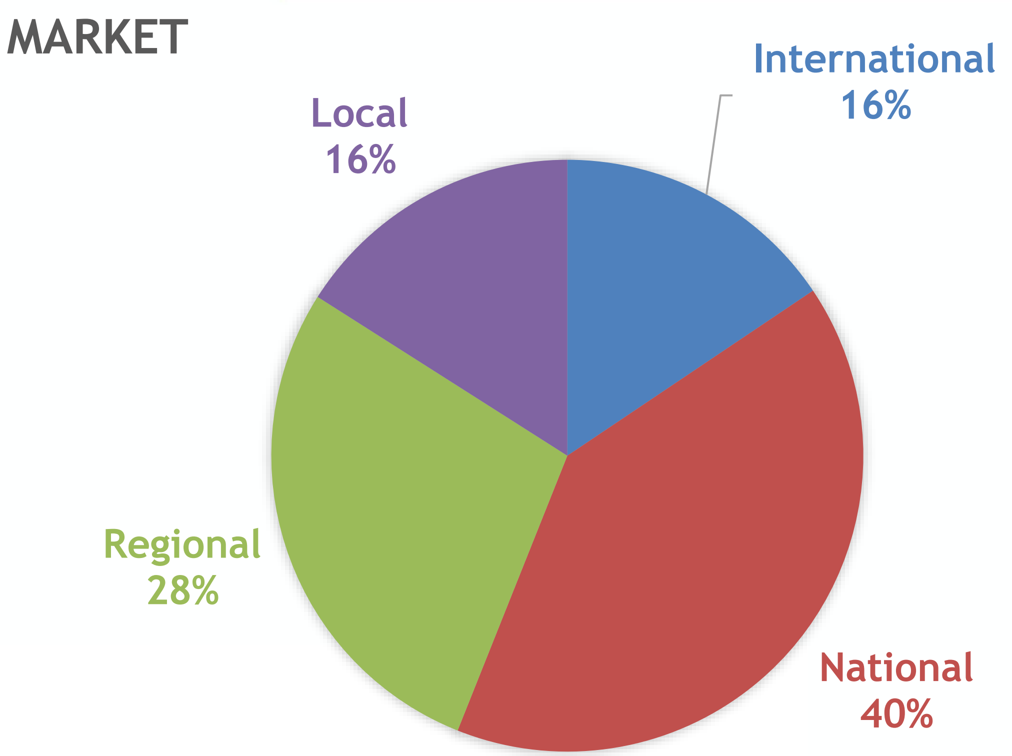


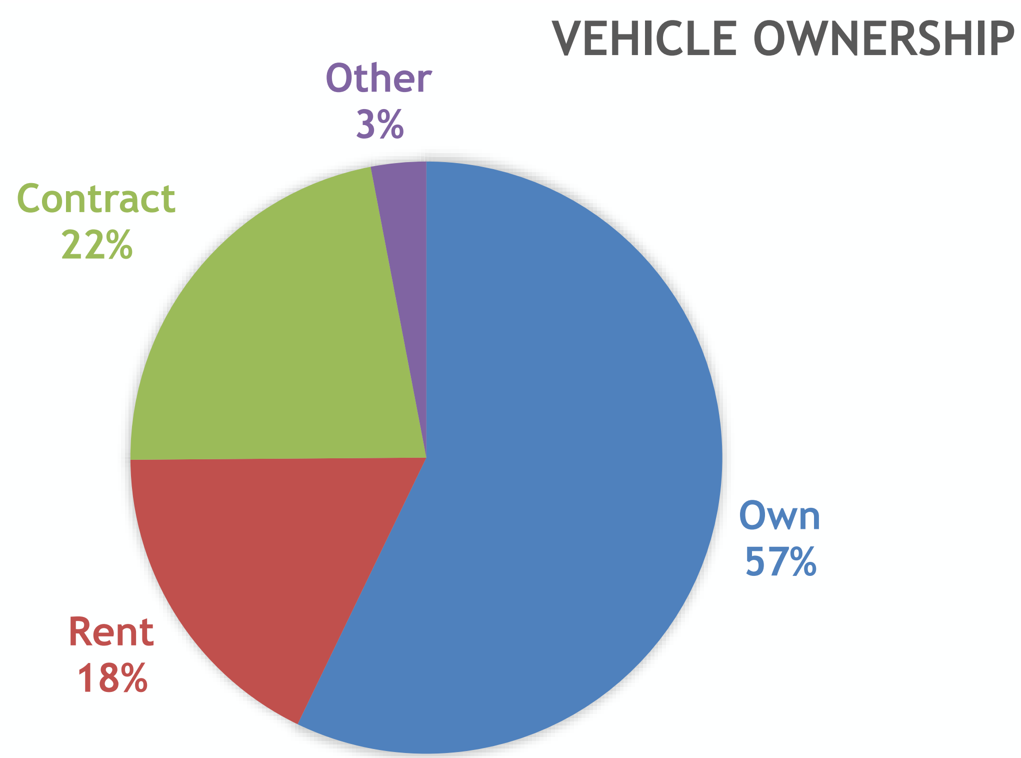


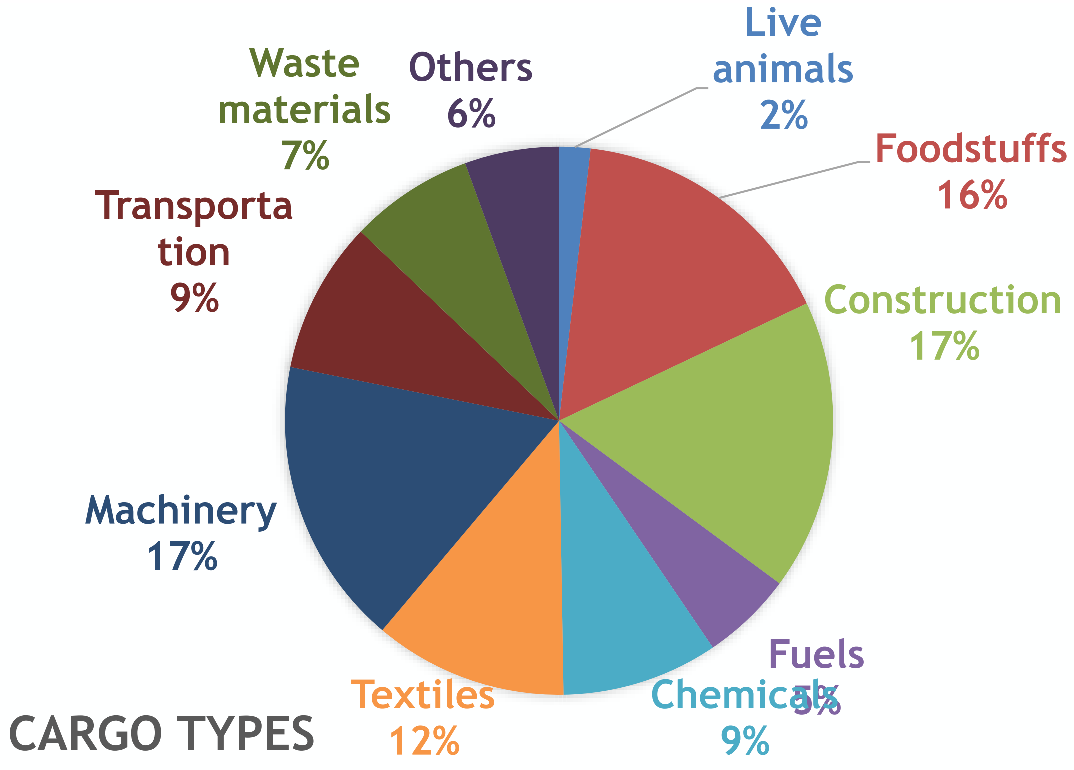


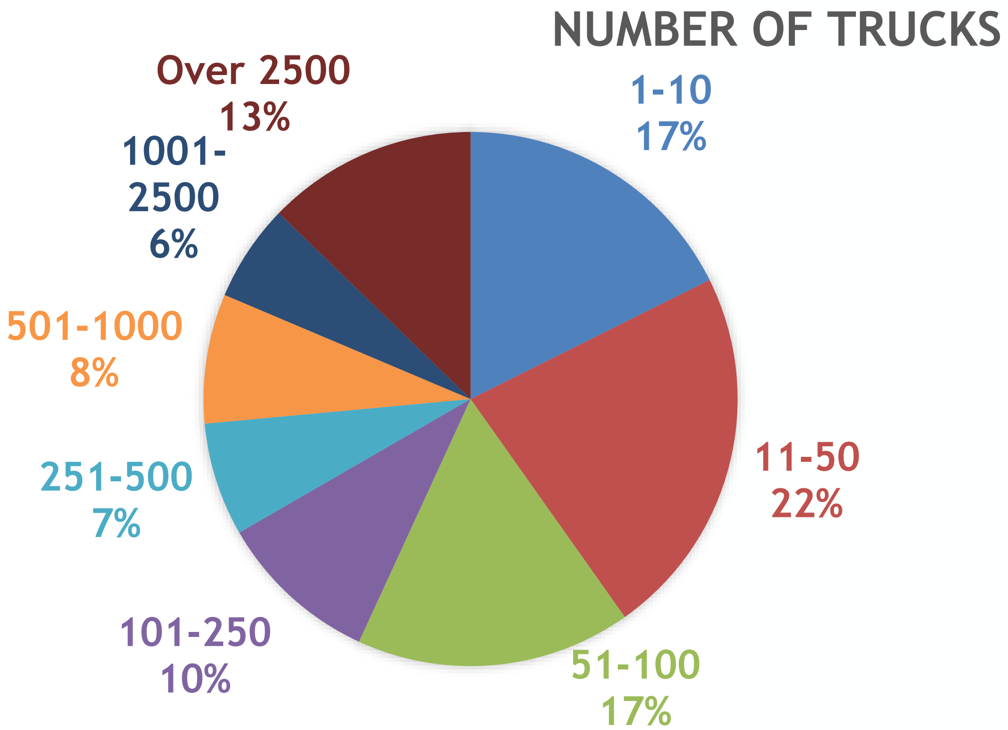


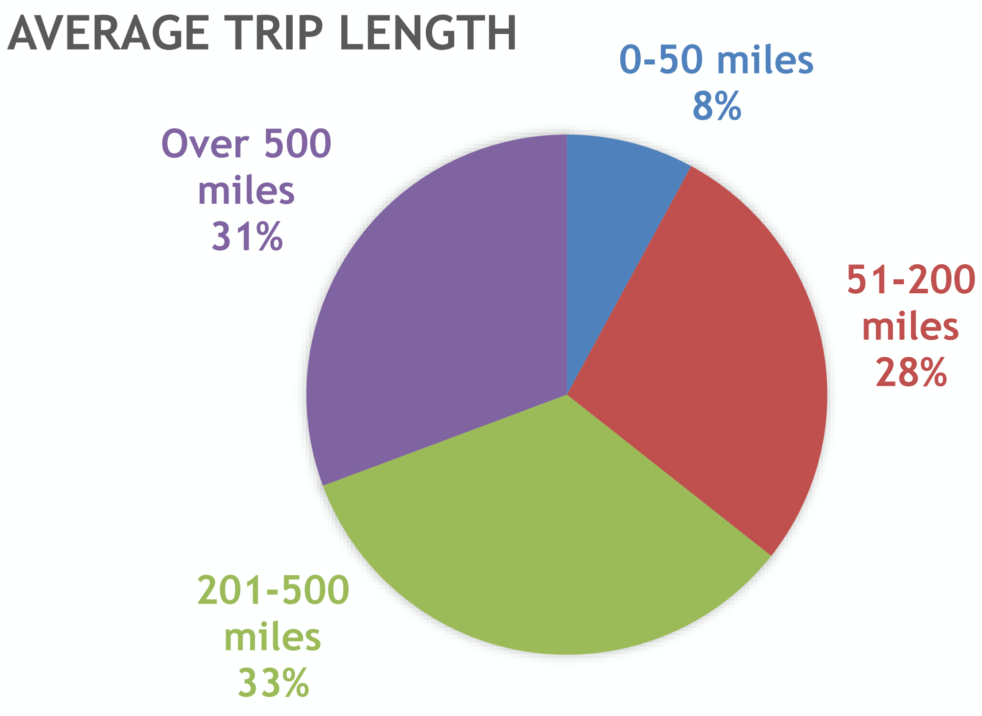
Survey Results (2)











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Stated Preferences

- Four scenarios are developed based on *additional* cost of automation (Level 1 and regular trucks are baseline)

Level of Autonomy	Additional Cost			
	Senario-1	Senario-2	Senario-3	Senario-4
Level 2	$10,000	$ 7,500	$ 5,000	$ 2,500
Level 3	$20,000	$15,000	$10,000	$ 5,000
Level 4	$30,000	$22,500	$15,000	$ 7,500
Level 5	$40,000	$30,000	$20,000	$10,000

Stated Preference in the Survey

- Example of Scenario-4 in the survey

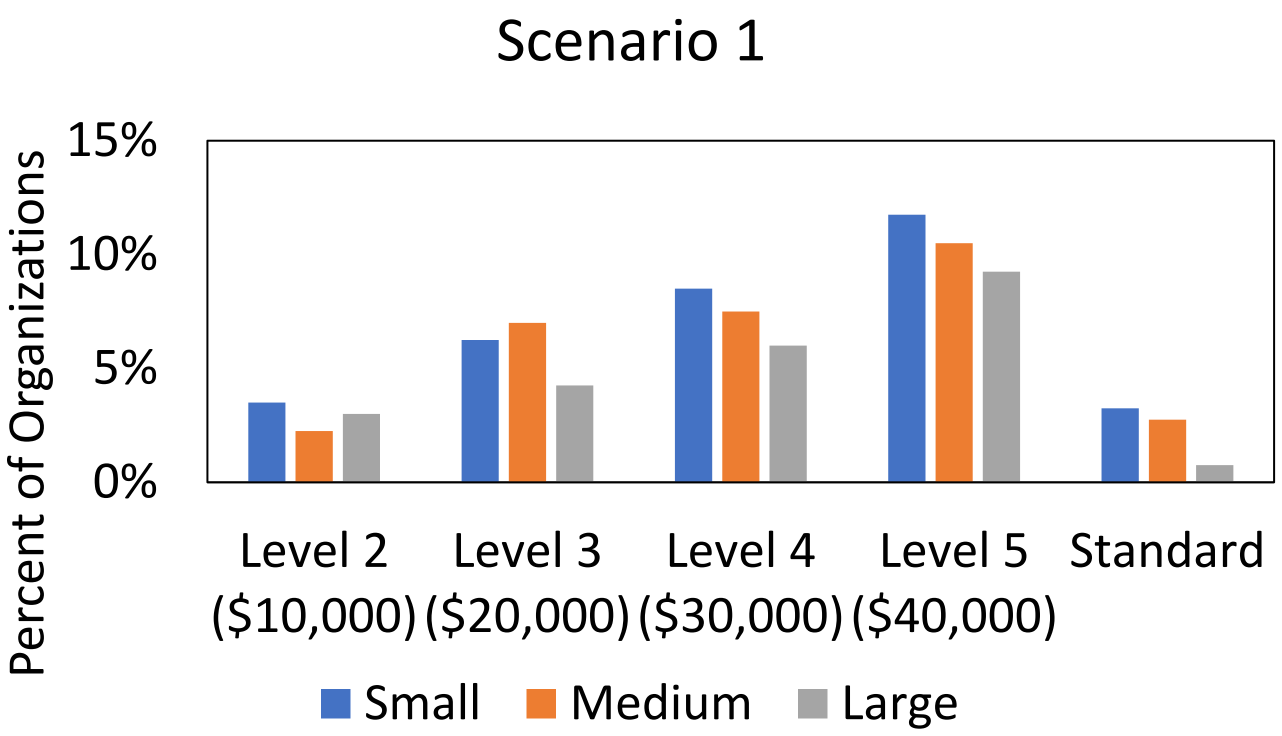
What would your company or you as owner-operator choose if the additional costs of automated technologies are as follows?

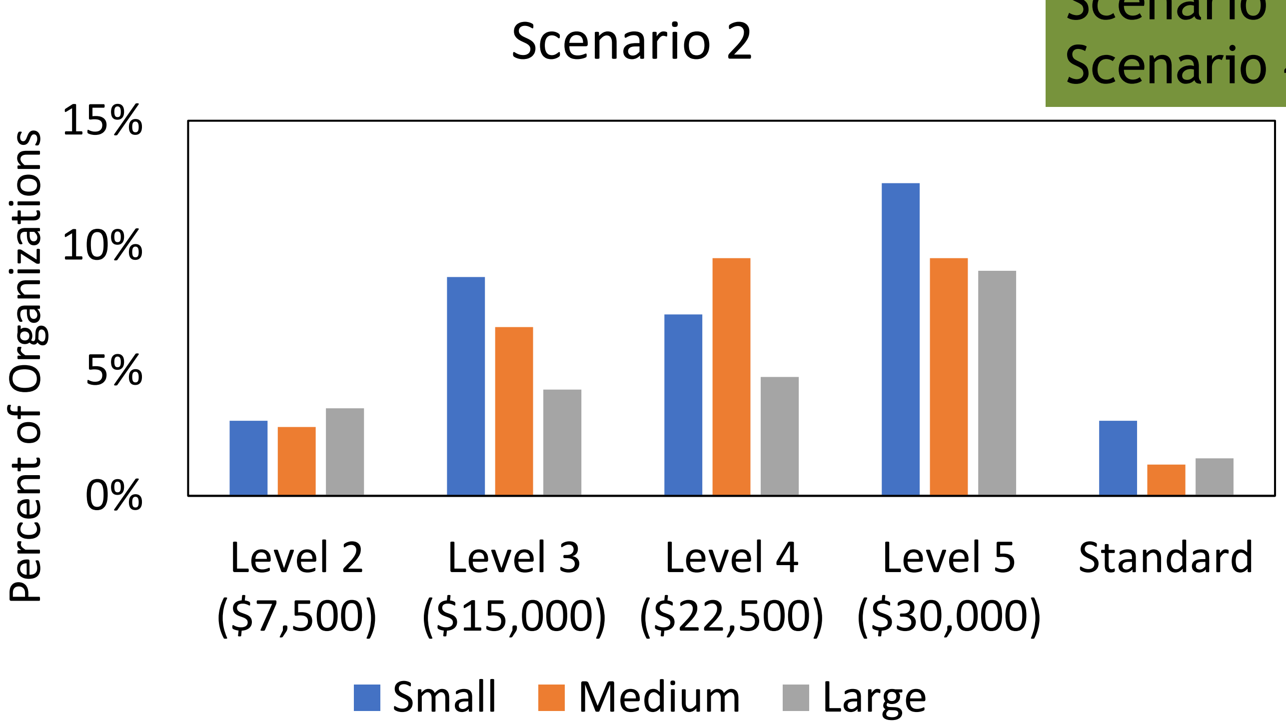
Autonomous Technology	Level 0 &1	Level 2	Level 3	Level 4	Level 5
Driver needed (cost reduction if driver is eliminated)	Yes	Yes	Yes	Yes	No
Platooning capabilities (max. 6% fuel economy)	No	No	Some	Full	Full
Capability to sync with other vehicles and traffic signals (max. 5% fuel cost reduction)	No	Low	Some	Full	Full
Safety benefits (max. 10% fewer crashes)	No	Low	Some	High	Full
More productivity (extending HOS beyond 11 hrs/day)	No	No	Low	Some	High
Additional cost of highly automated technologies	*None*	*$ 2,500*	*$ 5,000*	*$ 7,500*	*$ 10,000*

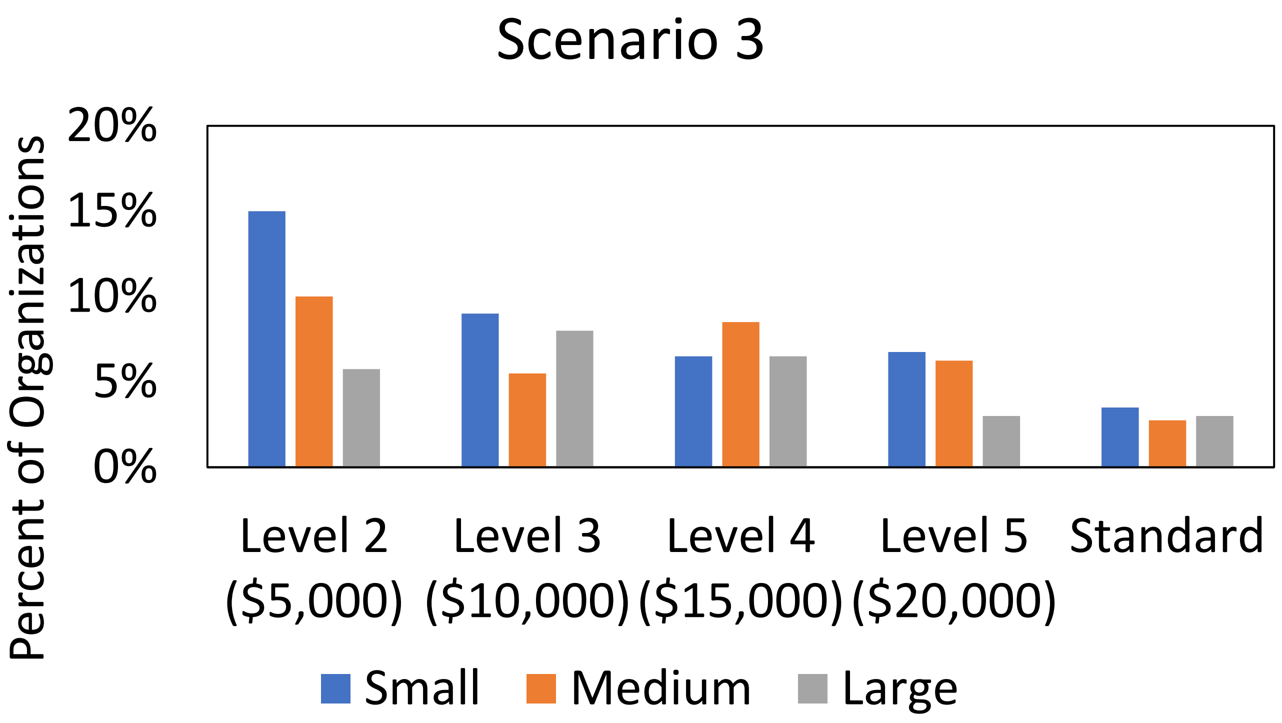
Next

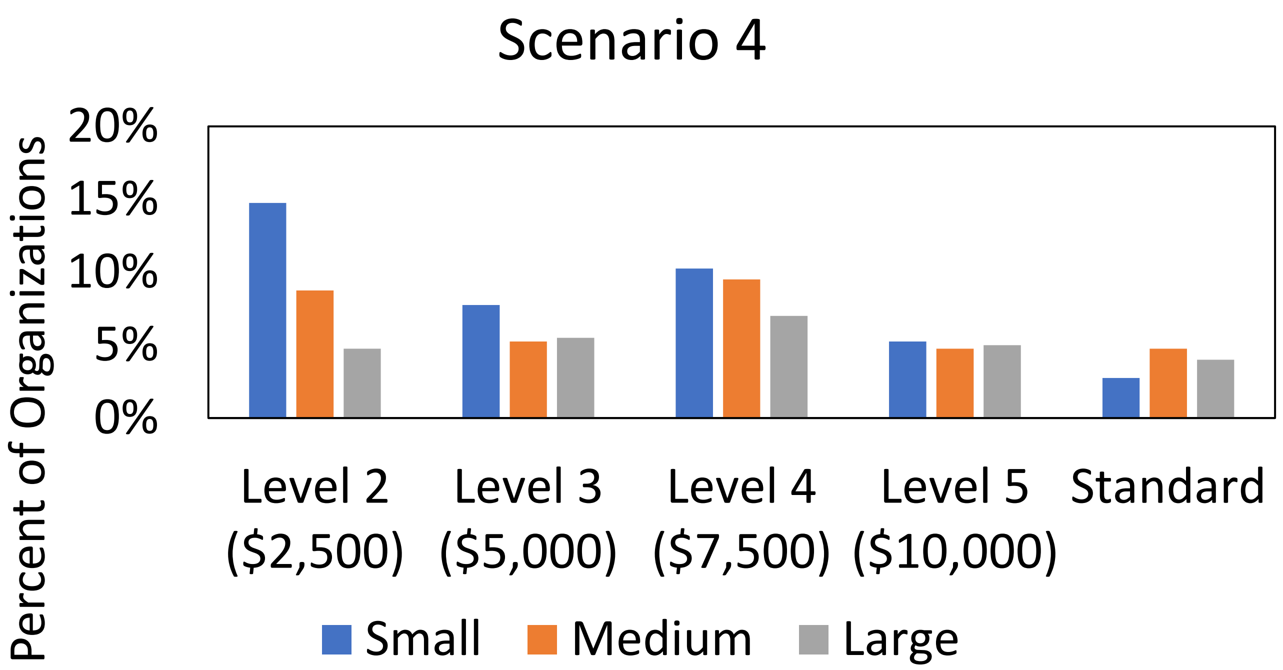
Willingness to Pay (stated) – By Firm Size

Scenario 1 Most Expensive
Scenario 4 Least Expensive









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Methodology (1)

- Choice modeling framework for analyzing SP data
- Utility of choosing alternative *i* for firm *n*: $U_{ni} = V_{ni} + \varepsilon_{ni}$
  - V_{ni} is known up to some parameters (i.e., $V_{ni} = \beta x_{ni}$)
  - ε_n is the error term
- Each $\varepsilon_{n\mathrm{i}}$ is independently, identically distributed
- If we assume that the distribution is Gumbel (Extreme Value type I), then the model is MNL
- Probability of firm *n* choosing alternative *i* can be given as
- $P_{ni} = \frac{e^{V_{ni}}}{\sum_i e^{V_{nj}}} = \frac{e^{\beta x_{ni}}}{\sum_j e^{\beta x_{nj}}}$

Methodology (2)

- Mixed logit models obviate obviates the three limitations of MNL
  - random taste variation,
  - unrestricted substitution patterns, and
  - correlation in unobserved factors over time
- Let the utility of choosing alternative *i* for person *n* be: $U_{ni} = \beta_n x_{ni} + \varepsilon_{ni}$
  - β_n is a vector of coefficients for person *n*
  - β varies over decision makers in the population with density $f(\beta)$
- $P_{ni}|\beta_n = \frac{e^{\beta_n x_{ni}}}{\sum_j e^{\beta_n x_{nj}}}$, β_n is unknown; thus we cannon condition on β
- Unconditional probability (or mixed logit probability): $P_{ni} = \int \left(\frac{e^{\beta_n x_{ni}}}{\sum_j e^{\beta_n x_{nj}}} \right) f(\beta) d\beta$
- A distribution (typically normal) is specified for the coefficients and the parameters of that distribution are estimated

Findings and Results – Model Types

- For each cost scenario, three models are developed

Model #	Model Type
Model-1	Alternative-specific cost: MNL
Model-2	Generic cost: MNL
Model-3	Individual-specific cost: Mixed Logit

- In total 12 models (4 scenarios * 3 models/scenario)
- Consistent with the relevant literature, MXL models are developed based on 1,000 draws for each individual.
- Random draw example-age:
  - we assign a random age uniform distribution between start and end values

Findings and Results – Effect of Age

- Significant variables in Scenario1, with Mod1 - Age
  - Age is significant for all alternatives, except for Level 5
  - Age has negative impact on adoption of higher levels of automation which means the higher the age of individual, the higher his/her negative impression about Levels 3-5 of automation.

Model-1

Coefficient	Est	Std Err	P-value
Age_Lev1	0.0222	0.00901	0.014
Age_Lev2	0.0157	0.00916	0.0994
Age_Lev3	-0.0298	0.00953	0.00384
Age_Lev4	-0.0434	0.0107	6.04E-05
Age_Lev5	-0.013	0.0134	0.323

Model-2

Coefficient	Est	Std Err	P-value
Age_Lev1	0.0143	0.009	0.113
Age_Lev2	0.00786	0.00916	0.411
Age_Lev3	-0.0377	0.00954	0.00026
Age_Lev4	-0.0513	0.0107	2.17E-06
Age_Lev5	-0.0209	0.0134	0.112

Model-3

Coefficient	Est	Std Err	P-value
Age_Lev1	0.115	0.0198	1.89E-10
Age_Lev2	0.0984	0.0126	2.89E-15
Age_Lev3	0.0449	0.00998	2.09E-05
Age_Lev4	0.0233	0.0144	0.0799
Age_Lev5	0.048	0.0217	0.0167

Findings and Results- Effect of Ownership Status

- Vehicle ownership status
  - Own (only for Level 1): negative coefficient, always significant at *p-value* of 1%
  - Contract (only for Level 1): negative coefficient, always significant at *p-value* of 10%
  - Companies owning vehicles can hardly incur the cost of buying autonomous trucks
  - The absolute value of B_Own is about two times of that of B_Contract
    - Strong resistance of fleet owners to adopt higher level of automation

Findings and Results- Effect of Education

Level of Autonomy	Additional Cost			
	Senario-1	Senario-2	Senario-3	Senario-4
Level 2	$10,000	$ 7,500	$ 5,000	$ 2,500
Level 3	$20,000	$15,000	$10,000	$ 5,000
Level 4	$30,000	$22,500	$15,000	$ 7,500
Level 5	$40,000	$30,000	$20,000	$10,000

Increasing adoption with lowering cost

- Education
  - Some college credit, no degree
    - Prefer Level 2 (positive likelihood with coefficient less than 1)
  - Associate's degree
    - Prefer Level 3 (positive likelihood with coefficient less than 1)
  - Professional degree, trade, technical, or vocational training
    - Prefer Level 4 and 5 compared to lower levels (positive likelihood with coefficient less than 1)
    - Focusing on Mod-3, the coefficient decreases as we move from scenario 1 to scenario 4 suggesting that the impact of this education level on **adoption likelihood increases** with **lowering technology cost** which makes sense
  - All significant at 5% level in all scenarios and with all models

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Findings and Results- Geographic Region

- Geographical variables
  - Midwest: higher significance for Level 5 (always at *p-value* 5%)
  - Northwest: : higher significance for Level 5 (at *p-value* 10% with Mod1 and Mod2, and at 20% with Mod3 in all scenarios)
  - South: only significant for Level 1 (always at *p-value* 5%) – conservative approach in Southern states?
  - Southwest: : higher significance for Level 3 (always at *p-value* 10%)

Findings and Results- Employment Time at Firm

- Employment time
  - If employment time is less than two years – say Type 1 Tenure
    - Higher inclination towards Level 2 automation (always significant at *p-value* 5%)
  - If employment time us between 5-10 years - say Type 2 Tenure
    - Higher inclination towards Level 5 automation (always significant at *p-value* 5%)
  - The intensity of preference of Type 2 Tenure is twice as that of Type 1 Tenure
  - Higher experience than Type 2 Tenure are not significant
    - May be lower sample size or need of additional data

Findings and Results-Goodness-of-fit

- Overall, a model with generic cost (i.e., Mod 2 or 3) offers a better fit
- Based on BIC, Mod2 is the based while Mod3 is the based if AIC is considered.
- The differences are not significant representing model results are comparable

Goodness-of-fit

Measure	Mod1	Mod2	Mod3
Final log likelihood	-522.7601	-522.76	-521.491
Rho-square	0.188	0.188	0.921
Adjusted Rho-square	0.134	0.138	0.916
AIC	1115.52	1109.52	1108.982
BIC	1255.221	1237.247	1240.7

Model #	Model Type
Model-1	Alternative-specific cost: MNL
Model-2	Generic cost: MNL
Model-3	Individual-specific cost: Mixed Logit

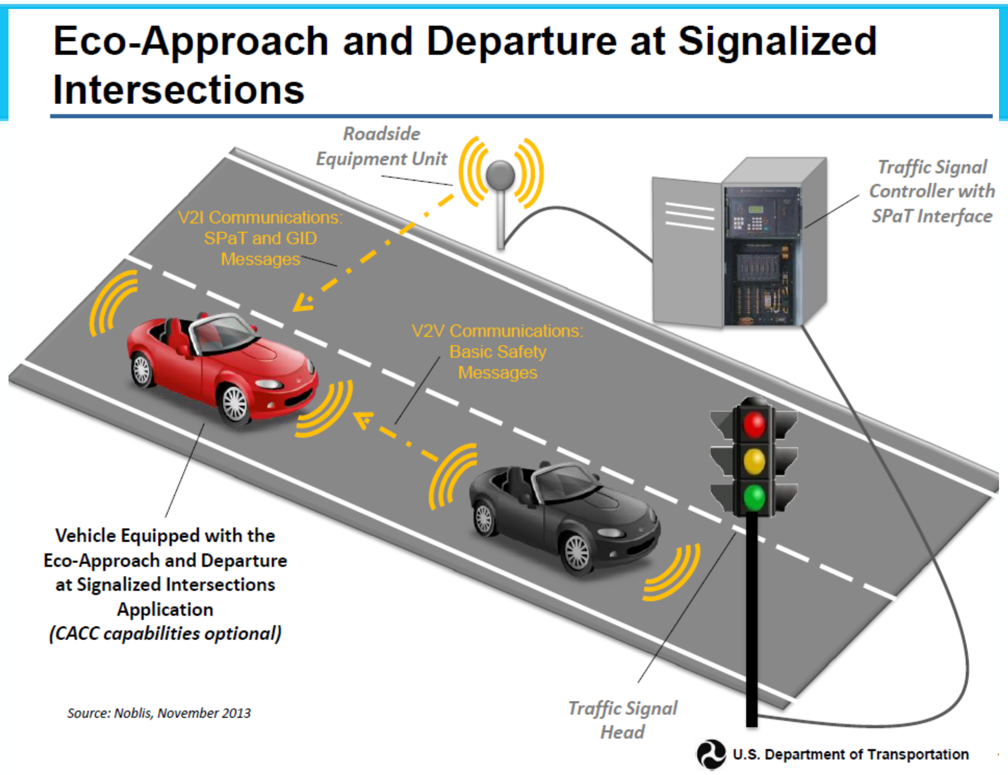
Conclusion

- The goal was to obtain industry preference towards autonomous trucks
- We designed a survey to capture preference based on number of variables
- Obtained a reasonable data for modeling and analysis
  - Sample size can certainly be improved as a part of future work
- Survey data itself is insightful
- Modeling approach provided us likelihood of adoption cross classified by
  - Age
  - Education
  - Type of fleet owner
  - Geographic Level
  - Tenure at work
  - Many other findings we did not discuss because of time limitation

Other Highly automated technologies – Industry Adoption

Platooning technology (*source: oemofhighighway.com*)

Automated transit buses *(source: olli.com)*



RSU*(source: dot.gov)*

Drones for last mile deliveries (*source: dhl.com*)

3-D printing technology *(source: cnn.com)*

Preliminary work

- Methodological groundwork for predicting the adoption rate of innovations by organizations.
- By incorporating peer effects, we provide an estimate of the market penetration rate of vehicle innovations.
- This research can help policymakers to prepare appropriate legislation and regulations for CAV operations.

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An estimation of the future adoption rate of autonomous trucks by freight organizations

Check for updates

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ARTICLE INFO

Keywords:
Connected autonomous trucks
Organizational adoption
Diffusion of innovations
Freight transportation
Market penetration predictions

JEL classification:
R42

ABSTRACT

This paper presents a model to estimate the future adoption of connected autonomous trucks (CATs) by freight transportation organizations. An accurate estimation of the market penetration rate of CATs is necessary to adequately prepare the infrastructure and legislation needed to support the technology. Building upon the theory of Diffusion of Innovations, we develop Bass models for various freight transportation innovations, including improved tractor and trailer aerodynamics, and anti-idling technologies for trucks. The proposed model accounts for heterogeneity between organizations by using a modified Bass model to vary parameters within a designated range for each of the potentially adopting organizations. The results of the paper are Bass models for existing freight organization innovation adoption and estimates of multiple scenarios of CAT adoption over time by freight organizations within the case study region of Shelby County, Tennessee and provide a foundation for organizational innovation adoption research. Our analyses suggest that the market penetration rate of CATs within 25 years varies from nearly universal adoption (i.e., more than 95%) to 20% or less depending on the rate at which autonomous technology improves over time, changes in public opinion on autonomous technology, and the addition of external influencing factors such as price and marketing.

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Research paper

Developing a methodology to predict the adoption rate of Connected Autonomous Trucks in transportation organizations using peer effects

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ARTICLE INFO

JEL classification
R42

Keywords
Organizational innovation adoption
Peer effects
Connected autonomous vehicles

ABSTRACT

This paper presents a methodology for predicting the adoption rate of Connected Autonomous Trucks (CATs) in transportation organizations using peer effects. There are a number of different factors that must be considered when developing innovation adoption models for organizations. This paper briefly describes each of the relevant variables and combines them into a discrete choice model for predicting the adoption rate of CATs by a hypothetical sample of transportation organizations. The model incorporates new peer effect modeling techniques to simulate the competition and informal communication network. Preliminary results suggest that organizations which are larger are less likely to change their decisions due to the decisions of other, competing organizations, whereas smaller organizations are more easily influenced by the decisions of larger organizations. The methodology developed in this paper produces reasonable results using a hypothetical dataset, and the methodology has been designed to be transferrable to any number of organizational innovations.

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  - Dr. Mihalis Golias (UofM)
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