An Estimation of the Future Adoption Rate of Autonomous Trucks by Freight Organizations

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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, anti-idling technologies for trucks, and other organizationally adopted innovations. The proposed model also 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 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.

Keywords: connected autonomous trucks, organizational adoption, diffusion of innovations, freight transportation, market penetration predictions

JEL classification R42

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1. Introduction

Many signs point to driverless vehicles joining the fleet within the next ten years. Connected Autonomous Vehicles (CAVs) have the potential to revolutionize transportation, and there has been significant research and development on the operational side of making automated vehicles a reality. However, there are a number of other barriers to overcome before widespread adoption is possible (Fagnant and Kockelman, 2015). Safety concerns, legality and liability questions, security/privacy matters, and infrastructure changes must be identified and addressed before autonomous technology reaches maturity (Fagnant and Kockelman, 2015; Kockelman et al., 2017). In order for policymakers to make informed decisions about these issues, it is essential to have an estimate of the market penetration rate of CAVs.

The freight transportation industry stands to benefit from integrating connected autonomous vehicle technology. One benefit would be a reduction in collisions, which translates to safer working conditions, increased profits, and reliability (Anderson et al., 2014; Bagloee et al., 2016). Of arguably greater interest to freight organizations, connected autonomous trucks (CATs) are predicted to increase fuel efficiency, reducing consumption by up to 10-15% (Anderson et al., 2014; Bagloee et al., 2016; Bullis, 2011; Fagnant and Kockelman, 2015; Huang and Kockelman, 2018; Kockelman et al., 2017). Integrating CATs into the fleet would also reduce the labor required to move goods, further reducing the cost of operations. Freight organizations are already attempting to address a shortage of drivers, and CATs may be the solution to the labor shortage (Rossman, 2017). The highest costs associated with long-distance trucking are driver salary and fuel costs, and CATs have the potential to greatly reduce both of these costs (Shankwitz, 2017). Reducing the manpower required to operate the vehicles may also allow organizations to be more productive, because laws that regulate the number of hours a driver may legally travel might not apply to driverless vehicles.

However, it is difficult to predict how policymakers will react to autonomous freight vehicles. Unlike individual CAVs, state and federal DOTs have not yet released significant regulations or guides for integrating CATs into the freight industry (Hook, 2017). In addition, organizations exhibit significant heterogeneity, and so their adoption behavior is challenging to anticipate (Frambach and Schillewaert, 2002; Ryan and Tucker, 2012). Without sufficient data on autonomous freight adoption, it is difficult to identify and address the various infrastructure, policy, and logistical changes that will need to be made as freight organizations switch to automation. It is, therefore, critical to develop a model to estimate the adoption rate of CATs for freight organizations.

One of the most widely recognized methods for explaining the rate of innovation adoption is the theory of diffusion of innovations (Mahajan et al., 1991; Rogers, 2003). Diffusion of innovations studies often focus on individual adoption rather than organizational adoption, or only discuss organizational adoption in a generalized manner. Most studies for organizational innovation adoption focus on attempting to identify characteristics of organizations that promote adoption (Damanpour, 1991; Hoerup, 2001; Kim and Srivastava, 1998; Moch and Morse, 1977; Pierce and Delbecq, 1977; Rogers, 2003; Subramanian and Nilakanta, 1996) or investigate the process of adoption within an organization (Eveland, 1979; Fidler and Johnson, 1984; Leonard-Barton and Deschamps, 1988; Meyer and Goes, 1988; Rogers, 2003). This pattern holds true for CAT adoption predictions. While there have been studies that predict the market penetration rate of CAVs for individuals (Bansal et al., 2016; Bansal and Kockelman, 2017; Lavasani et al., 2016; Perrine et al., 2018; Quarles and Kockelman, 2018), the issue of CATs and the freight industry has received little attention from academia. The literature only briefly mentions CATs in freight transportation (Catapult Transport Systems, 2017; Fagnant and Kockelman, 2015; Kockelman et al., 2017) or focuses on the costs and benefits of implementing CATs for freight without approaching the question of demand (Csiszár and Földes, 2018; Flämig, 2016; Kunze et al., 2011; Rossman, 2017; Shankwitz, 2017). In addition, the data available to form a predictive model for organizations is lacking. There is speculation on the potential benefits and drawbacks of organizational CAT adoption (Anderson et al., 2014; Bagloee et al., 2016; Bullis, 2011; Kockelman et al., 2017; Rossman, 2017; Shankwitz, 2017), but without some of the basic information such as willingness to pay (WTP), organizational structure, strength of inter-organizational communication, upkeep and maintenance costs for CATs, and differences between consumer and both public and private corporate innovation behavior, it is very difficult to obtain accurate predictions regarding the adoption of innovations by organizations (Damanpour, 1991; Frambach and Schillewaert, 2002; Kim and Srivastava, 1998; Moch and Morse, 1977; Palmer et al., 2018). Research is needed in the area of predictive analysis regarding the potential market penetration rate of CATs in freight organizations.

This paper uses diffusion of innovations theory to provide an estimation of the future adoption rate of CATs in freight industries. A modified version of Bass model is used to account for heterogeneity between organizations. Due to the lack of currently available data, a number of reasonable assumptions are made regarding organizational innovation adoption behavior in order to better understand how the various factors influencing the adoption of CATs may interact. Applicability of the developed model is shown with a dataset containing all freight organizations within Shelby County, the largest county both in terms of population and geographic area in the State of Tennessee, and a center for both air and ground freight transportation.

The remainder of the paper is organized as follows. The following section outlines the process for modeling the adoption rate of CATs by freight organizations. Section 3 contains a brief description of the data gathered for analysis, followed by Section 4, which details the results of our model, the implications of the results, and a sensitivity analysis is performed on the model output. Finally, Section 5 concludes and summarizes major findings.

2. Methodology

This section elaborates on the methodology being used to forecast CAT adoption. We start with an overview of classic Bass models to offer an understanding about how this modeling approach forecast adoption of an innovation, and then move to a disaggregate Bass model operationalized to generate adoption probability for each firm.

The Bass model is primarily used to describe the diffusion of innovations process (Bass et al., 1994; Mahajan et al., 1995; Massiani and Gohs, 2015; Meade and Islam, 2006; Moch and Morse, 1977; Rogers, 2003; Wright and Charlett, 1995). Diffusion of Innovations theory identifies a number of factors that cause innovation adoption, including relative advantage, compatibility, complexity, trialability, reinventability, and observability (Greenhalgh et al., 2004; Rogers, 2003). Bass estimates the adoption rate of an innovation by consolidating these factors into two parameter: one which is positively influenced by the number of previous adopters, and one which is independent of the previous adopters (Bass, 2004; Bass et al., 1994; Rogers, 2003). The parameter which is not influenced by the number of adopters is commonly referred to as the Coefficient of Innovation (CoN), or external influences. CoN accounts for factors like compatibility, which are independent of the behaviors of other individuals. The parameter influenced by the number of previous adopters is referred to as the Coefficient of Imitation (CoM), or internal influences. CoM accounts for variables such as observability, which grow stronger as more people adopt the innovation. The Bass model lays the foundation for quantifying the social aspect of innovation adoption, which is central to diffusion of innovations theory. The Bass model is:

$$n(t) = p * [m - N(t)] + \left(\frac{q * N(t)}{m}\right) * [m - N(t)] \tag{1}$$

where *n(t)* is the number of adopters at time *t, m* the market potential, or maximum potential adopters of the innovation, *N(t)* the cumulative number of adopters at time *t, p* the coefficient of innovation (CoN), and *q* the coefficient of imitation (CoM) (Mahajan et al., 1995, 1985; Rogers, 2003). By integrating over *t*, a closed-form expression for the cumulative number of adopters can be obtained as:

$$N(t) = m\left(\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}\right) \tag{2}$$

Initially, very few potential adopters choose to adopt the innovation due to the fact that the initial number of adopters is near or equal to zero, making the power of the imitative force small. Therefore, early adopters almost exclusively adopt due to the innovative force (Lavasani et al., 2016; Mahler and Rogers, 1999; Rogers, 2003). However, as more adopters choose to accept the innovation, a point is reached where the adoption rate rapidly increases due to an increase in imitative influence. This point is referred to as the critical mass, and it typically occurs somewhere between 10 and 20% of the market potential (Mahler and Rogers, 1999). Once the point of critical mass has been achieved, an innovation is likely to gain widespread adoption of 90% or greater of the market potential (Rogers, 2003). The resultant curve of the Bass model is S-shaped, but unlike most other S-curve models, the Bass model also includes practical insight into the innovation adoption behavior due to its initial premise of innovative and imitative forces (Bass, 2004). For example, a Bass model with the parameters of 0.01 for the CoN and 0.1 for the CoM are comparable to the sigmoidal curve with parameters of 3.2 for alpha and -0.14 for beta. The main advantage that the Bass model provides over a sigmoidal curve is that the sigmoidal curve would need to be modified to provide the number of adopters over time, and the alpha and beta parameters do not carry any obvious behavioral implications in the way that the Bass parameters do.

Over the years, a number of advancements have been made to the original Bass model. An important improvement has been the addition of external influencer variables. This addition is presented in equation 3:

$$n(t) = \left\{p * [m - N(t)] + \left[\frac{q * N(t)}{m}\right]\right\} * X(t) + \epsilon \tag{3}$$

where $X(t)$ is the factor which accounts for all external influencer variables that are not covered explicitly by the CoN and CoM. The general form of $X(t)$ is:

$$X(t) = 1 + \beta_i X_i \tag{4}$$

where X_i represent the external influencer variables, and β_i represents the corresponding coefficients for each of the variables. When no external influencing variables are included, $X(t)$ is equal to 1. These external influencing variables can include the price of the innovation, willingness to pay, and marketing strategies (Lavasani et al., 2016; Mahajan et al., 1991). Because data on these external influencing variables does not exist at this time, we provide placeholders for these variables to demonstrate how they will affect the model.

The full process of estimating the market penetration of CATs over time at disaggregate level is demonstrated in Figure 1. The first step is to estimate the Bass parameters for CATs. One of the difficulties in using the Bass model for forecasting is determining the values of the Bass parameters for the new innovation. Bass parameters are traditionally estimated using regression methods after the innovation has been fully adopted. Therefore, to estimate an innovation's Bass parameter values prior to adoption, it is necessary to compare the innovation in question to previously adopted innovations (Lavasani et al., 2016; Massiani and Gohs, 2015; Meade and Islam, 2006; Sultan et al., 1990).

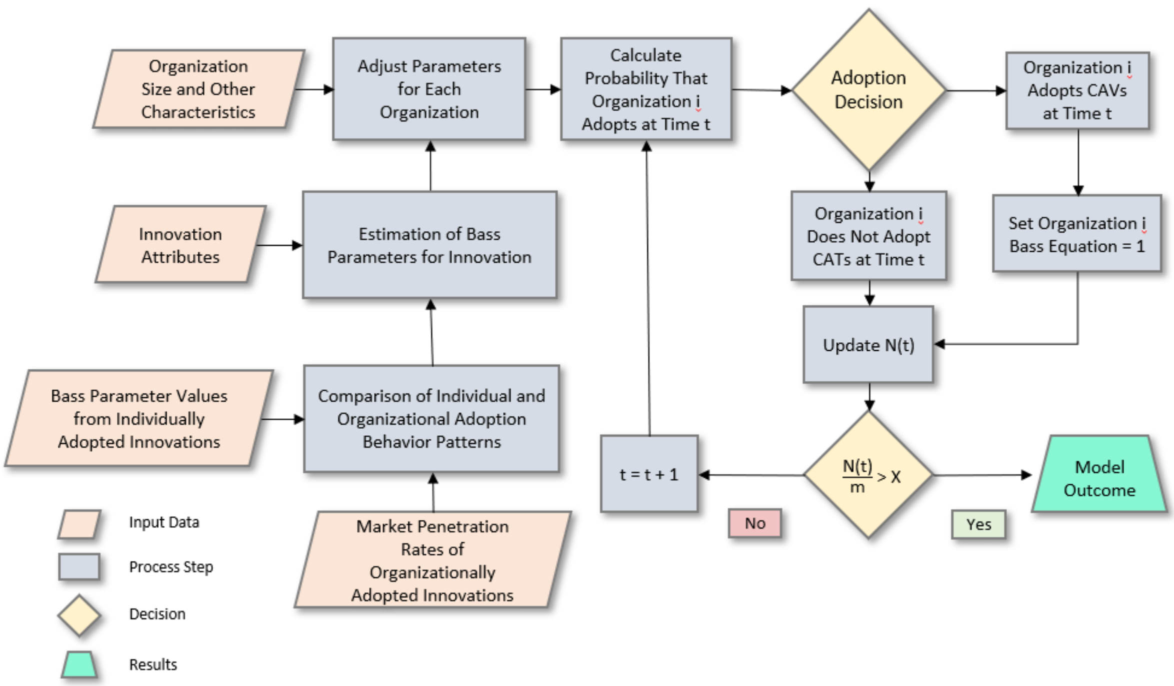

Fig. 1. Flowchart of model process

The Bass model parameters for individually adopted innovations are well-documented, but organizational adoption has received less attention, and this is a problem because there are few studies providing data for organizational adoption parameters. Therefore, it is necessary to first investigate the rate of organizational innovation adoption and how it differs from individual adoption rates. To this end, we gather organizational innovation market penetration data from multiple sources and perform non-linear regression to calculate Bass model parameters. These parameters are then compared to Bass model parameters for individual organizations found in multiple sources. From this comparison, conclusions are drawn regarding the behavior of organizational innovation adoption and how it differs from individual adoption behaviors.

Once the behavior of organizational innovations has been established, it is possible to estimate the Bass model parameters for the specific innovation in question. In the case of freight organization CAT adoption, we can form this estimation by examining both the innovation attributes and the estimated parameters for individual CAV adoption (Lavasani et al., 2016; Rogers, 2003). By examining the behavior patterns for innovation adoption by both individuals and organizations, we can estimate the expected Bass model parameters for CATs.

Organizations are heterogeneous, and so they may have slightly different values for CoN and CoM (Ryan and Tucker, 2012). As Figure 2 illustrates, local organizations have lower ability to innovate than larger, national organizations, and so the adoption model must account for this heterogeneity. To address organizational heterogeneity, each organization is assigned parameter values within the proposed range for CoN and CoM based on the number of employees in the organization. Organizational size is chosen as the independent variable because larger organizations are more inclined to innovate than smaller organizations (Frambach and Schillewaert, 2002; Mahajan et al., 1995; Rogers, 2003), and size is far easier to measure than other organizational attributes linked to innovativeness (Rogers, 2003).

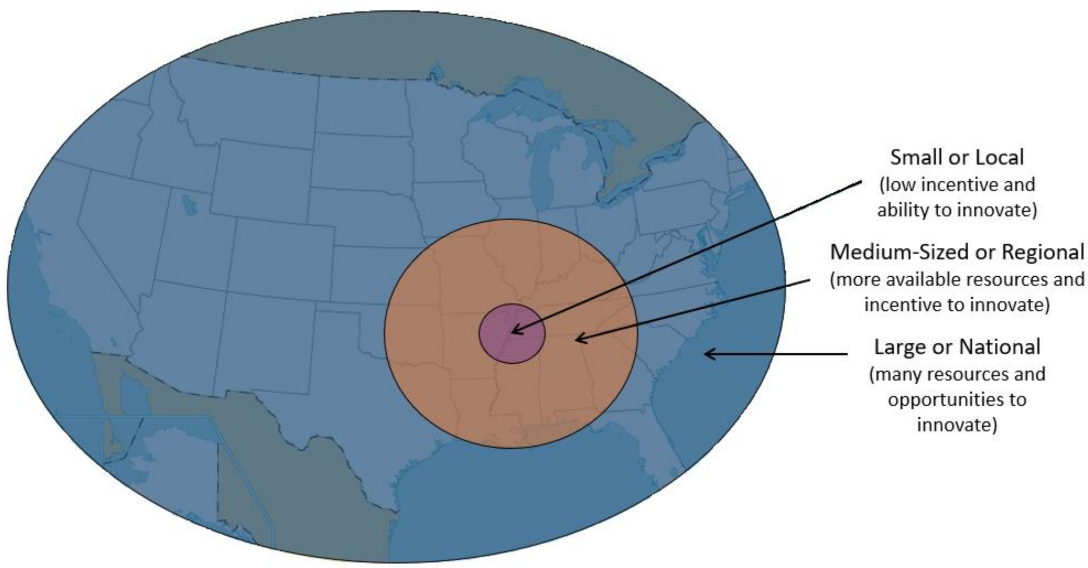

Fig. 2. Spheres of influence and tendency toward innovativeness for organizations of differing sizes

Once each organization has been assigned Bass parameter values, it is possible to simulate the adoption decision process using the modified version of the Bass model described by equation 5:

$$Org_{i,t} = \left[p_i + \left(\frac{q_i * N(t)}{m}\right)\right] * X(t) + \epsilon \tag{5}$$

In the original Bass model, the p and q values are multiplied by $[m - N(t)]$, which represents the number of potential adopters that have not yet decided to adopt. By creating a Bass equation for each individual, this $[m - N(t)]$ term becomes equal to 1, and this converts the Bass model into an equation to calculate the probability $Org_{i,t}$ that organization i will adopt a CAT at time t (Amini et al., 2012; Kumar et al., 2009). A Monte Carlo simulation is then performed to estimate the adoption rate of CATs by freight organizations. To characterize the adoption decision, a cutoff-based approach is employed, where a random number (r_i) is drawn from the uniform distribution between 0 and 1, and compared to a pre-specified cutoff value. For example, if $Org_{i,t}$ is 0.5%, then organization i adopts if $r_i > 0.005$, otherwise it does not adopt at time t. The model is run 100 times, and an ANOVA test is performed to confirm that there is no statistically significant variation in the output over multiple runs.

If organization i chooses to adopt at time t, then $Org_{i,t}$ is set equal to 1 for all future cycles, as it is assumed that the decision to adopt CATs is non-reversible. The model is run until the market penetration rate is greater than or equal to the parameter X, where X is a predetermined end condition value between 0 and 1. Because the simulation model is based on Bass principles, each organization maintains communication with all other organizations. This is a more reasonable assumption to make for organizational adoption than individual adoption because organizations clearly exhibit some communicative behavior, however a formal social network does not exist between organizations (Czepiel, 1975).

3. Bass Parameter Estimations

In order to estimate the Bass parameters for CAT adoption by freight organizations, we first examine the organizational adoption behavior exhibited for previously adopted innovations. In 2015, the North American Council for Freight Efficiency (NACFE) published a report investigating the adoption of 68 fuel efficiency innovations for 14 major North American fleets. These innovations are aggregated into seven categories: trailer aerodynamics, chassis, idle reduction, tires/wheels, powertrain, practices, and tractor aerodynamics. The study covers a span of 11 years, from 2003 to 2014 (NACFE, 2015), and it provides a solid foundation for the development of Bass model parameter values for freight organizations ("NACFE Conducts Extensive Benchmarking Study on Fleet Fuel Efficiency," 2016). Figure 3 shows the market penetration of these organizational innovations. As the data was presented in terms of percentage adopted, the market potential m for all calculations is assumed to be 100%.

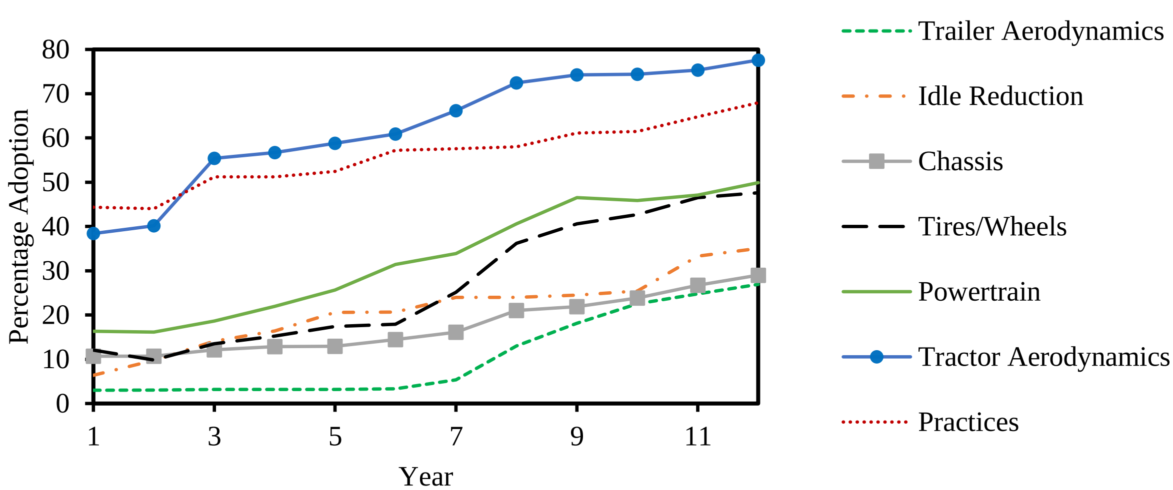

Fig. 3. Market penetration of organizational innovations by year

Regression estimations are performed on each technology category to determine CoN and CoM values. The regression equation is the same as equation 1, where the number of adopters is the dependent variable, and CoN and CoM are the parameter estimates. The results of the regression model and other reported organizational Bass model parameters are shown in Table 1 (NACFE, 2015).

Table 1

Estimated bass model parameters for organizational innovation adoption

Technology Category	CoN (p)	CoM (q)	*Adj.* R^2
Trailer Aerodynamics	0.0043	0.1927	0.951
Idle Reduction	0.0122	0.0984	0.875
Chassis	0.0000	0.1300	0.889
Tires/Wheels	0.0038	0.1605	0.931
Powertrain	0.0167	0.0927	0.929
Tractor Aerodynamics	0.0713	0.0996	0.847
Practices	0.0000	0.1084	0.834
Average:	0.0155	0.1261	0.894

While not a perfect fit, an R^2 value that is greater than 0.75 is reasonable for the number of data points available. Interestingly, the chassis and practices categories have a value of 0 for CoN. This could be due to these innovations appearing as undesirable to organizations for economic, political, or social reasons. The reason that the innovation curves in Figure 3 do not represent the classic S-curve expected by the Bass model is due to the small sample size. Each of these innovations' market penetration rate is slow enough that it does not reach the critical points of the Bass model within the study period. However, if the CoN and CoM values that were estimated by the regression model are plotted next to the innovations, the estimated market penetration rate and the actual market penetration rate line up remarkably well.

Now that a baseline for organizational adoption parameters has been established, we examine individual adoption parameters for the sake of comparison. Table 2 shows Bass model parameters for individual innovation adoption from other selected studies (Dodds, 1973; Jensen et al., 2016; Lavasani et al., 2016; Massiani and Gohs, 2015; McManus and Senter Jr, 2009; Van den Bulte and Lilien, 1997).

Table 2

Bass model parameters for individual innovation adoption from selected studies

Innovation	CoN (p)	CoM (q)	Reference
Internet	0.0067	0.3906	(Lavasani et al., 2016)
Cellphone	0.0017	0.2644	(Lavasani et al., 2016)
Electric Vehicles	0.0019	1.2513	(Massiani and Gohs, 2015)
Electric Vehicles	0.0020	0.2300	(Jensen et al., 2016)
Electric Vehicles	0.0026	0.7090	(McManus and Senter Jr, 2009)
Air Conditioner	0.0127	0.0462	(Van den Bulte and Lilien, 1997)
Color T.V.	0.0054	0.8369	(Dodds, 1973)

Cable T.V.	0.0089	0.4428	(Dodds, 1973)
Average:	0.0052	0.5214	

When compared to individual adoption parameter values, the CoN values for organizations are much larger, with the exception of the Chassis and Practices categories in Table 1. Conversely, the CoM value for individual adoption plays a larger role in the adoption rate than in organizational adoption. This indicates that organizations are more independent than individuals, and that the actions of one organization have less effect on other organizations than would be seen in individual adoption. This analysis is compatible with findings of other researchers studied organizational innovation adoption (Pierce and Delbecq, 1977). It is also intuitive that organizations would be less reliant on imitating other organizations, because most organizations are competing with one another, and they do not directly communicate as frequently as individuals. Further, organizational adoption lacks some of the social influences that contribute to individual adoption, such as peer pressure. Therefore, an innovation that provides a relative advantage over current practices will more likely be adopted based on its own merit rather than because of outside pressures.

It is reasonable to assume that the trend of higher CoN and lower CoM values for organizational adoption will also be true for CATs. Lavasani et al. generated the following estimations for the Bass model parameters for individual CAV adoption: 0.001 for CoN, 0.3419 for CoM (Lavasani et al., 2016). These values are more conservative than the average values for other individual innovations seen in Table 2. This is reasonable because autonomous technology is revolutionary enough to warrant caution from new adopters (Bansal et al., 2016; Bansal and Kockelman, 2017; Fagnant and Kockelman, 2015; Lavasani et al., 2016), although some have argued that organizations may be more likely to adopt CATs for economic reasons (Wadud, 2017). However, most research on the subject suggest that organizations are likely to be conservative concerning autonomous technology for a number of reasons, and so the range of values for CoN and CoM selected for this study reflect this (Bansal et al., 2016; Bansal and Kockelman, 2017; Fagnant and Kockelman, 2015; Kockelman et al., 2017; Lavasani et al., 2016; Wadud, 2017).

Based on the comparison of organizational and individual innovation adoption behaviors and the estimated parameters for individual CAV adoption, the CoN values selected for small, medium-sized, and large organizations are 0.005, 0.008, and 0.01, respectively. These values are also slightly more conservative than the values reported for most other organizational innovations such as trailer aerodynamics and powertrain, but still fall within the range of reasonable values for organizational innovations. Selected CoM values are 0.08, 0.09, and 0.1 for small, medium-sized, and large organizations, all of which are conservative without deviating from the established range of values.

4. Results

To estimate the market penetration of CATs for all freight organizations in Shelby County, organizational data including number of employees, organization type, and sales volume is required. This dataset was obtained from InfoUSA. Each location is considered to be a unique firm within the dataset. Most organizations are located near major cities, with clusters around Memphis, Nashville, Chattanooga, Knoxville, and Johnson City. This study uses the data from Memphis and Shelby County for analysis, as Shelby County is both the most populous county in Tennessee and a major center for both ground and air transportation.[1] This dataset contains 1,519 organizations in industries such as trucking, freight transportation and consolidation, and moving agencies.

The K-Means clustering method is used to categorize the organizations into small, medium-sized, and large groups. The K-Means clustering approach is employed as it groups the observation systematically and thus arbitrary cutoff points are avoided. Organizations with less than 85 employees per location are considered to be small, medium-sized organizations employ between 86-500 people, and large organizations contain over 500 employees. Organizations with 10 or fewer employees per location are the most common, and roughly 94% of all organizations within Shelby County qualify as small organizations.

The total fleet size of each organization is estimated based on the average yearly revenue of the organization. For-hire carriers have an average yearly revenue of roughly $200,000 per truck, where owner-operators average closer to $175,000 per truck (DAT, 3/13). Because information regarding the type of freight organization is not available, an average of $187,500 yearly revenue per truck is used to determine the fleet size of the organizations. Based on this estimate, Figure 4 shows a logarithmic histogram of the estimated fleet size of each organization in the data set.

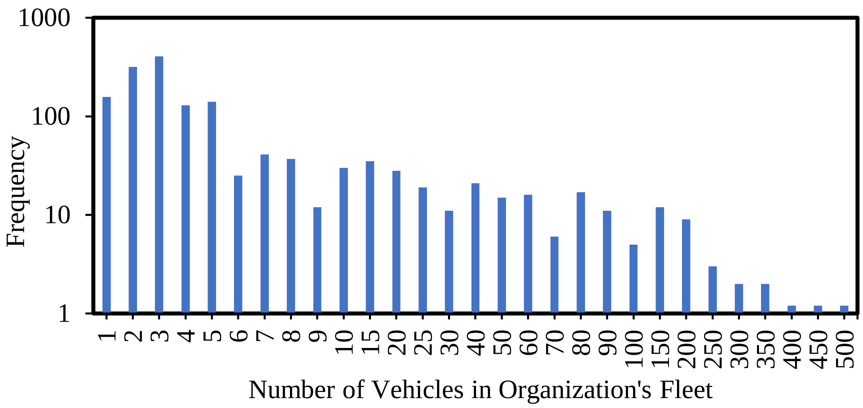

Fig. 4. Histogram of fleet size by freight organizations in Shelby County

The Bass model parameters are then applied to the data for Shelby County organizations. 1,519 organizations are included in the Shelby County dataset, so the *m* Bass model parameter is set to 1,519. Based on the assumed fleet size by organizational size and revenue, the actual market penetration of CATs is estimated. The total assumed fleet size is equal to 21,000 trucks. Figure 5 shows the CAT adoption curve for Shelby County dataset using the estimated CoN and CoM values with no external influencing variables, and Figure 6 shows the adoption curve of CATs by freight organizations given the result demonstrated in Figure 5.

1 According to the 2002 vehicle inventory and use survey (Census, 2004), Tennessee had, in total, roughly 2 million trucks, of which about 5% were heavier duty trucks. The distribution of trucks for the entire United States was 93.5% light and 6.5% heavier, so Tennessee is lower to the national average. (The vehicle inventory and use survey does not disaggregate the data further into counties.) Considering the highly active role of Shelby County in the state's freight transportation system, we expect that this study's results can offer some insights into CAT adoption at greater levels (e.g., state level).

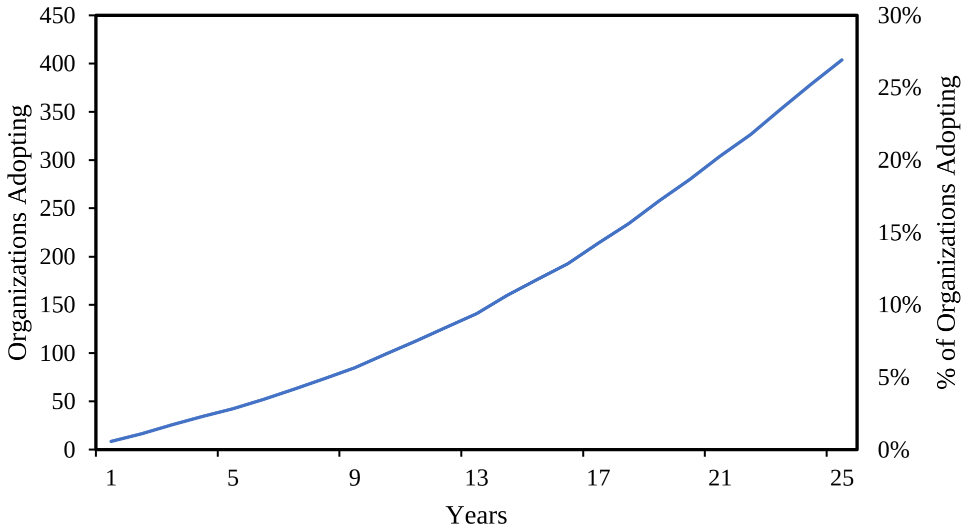

Fig. 5. Total number of Shelby County firms adopting CATs with time

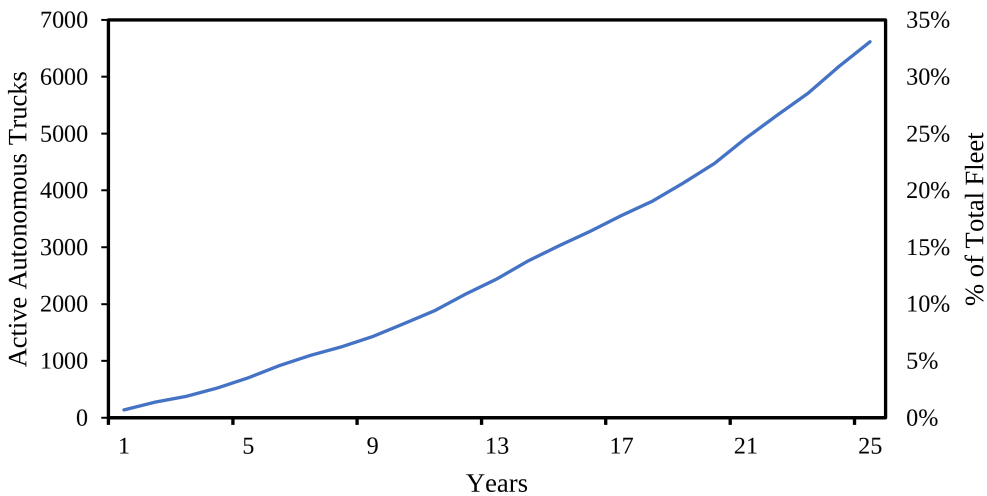

Fig. 6. Total number of active autonomous vehicles over time

Due to the uncertainty caused by the assumptions made in developing the model, as well as the inherent difficulty in predicting how organizations will behave in the more distant future, the model only considers the first 25 years after CATs become commercially available. The figure illustrates a very slow adoption curve, indicating that without any changes to autonomous technology after the initial introduction of CATs, organizations will be very slow to incorporate the technology. While the Bass model would indicate that eventually all of the organizations would adopt CATs, a curve as slow as the one demonstrated by Figures 5 and 6 would likely indicate a failure for CATs to reach the critical mass required for widespread adoption. This may not necessarily be the case, however, as Figure 3 indicates that very slow market penetration rates are not uncommon for freight innovations.

The estimation comes from a Monte Carlo simulation with 100 iterations. To ensure that there is no statistically significant difference between the results of each iteration, an ANOVA test is performed on the data. The results of the ANOVA test are described in Table 3.

Table 3
ANOVA test on the output of the Monte Carlo simulation

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	1.87E+09	99	18930845	0.369233	0.9999	1.246962
Within Groups	3.69E+11	7200	51270742			
Total	3.71E+11	7299				

The test fails to reject the null hypothesis that there is no significant difference between the results of the model to a confidence interval of greater than 99.9%. Therefore, it is reasonable to conclude that the model provides stable results.

The estimated organizational CAT adoption relies on a number of variables, most of which are inferred from other innovations or estimated by other means. Because it is possible that the base scenario has overestimated or underestimated the values of the Bass parameters, a sensitivity analysis is performed for the values of CoN and CoM. Another strong limitation of Bass model is that it is not explicitly policy responsive. This sensitivity analysis also intends to address this limitation implicitly by associating different values of CoN and CoM parameters to changes in policy, infrastructure, or public opinion. Table 4 describes six possible scenarios that might alter the estimated Bass parameters, and Table 5 shows the altered values of CoN and CoM selected for the scenarios.

Table 4
Description of six potential adoption scenarios

Scenario	Description
Scenario 1	A number of accidents cause Organizations to have less faith in CAT technology
Scenario 2	CATs are not as economically viable as anticipated, and a number of problems with CAT technology are not sufficiently resolved
Scenario 3	The financial benefits of operating CATs are not high enough to give an adopting organization a substantial competitive edge
Scenario 4	CAT technology is responsible for preventing a number of crashes, which reduces the perceived risk of the technology
Scenario 5	CATs provide substantial economic benefits and perform better than standard trucks in most situations
Scenario 6	The advantages of using CATs are such that non-adopters have a difficult time staying competitive with adopters

Table 5
Original and altered values of variables used in sensitivity analysis

Scenario	Organization size	CoN	CoM

Base	Small	0.005	0.08
	Medium	0.008	0.09
	Large	0.010	0.10
Scenario 1	Small	0.003	0.08
	Medium	0.006	0.09
	Large	0.008	0.10
Scenario 2	Small	0.003	0.07
	Medium	0.006	0.08
	Large	0.008	0.09
Scenario 3	Small	0.005	0.07
	Medium	0.008	0.08
	Large	0.010	0.09
Scenario 4	Small	0.007	0.08
	Medium	0.010	0.09
	Large	0.012	0.10
Scenario 5	Small	0.007	0.09
	Medium	0.010	0.10
	Large	0.012	0.11
Scenario 6	Small	0.005	0.09
	Medium	0.008	0.10
	Large	0.010	0.11

Each of the values in Table 5 represents a potential scenario for organizational CAT adoption. If CATs receive negative publicity, drivers resist CATs, or if infrastructure/legislation prevent the rapid adoption of CATs, then the more conservative values represented by Scenarios 1-3 may be accurate. Conversely, if legislation promotes the adoption of CATs, or if autonomous vehicles receive positive publicity due to a reduction in crashes or an increase in fuel efficiency, the adoption rates may align more closely with the more optimistic values in Scenarios 4-6. Figure 7 demonstrates the results of the potential adoption scenarios.

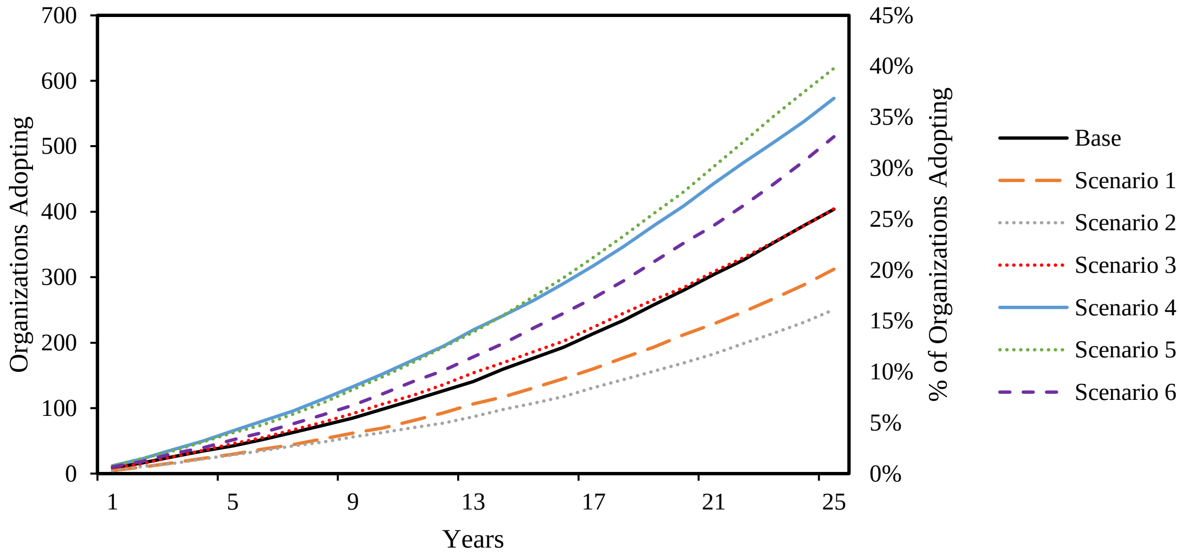

Fig. 7. Output for base model and 6 alternative scenarios

Varying the CoN value has a much more substantial impact on the adoption rate than the CoM parameter. This is reasonable because the model is only considering the first 25 years of potential adoption, and reducing or increasing the CoN value has a greater impact on the initial adoption rate than CoM, since CoM is multiplied by the fraction of previous adopters. In addition, increasing initial adoption causes critical mass to be reached earlier, and this results in a faster overall market penetration rate. Similarly, reducing initial adoption pushes critical mass farther down the timeline and slows the adoption rate (Mahajan et al., 1995).

It is worth noting that these models do not account for the fact that CATs are likely to change over time, becoming more cost-efficient and attractive to the potential adopter with each new generation of CAT technology (Chottani et al., 2018). The average lifespan of a traditional truck is between 5 and 6 years (Wadud, 2017), and it is possible that the CAT technology may improve faster than the average truck lifespan. Therefore, to estimate the potential effects of improvements in technology over successive generations, the CoN and CoM of the base scenario are multiplied by an Improvement Factor “I” at intervals of 3 years and 5 years. These results are shown in Figures 8 and 9.

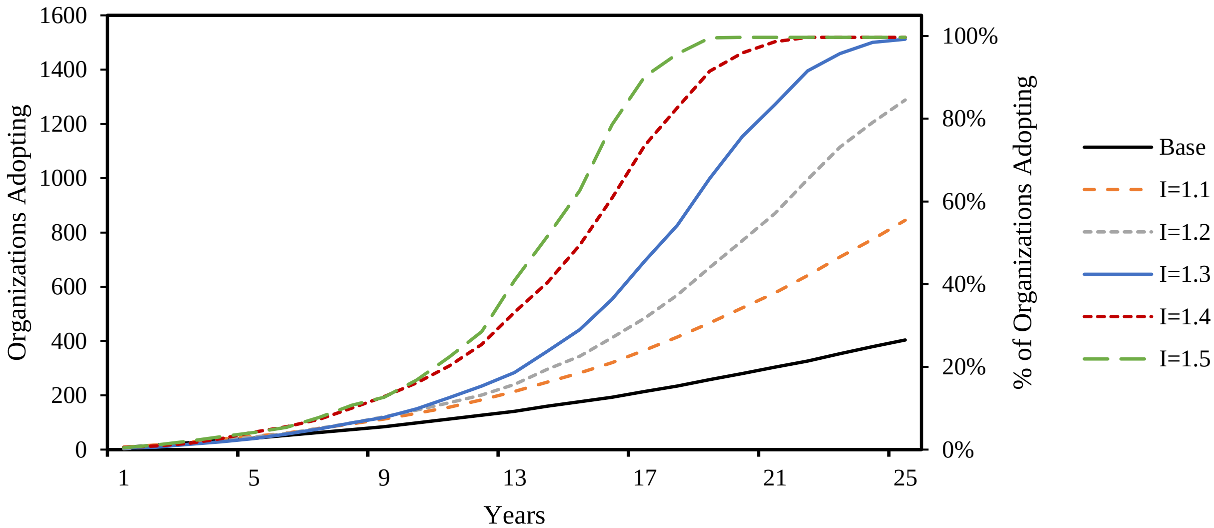

Fig. 8. Adoption of CATs assuming new generations of CATs are developed every 3 years

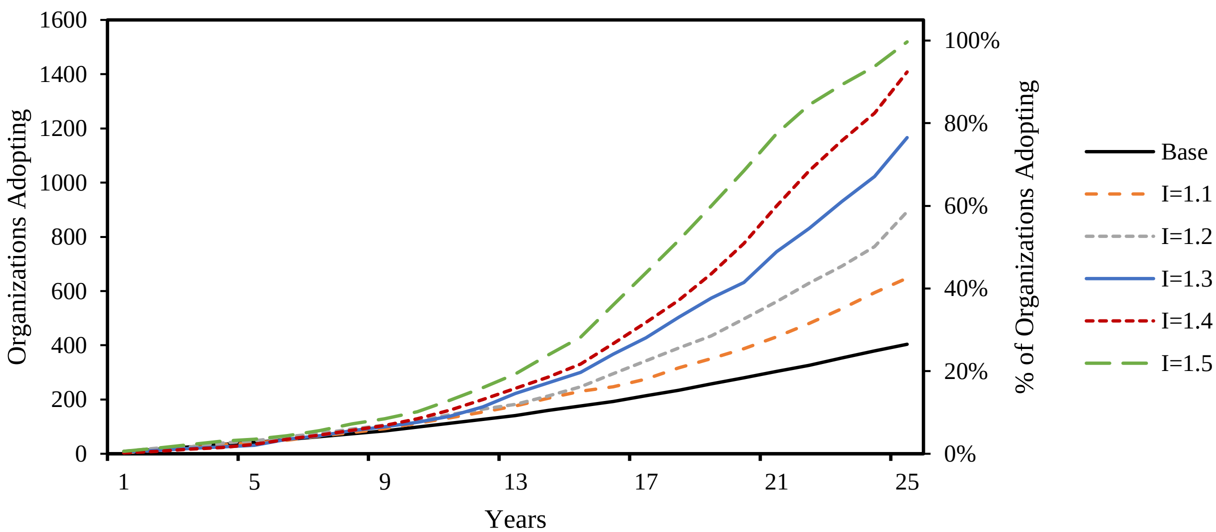

Fig. 9. Adoption of CATs assuming new generations of CATs are developed every 5 years

Adding the consideration that CAT technology will improve over multiple generations generates a much steeper adoption curve. It is, of course, impossible to know exactly how quickly and to what degree CAT technology will evolve, but it is reasonable to assume that because of the public interest and economic benefits of CATs, the technology will be advanced quite rapidly.

Finally, all models demonstrated up to this point do not consider the impact of the external influencing variables accounted for in the Generalized Bass Model shown in equation 3. Because no data exists to validate any supposed values for X_i and β_i, the base model does not include the impact of these variables. However, three scenarios were tested under multiple potential values of β_i, where the effect of a single variable and coefficient on the model can be observed. While there is no theoretical limit to the value of $\sum \beta_i X_i$, the value tends to be small - rarely exceeding a range between 0.4 and -0.4. This is intuitive because values greater than this would mean that the external influencing factors would have a greater effect on adoption behavior than the CoN and CoM. Therefore, the β_i values tested are between 0.1 and 0.4, and the first scenario assumes that the value of the external variable for each organization is positive between 0 and 1, the second scenario assumes that the value is negative between -1 and 0, and the final scenario assumes that the value can be either positive or negative between -1 and 1. The value of the external influencing variable is randomly distributed between the ranges described in the three scenarios. Although in reality, these variables are likely to not be randomly distributed among organizations, this hypothetical example is sufficient to demonstrate the effect that these variables may have on the adoption rate of innovations. The results of these three scenarios are shown in Figures 10-12.

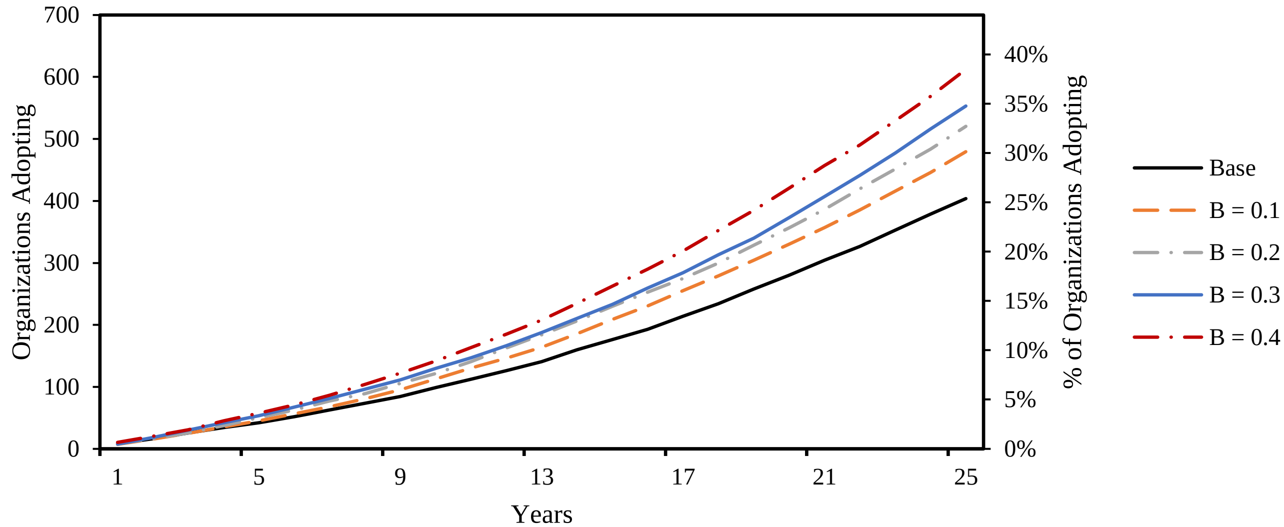

Fig. 10. Adoption of CATs when X_i is between 0 and 1

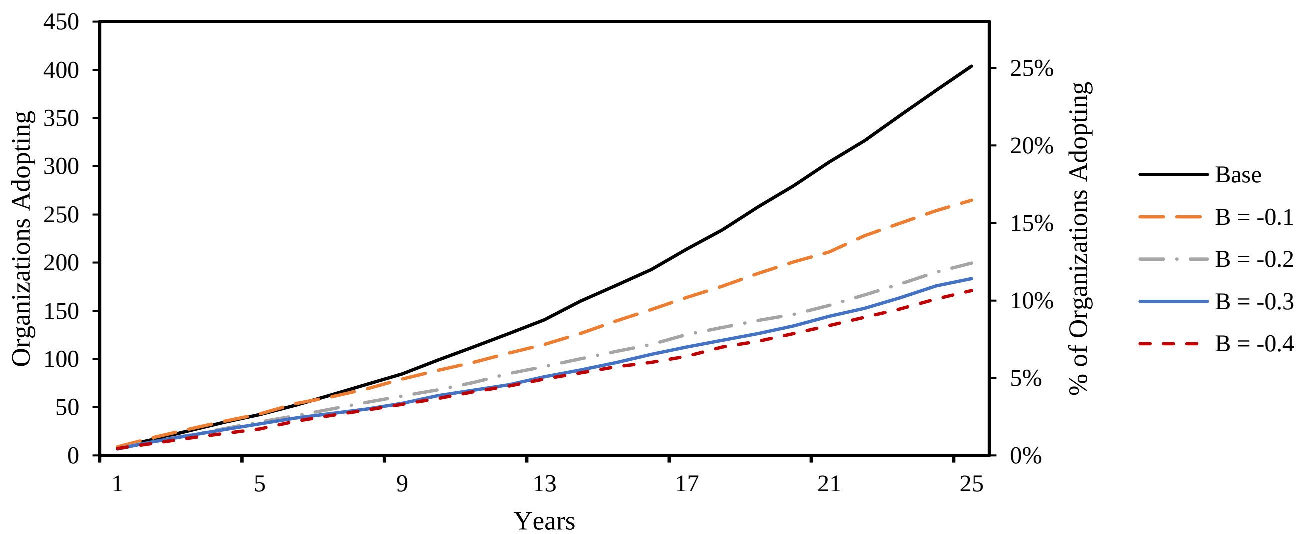

Fig. 11. Adoption of CATs when X_i is between -1 and 0

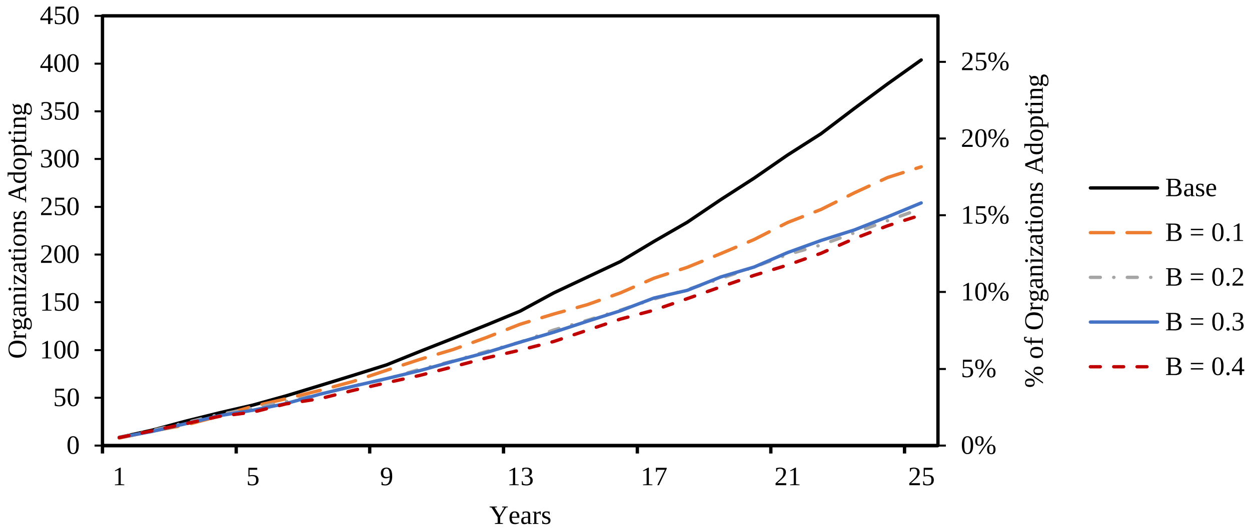

Fig. 12. Adoption of CATs when X_i is between -1 and 1

Interestingly, the estimated adoption rate when the external variables are allowed to be either positive or negative always fall below the base scenario adoption rate. Since the variables for each organization are randomly distributed between -1 and 1, there should be a perfect balance between organizations that are more inclined to adopt and those that are less inclined to adopt based on these variables. Because the overall adoption rate still falls below the base case, it is reasonable to state that negative external influencing variables have a greater impact on the aggregate adoption rate than positive variables, holding all else equal. This is further supported by the increased gap between the base case and the alternate scenarios in Figure 11 when compared to Figure 10. The positive valued variables have less of an effect on adoption rate than the negative valued variables.

5. Conclusions and future work

This study investigates the market penetration patterns of CATs in freight transportation organizations. An accurate projection of the adoption rate of CATs is critical to manufacturers and policy makers because it will allow them to prepare for and manage the new technologies and infrastructure changes that will accompany the introduction of CATs to freight transportation. This paper provides several contributions to the literature. First and foremost, it provides a model framework for estimating the market penetration rate of CATs by freight organizations, given that the appropriate data is provided. Second, it demonstrates the need for further research into organizational innovation adoption behavior, particularly in the case of CAT adoption. And finally, it introduces heterogeneity into the typically homogenous Bass model, allowing for organizational characteristics to play a role in the estimation process. This also allows for easy conversion from an aggregate to a disaggregate model once sufficient data is produced.

The projected market penetration rate is generated by examining the Bass model parameters of several other innovations, both individually and organizationally adopted. Organizational innovations provide a baseline for how freight organizations are likely to respond to an innovation, and individually adopted innovations are compared to the estimated market penetration rate of individually adopted CAVs to estimate the relationship between CATs and other innovations. From these observations, an estimated range of Bass model parameter values is generated for freight organizations adopting CATs. Data on organizations within Shelby County is gathered, and organizations are assigned Bass model parameter values based on the number of employees at the organization. It should be stressed that these values are strictly estimates based on existing information about organizational adoption behavior and predictions of CAT characteristics.

The base model is then compared to a variety of scenarios to determine how the components of the Generalized Bass Model interact with each other. This sensitivity analysis demonstrates that variations in the CoN tends to have a greater impact on adoption rate than CoM, and that rapid iteration on CAT technology may have a substantial impact on the adoption rate. Further, negative external influencing factors such as high price or low willingness to pay will likely have a greater impact on the adoption rate than positive influencing factors of equal weight.

While it is difficult to discuss specific results due to the number of assumptions that must be made to account for the data that does not exist, a number of insights can still be gleaned from this study. First and foremost, if autonomous technology does not significantly improve over time from its initial launch, we can expect a very slow adoption of CATs, and possibly even an eventual failure of the technology to become widely adopted. However, if the technology rapidly improves and becomes viewed as both safe and advantageous, it is possible that widespread adoption may occur in as little as 20 years. We also see that negative publicity and performance will likely have a greater impact on market penetration rates than positive publicity/performance.

While there are a number of contributions provided by this study, there are several key limitations which must be addressed. The greatest limitation of this study stems from the lack of data surrounding both CATs and organizational innovation adoption. This study provides a foundation for future studies by developing and exploring the limits of the Generalized Bass Model for organizational innovation adoption, but further research is clearly still needed in this field. The results of this study are based upon numerous assumptions of business practices, and while there is sufficient backing in the literature for these assumptions, true behavior can only be captured through a stakeholder survey. Therefore, future work will include designing a survey to be distributed to freight stakeholders to determine more accurate business practices for the model. Further research is also needed in the area of transferability of results. In general, behavioral (disaggregate) models are more transferable, compared to aggregate models. An aggregate model may not be used somewhere else to predict CAT adoption unless there are strong similarities among the regions of interest. A disaggregate model, on the other hand, can more transferable if it accounts for various determinants of adoption decision. In this paper, we propose a disaggregate Bass-based diffusion model that uses synthetic coefficients; we speculate that the results could be transferable both spatially and temporally. Nonetheless, further research is warranted to shed light on international/interregional organizational adoption behavior.

This study includes some limited heterogeneity into the model by assigning different Bass parameter values to organizations based on their size. However, while size is generally considered to be a reasonable indicator of an organization's ability to adopt innovations, there are certainly additional variables which will have a significant impact on the adoption decision, including organizational structure, corporate culture, and managerial support. Due to the lack of data on these variables, as well as their somewhat nebulous and qualitative nature, this study only considered organizational size. However, future studies should attempt to include additional characteristics of the adopting organizations into their models. Future studies may also wish to include a method to add organizations over time, as the current methodology does not allow for the market potential or the total fleet size to change over time. The impact of organizational size may also be further explored, as it is likely that larger organizations have a greater impact on the behavior of small organizations.

It should also be mentioned that, due to the absence of a more rigorous method of estimating CoN and CoM values for an innovation which has not yet been adopted, the actual results produced by the model contained in this paper should only be considered as estimations to be further refined once sufficient data has been gathered. The greater contribution of this study is the framework of the model and the sensitivity analysis of the various parts that form the model. Future work in this field should seek better data and estimation methods to form a more robust prediction of future adoption rate.

One criticism of the Bass model is that it assumes that the innovation in question will succeed, given enough time; there is no mechanism inherent in the model that allows for innovation failure (Przybyla et al., 2014; Ram, 1987). Innovations can fail for a number of reasons: the innovation may not provide sufficient advantage over current systems, it may never reach the point of "critical mass" where the CoM becomes the dominant factor in adoption, other innovations may supplant the original innovation before widespread adoption can occur, or adopters may grow dissatisfied with the innovation and choose to reject it at a later time (Przybyla et al., 2014; Ram, 1987; Rogers, 2003). Other methodologies such as Agent-Based modelling may be more suited to accounting for the possibility of adoption failure in future work (Przybyla et al., 2014).

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