1	Developing a Methodology to Predict the Adoption Rate of Connected Autonomous Truck				
2	in Transportation Organizations Using Peer Effects				
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1 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, including relative advantage, perceived risk, organizational size, public opinion, compatibility with the organization's needs, and competition. 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. Organizations are placed in a 4-dimensional space, and the peer effects on organizational adoption decisions are simulated using a graph theory model. 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 and useful results using a hypothetical dataset, and the methodology has been designed to be transferrable to any number of organizational innovations. Keywords: organizational innovation adoption, peer effects, connected autonomous vehicles

1 INTRODUCTION

2 The concept of Connected Autonomous Vehicles (CAVs) has gained much popularity over 3 the last decade. Many modern vehicles are implementing some automation features such as lane 4 departure warnings, adaptive cruise control, and collision avoidance systems, and test vehicles 5 have already been allowed onto public roads in some areas (1-3). CAVs are anticipated to bring a 6 multitude of benefits, including a reduction in collisions and congestion, increased fuel efficiency, 7 easier mobility for non-driving individuals, a reduction in transportation costs, and more 8 predictable travel times (1, 4-11). However, despite the potential benefits to CAV technology, a 9 number of issues with CAVs remain unresolved. Aside from operational concerns, questions about 10 legality, liability, security, privacy, and infrastructure must be addressed before CAVs can be fully 11 adopted by the public. However, it is difficult to prepare for these problems unless policymakers and legislators know how quickly the public is likely to adopt CAVs. Research is needed regarding 12 13 the expected behavior patterns for CAV adoption.

14 The study of innovation adoption behavior stretches back to the 1930s when a new variety of corn was introduced to farmers in the American Midwest, and it has remained a popular domain 15 16 for research to this day (12). Researchers have studied innovation adoption in nearly every field, 17 including health care (13-20), transportation (21-27), information systems and technologies (28-27)18 35), communications (36–39), education (40–43), and entertainment (44–46), to name a few. 19 These studies provide insight into why some innovations have successfully permeated throughout 20 society while others fail to reach their market potential. By analyzing the psychological (47–50), sociological (51-54), and economic factors (14, 53-57) that influence innovation adoption 21 22 behavior, researchers have been able to come to understand not only why innovations succeed or 23 fail but also how potential adopters may respond to future innovations.

24 Some studies have already been performed to estimate the adoption of CAVs for private 25 consumers (21, 27), but despite the depth of research in the field of innovation adoption behavior, 26 one area of study that has received less attention from academia is the behavior of organizations 27 such as corporations and governmental agencies. While some studies have been performed 28 regarding organizational innovation adoption behavior (17, 18, 38, 58–66), these studies tend to 29 be theoretical in nature, examining the effects of specific aspects of organizational adoption 30 behavior such as managerial influence (38, 65) or the structure of the organization (59, 61, 62). 31 While these studies are useful in that they provide further insight into the factors that influence 32 organizational innovation adoption behavior, they fail to establish a solid theoretical baseline from 33 which other works may begin (66).

34 The purpose of this study is to establish a generalized methodology for estimating 35 organizational innovation adoption behavior using a hypothetical dataset regarding the adoption of Connected Autonomous Trucks (CATs). Utilizing the findings of previous studies in the field 36 37 of organizational innovation adoption behavior, a discrete choice modeling framework is 38 developed to estimate the adoption of CATs by transportation organizations. This model 39 incorporates elements from both traditional innovation adoption theories and peer effects research. 40 The remainder of the paper is organized as follows. The following section briefly discusses the 41 various innovation and organizational variables that influence the innovation adoption process. 42 Section 3 provides details about the methodology used in the paper, and section 4 contains the 43 construction of the hypothetical network and the results of the model. Section 5 concludes the 44 study with a summary of the findings and information about future research opportunities in this 45 field.

1 FACTORS INFLUENCING INNOVATION ADOPTION BEHAVIOR

Because innovation adoption behavior is such a popular field of research, there are many variables that have been identified as influencing adoption behavior. Different variables are chosen for any given study depends on the theoretical framework that is being used, but there are several common elements to most innovation adoption studies. The variables can generally be grouped into innovation variables and organization variables.

8 Innovation Variables

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9 The first innovation variable that most studies mention is "Relative Advantage" (13, 14, 10 55, 67–70). Relative advantage is the degree to which an innovation is perceived as being better 11 than the idea or system it supersedes. It can be stated in economic terms if saving time, energy or money is the primary goal of the innovation. It could also be considered in social terms if it is 12 13 considered desirable or prestigious to adopt an innovation (55). Relative advantage is based on the 14 perception of the potential adopter; not every individual will place the same value on the advantages an innovation may bring (13). Some studies choose to separate relative advantage from 15 16 cost (67), but the prevailing tendency is to assume that cost is a factor included in relative 17 advantage (55, 67).

"Compatibility" is the degree to which an innovation is consistent with the goals and needs of the adopter (14, 55, 64, 68–70). This attribute is also largely based on the perception of potential adopters. An innovation may be intended to solve a problem or meet a need, but if the adopter does not recognize the need for the innovation, he or she is less likely to choose to adopt (68). The perception of compatibility for an innovation is largely reliant on effective marketing. Everything from the name of the innovation to the intended purpose and use of the innovation has an effect on the potential adopters' perceived compatibility (67).

25 Like compatibility, "complexity" is largely based on the perception of the potential 26 adopter. Complexity is the belief that an innovation will be either difficult to use or difficult to 27 understand. Complexity is an inherently negative attribute of an innovation (14, 55, 64, 68, 70). 28 More complex innovations are less likely to be adopted and will permeate throughout a field more 29 slowly than simpler innovations. Proper instruction and a user-friendly interface can reduce the 30 perceived complexity of an innovation, causing it to be diffused more rapidly (13, 68). Innovations which can be adopted in small, manageable pieces over time can also greatly increase the 31 32 innovation's attractiveness (14, 19, 55). Some studies prefer to capture the effect of complexity 33 with its opposite attribute, which is typically referred to as "Ease of Use" (69, 71).

34 "Trialability" is a measurement of how easily an innovation can be tested before full 35 adoption (14, 55, 68, 69). The adoption of innovations is a process of reducing the uncertainty 36 surrounding an innovation, and the ability to test an innovation before fully adopting it is an 37 effective way to reduce uncertainty (55). Trialability is especially important early in the diffusion 38 process, because there are few existing examples of the innovation succeeding. As more people 39 successfully adopt the innovation, potential adopters have more references to draw from to reduce 40 their uncertainty, reducing the impact of an innovation's trialability (19, 67).

"Observability" – sometimes referred to as visibility - is a measure of how easily the effects
of an innovation are noticed and understood, especially by other potential adopters (14, 55, 64, 68,
69). Observability is important to adoption rate because an innovation which is easily observable
will be noticed and accepted more rapidly than an innovation which is difficult to observe (55).
Direct observation is often a key factor in motivating potential adopters to more thoroughly
investigate an innovation (72). Some effects of innovations may be readily apparent to a casual

observer, whereas other aspects may be much harder to observe (55, 69). Observability is often
inversely correlated with perceived complexity, because more complex innovations are more
difficult to understand, and so it is more difficult to perceive the effects they may have (13).

"Risk" is the degree of uncertainty surrounding the innovation (14, 49, 64). Risk is typically
viewed in the context of the innovation's relative advantage, as it can be considered in physical,
economic, social, or political terms, and it is highly dependent on the perception of the individual
adopter (14, 33, 49, 50, 64).

8 "Reinvention" is the degree to which an innovation is able to be modified for purposes 9 other than its original intended use (14, 20, 73). Innovations that are perceived to be highly flexible 10 are likely to be perceived as more advantageous (14). In addition, an innovation which has a high 11 reinvention capacity is much more likely to be perceived as highly compatible with the adopter's 12 needs (73).

14 **Organization Variables**

15 "Organizational size" is the most commonly discussed organizational characteristic for 16 innovation adoption studies. The size of an organization can be measured as total employment, the 17 number of clients or customers, or the annual budget/revenue of an organization. Larger 18 organizations tend to display greater innovativeness than organizations which are smaller (55, 63, 19 70, 74). Some studies suggest that organizational size is merely a useful proxy for other 20 organizational variables such as specialization and centralization, and that size is not actually 21 indicative of greater innovativeness (61, 62). While further research is needed to determine 22 whether or not organizational size in isolation promotes innovative behavior, there does seem to 23 be a correlation between the size of an organization and its ability or desire to innovate (55, 59, 24 61-63, 74).

25 "Specialization" is defined as the level of knowledge and expertise that the organization 26 can draw upon (55, 58, 62, 63). Highly specialized members of an organization will require less 27 training to acquire the skills necessary to adopt innovations. Specialization is a counterbalance for 28 the complexity of an innovation; if an organization has highly specialized members, then that 29 organization will be better able to adopt and integrate complex innovations (58, 62, 63).

30 "Centralization" is defined as "the degree to which power and control in a system are 31 concentrated in the hands of relatively few individuals" (55, 60–62, 74). More centralized 32 organizations tend to be slower to adopt innovations than less centralized organizations, as the 33 decision-makers are further removed from the places where the innovation is needed (55, 60, 62, 34 74). However, once the decision to adopt has been made, organizations which are more centralized 35 tend to implement the innovations more quickly (55, 74).

36 "Formalization" is the degree to which an organization expects its members to follow pre37 established protocol (55, 60, 63). More formal organizations are less likely to consider innovation
38 as a solution to a problem, but they are also better able to implement an innovation after the
39 adoption decision has been made (55, 60, 63).

40 "Organizational slack" is a quantification of the resources that are available to an 41 organization that have not been committed to other tasks (63, 75, 76). Businesses often view 42 organizational slack as a negative attribute, but high levels of organizational slack indicate that the 43 organization is able to experiment with innovations (63, 75, 76). Higher levels of organizational 44 slack are associated with lower perceived risk, which is intuitive because many of the resources 45 that would be devoted to adopting and implementing an innovation will not be needed for other 46 tasks (77).

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1 "Privatization" is the degree to which an organization is controlled by private owners rather 2 than the general public. Many organizations are strictly public or private, but there are other 3 organizations that can be most accurately described as "quasi-public," and so the degree of 4 privatization for each organization needs to be accounted for. Private organizations tend to be more 5 innovative than public organizations, as public organizations tend to be less focused on 6 competition and more focused on public opinion (58, 78-82). Contrary to popular belief, public 7 organizations do not tend to have higher formalization than private organizations (83). Also of 8 note is that the decisions of public organizations tend to be less influenced by many of the other 9 organizational characteristics, and they tend towards lower estimations of relative advantage for 10 innovations than private organizations (59, 82, 84).

Another important factor to consider is the effect of managerial innovativeness. An organization which is managed by a highly innovative manager or a manager which champions a particular innovation will be much more likely to adopt (*38*, *55*, *65*, *79*, *85*). Youth and advanced education tend to be correlated with an increased level of managerial innovativeness (*86*).

Governmental influences must also be taken into account when examining organizational 15 16 innovation adoption behavior. In some cases, regulations have been introduced that encourage or 17 even mandate adoption (87). However, legislation can just as easily discourage or prohibit the use 18 of a particular innovation. The weight of these influences must be examined on a case-by-case 19 basis (88, 89). In a similar manner, it is important to consider the influence that public opinion 20 may have on an organization's decision to adopt an innovation. While organizations are less influenced by social factors, public opinion is still a powerful indicator of what an organization 21 22 will decide to do (90).

24 Peer Effects

25 One of the most important factors to consider in innovation adoption studies is the effect 26 of social influences on the adopter (51-55, 91-93). Individuals tend to make decisions based on 27 not only their own interests but the actions of their peers. Figure 1 illustrates the impact of peer 28 effects on a network.

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23



31 Figure 1 Impact of peer effects on a network

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1 The left panel of Figure 1 shows four types of organizations and their status of adoption. 2 The thickness of arrows in which each organization is connected with other shows the strength of 3 connection, and size of each node represent their firm size in terms of employees. Each 4 organization is connected with others to form a sub-network. The peer effect literature in non-5 transportation domains suggest that organizations who have adopted a specific innovation will 6 potentially affect others who are in their subnetwork. Similarly, organizations who have not 7 adopted and pose a negative view towards the innovation will potentially affect others towards 8 non-adoption or deferred adoption. The current literature lacks quantification of peer effects, i.e. 9 some organizations adoption decisions because of their size, business pattern, geographical 10 operation boundaries, etc.

An important aspect of peer effects is the concept that not all players are equal in their ability to influence their peers (94). Depending on factors such as personality, position within the social network, experience, and authority, individuals have widely varying levels of influence over their peers (95). When applying the concept of peer effects to organizations, this variability in influence is greatly magnified due to the extreme heterogeneity found in organizations (74, 96). Organizations which are larger tend to have greater spheres of influence than smaller organizations.

18 Recent studies have demonstrated the power of these peer effects in other fields, but 19 innovation adoption behavior studies have not yet incorporated many of the findings that this 20 research has provided (94, 95, 97–100). Innovation adoption studies almost always include some 21 way of measuring how peers of a potential adopter influence the decision-making process (33, 55, 22 71, 92, 101, 102). While organizations tend to be much less reliant on social influences than 23 individuals (61), informal communication networks and inter-organizational competition are still 24 strong social influences that must be considered (103).

26 **METHODOLOGY**

27 Data is gathered on N organizations, including all relevant characteristics and perceived 28 attributes for the innovation. The innovation is denoted as set I, where *i* can take values from 1 to 29 4 (such as 1 = complete rejection of the innovation, 2 = a decision to test a prototype of the innovation, 3= a partial adoption, and 4 = full adoption). The dependent variable is denoted as Y_{ni} , 30 which is the choice that organization n makes regarding adoption of the innovation i. Y_{ni} is an 31 integer with values from 1 to 4 and the vector of all Y_{ni} outcomes is denoted as Y. Each 32 33 organization n also has K attributes, which are denoted as the K-vector X_n (organization size, 34 number of employees, centralized or decentralized business approach, local, regional or national 35 operation etc.) and each alternative as unique characteristics such as X_i (capital cost of the innovation, operation and maintenance cost of the innovation, technological advantages, reduction 36 37 in labor cost, annual profit accrued etc.). We can form an N by K matrix **X**, where the nth row is 38 equal to the vector X_n (97).

The organizations will be connected in a network, and this network will be captured in the adjacency matrix **M**, where the typical element M_{pq} is a continuous variable greater than 0. Greater values of M_{pq} indicate that strong communication, competition, or influence exists between organizations *p* and *q*. Because some organizations are more influential than others, Matrix **M** is not symmetrical. A graph theory model is used to generate matrix **M**. We first define a δ dimensional coordinate system. We then place each organization within the δ -dimensional space (27). The distance between each organization D_{pq} is calculated as

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$$D_{pq} = \sqrt{\sum_{A \in S} \sigma_A \left(\frac{V_{A_{ip}} - V_{A_{jq}}}{maxV_A}\right)^2} \tag{1}$$

1

where *S* is the set of characteristics that define the δ -dimensional space, V_{A_p} is the value of attribute A for organization *p*, and σ_A is the weight given to attribute *A*. We also assign a weight W_n to each organization according to the organizational size and fleet size. W_n is calculated as

$$W_n = \sum_{C \in R} \frac{Z_{C_{in}}}{maxZ_C}$$
⁽²⁾

7 where *R* is the set of *H* attributes that define the weight of the organizations, and $Z_{C_{in}}$ is the value 8 of attribute *C* for organization *p*. M_{pq} is then calculated as

9

6

$$M_{pq} = \frac{W_{ip}}{D_{pq}} \tag{3}$$

10

11 Note that M_{pq} does not account for the weight of organization q because $M_{pq} \neq M_{qp}$. The 12 influence of organization p on organization q is dependent only on the distance between them in 13 the δ -dimensional space and the weight of organization p. Although M_{pq} will always be greater 14 than zero, very low values for M_{pq} may indicate that there is no significant connection between 15 organizations i and j. Therefore, a cutoff value γ should be determined on a case-by-case basis 16 where all M_{pq} lower than γ are assumed to be equal to 0. Once M_{pq} is defined, we can calculate 17 the influence that the organizational network exerts on organization n using equation 4:

18

$$\theta_n = \frac{1}{R_n} \sum_{q=1}^N M_{qp} Y_q \tag{4}$$

19

20 where θ_n is the influence of the organizational network on organization *n*, and $R_n = \sum_{q=1}^N M_{qp}$.

21 The organization's choice for a specific innovation can be obtained using discrete choice 22 models. We propose to utilize a linear in parameter specification to determine the utility of an organization *n* towards an innovation *i*, i.e. U_{in} : $U_{in} = \beta'_i X_{in} + \varepsilon_{in}$ where X_{in} is a $K_i \times 1$ vector 23 24 of exogenous covariates (including organizational characteristics such as number of employees, 25 geography of operation, centralized or decentralized business, number of CEOs, male female 26 employee ratio etc., and innovation attributes such as capital cost, operation and maintenance cost, expected annual profit, labor cost reduction, etc.). β'_i is the corresponding $K_i \times 1$ vector of 27 28 coefficients and ε_{in} denotes all the unobserved factors that influence the innovation function for 29 outcome i in organization n. In the unordered framework, the observed innovation adoption 30 outcome is the highest latent adoption alternative function value. So, the probability that 31 organization *n* prefers specific innovation outcome *i*, $P_n(i)$ is given by:

The choice modeling framework can be unordered or ordered. In unordered framework, the stochastic components ε_{in} in the latent innovation adoption functions U_{in} are assumed to be independent and identically distributed (*i.i.d.*) across different adoption outcomes and organizations. Moreover, the identical distribution is assumed to be standard type-1 extreme value distribution (also known to as Gumbel distribution). Given these assumptions on the stochastic term ε_{in} , $P_n(i)$ is:

4

$$P_n(i) = \frac{\exp(\boldsymbol{\beta}_i' \boldsymbol{X}_{in})}{\sum_{\forall I} \exp(\boldsymbol{\beta}_j' \boldsymbol{X}_{jn})}$$
(6)

5

6 The $\sum_{i=1}^{I} K_i$ parameters in the multinomial model are estimated by maximizing the log-likelihood 7 (ML) function obtained by taking the natural logarithm of the product of probabilities of observed 8 severity outcomes given by Equation (2) as follows:

$$LL = \sum_{n=1}^{N} \left(\sum_{i=1}^{I} \delta_{in} \right) \tag{7}$$

9

10 where δ_{in} is defined as 1 if the observed adoption outcome for organization *n* is *i* and zero otherwise.

12 In the ordered framework, latent propensity y_n^* is translated into observed innovation 13 adoption outcomes by threshold parameters. We propose a linear-in-parameter specification for 14 the observed part of y_n^* and a standard logistic distribution that is *i.i.d.* across organizations for the 15 stochastic component ε_n . The equation system for the ordered logit model is (McKelvey and 16 Zavoina, 1975): 17

$$y_n^* = \boldsymbol{\beta}' \boldsymbol{X}_n + \boldsymbol{\rho}' \boldsymbol{\theta}_n + \boldsymbol{\varepsilon}_n \tag{8}$$

18

 $P_{n}(i) = P(\psi_{i-1} < y_{n}^{*} < \psi_{i})$ (9) $P_{n}(i) = P(\psi_{i-1} < \boldsymbol{\beta}' X_{n} + \boldsymbol{\rho}' \boldsymbol{\theta}_{n} + \varepsilon_{n} < \psi_{i})$ $P_{n}(i) = P(\psi_{i-1} - \boldsymbol{\beta}' X_{n} - \boldsymbol{\rho}' \boldsymbol{\theta}_{n} < \varepsilon_{n} < \psi_{i} - \boldsymbol{\beta}' X_{n} - \boldsymbol{\rho}' \boldsymbol{\theta}_{n})$ (9)

21
$$= F(\psi_i - \boldsymbol{\beta}' \boldsymbol{X}_n - \boldsymbol{\rho}' \boldsymbol{\theta}_n) - F(\psi_{i-1} - \boldsymbol{\beta}' \boldsymbol{X}_n - \boldsymbol{\rho}' \boldsymbol{\theta}_n)$$

22

where X_n is $K \times 1$ vector of covariates and $\boldsymbol{\beta}$ is the corresponding $K \times 1$ vector of coefficients; $\psi_i's$ are threshold parameters; $\psi_0 = -\infty$ and $\psi_{l+1} = \infty$; F(.) is the standard logistic cumulative distribution function. The model structure requires that the thresholds to be strictly ordered for the partitioning of the latent risk propensity measure into the ordered innovation in adoption categories(*i.e.*, $-\infty < \psi_1 < \psi_2 < \cdots < \psi_{l-1} < \infty$). The parameters in the ordered logit model ($\boldsymbol{\beta}$ and $\psi_i's$) can be estimated using the ML method.

29

30 HYPOTHETICAL DATASET AND NETWORK GENERATION

In order to test the proposed methodology for estimating organizational innovation adoption behavior, a hypothetical dataset is generated. Each of the *K* attributes is assigned a distribution based off of findings from other datasets and literature. Table 1 lists each of the variables, their definitions, and the distribution assigned to the variable. Most of the variables listed can be considered universal for innovation adoption studies, but a few such as Fleet Size and Driver Opinion are also included to account for specific factors that will influence an organization's decision to adopt CATs.

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- 39

TABLE 1	Distribution	of Values	for Hypotheti	cal Variables
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Variable	Definition	Distribution
Relative Advantage	The degree to which an innovation is perceived	Normal (55)
	as being better than the idea or system it	`
	supersedes	
Compatibility	The degree to which an innovation is consistent	Normal (55)
	with the goals and needs of the adopter	× /
Observability	The degree to which an innovation's effects are	Normal (55)
	easily noticed and understood	× /
Complexity	The degree to which an innovation is difficult	Normal (55)
	or understand	× /
Trialability	The degree to which an innovation may be	Normal (55)
	experimented with on a limited basis	
Reinventability	The degree to which an innovation is able to be	Normal (55)
	modified for purposes other than its original	
	intended use	
Perceived Risk	The degree of uncertainty surrounding the	Triangular (104, 105)
	innovation	
Public Opinion	The perceived attitude of the public toward the	Normal (104, 105)
	innovation	
Organizational Size	A description of the size of the organization in	Exponential
	question, typically in terms of employment	
Specialization	A measurement of the knowledge and expertise	Exponential (61, 62)
	of an organization's members	
Centralization	The degree to which power and control in a	Exponential (61, 62)
	system are concentrated in the hands of	
	relatively few individuals	
Formalization	A measurement of how strictly an organization	Exponential (106)
	requires its members to follow established rules	
	and protocol	
Organizational	The resources an organization is capable of	Exponential (106)
Slack	committing to adopting an innovation, typically	
Duivotination	The degree to which an enconization is	600 multiplane 400 minute
Privatization	antrolled by private owners, rather than the	00% public, 40% private
	controlled by private owners, rather than the	(107)
Covernmental	The degree to which regulations and logislation	Normal (accumption: no
Influences	restricts or promotes the adoption of the	data exists)
muchees	inpovation	data exists)
Managerial	The degree to which the decision-maker(s) of	Normal (55)
Innovativeness	an organization are inclined to innovate	
Manager Gender	The gender of the organization's primary	82% Male 18% Female
Tranager Genuer	decision-maker	5270 maie, 1070 i cillate
Manager Socio-	The socio-economic characteristics of the	Normal (55)
Economic Factors	organization's primary decision-maker	

TABLE 1 cont.	
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Variable	Definition	Distribution			
Fleet Size	The total number of trucks owned or operated	Exponential			
	by the organization				
Driver Opinion The degree to which the current truck operators		Normal (104, 105)			
	will oppose (or support) automation				
Ownership Type	Whether the organization owns and operates	5% outsourced trucks,			
	their own trucks, rents trucks, or contracts with	35% mix, 60% owned			
	independent truck owners	trucks (108)			
Average Trip	The average distance that trucks travel for the	Exponential (109)			
Length	organization				

1 2

We define the multi-dimensional space using four variables: manager socio-economic 3 factors, manager innovativeness, ownership type, and average trip length. These are the variables 4 that we expect will best indicate the existence of informal communication and direct competition 5 between organizations. The weight W_n for each organization is calculated using organization size 6 and fleet size. This is intuitive because the larger organizations will have a greater influence on 7 the CAT adoption decisions for the rest of the organizations in their network. The hypothetical 8 network is visualized in Figure 2.



9

10 Figure 2 Visualization of hypothetical network

11

12 We assume that on average each organization is at connected to 50 other organizations 13 (10% of the population), and so our cutoff value γ is set at a value of 2.04. However, even limiting the network to connections with an M_{pq} of greater than 2.04, the edges are too numerous to be 14 15 visible, and so Figure 1 only illustrates the placement and weight of the organizations and a close-16 up of a small sample of organizations. The size of the nodes is correlated with the weight of the

associated organization. The position of the nodes is determined by the distance between nodes in
the 4-dimensional space; Figure 1 is a best-fit visualization of the relative position of each of the
nodes.

4 In the discrete choice analysis, each organization was assigned a decision variable Y_i from 5 an exponential distribution, and the coefficients for each independent variable were calculated 6 using maximum likelihood approach. The analysis was carried out in open source R software using 7 mlogit package. Because the hypothetical variables were each extracted from an assumed 8 distribution, there was high collinearity between variables extracted from the same distributions. 9 To address this, the number of variables was reduced from 23 to 7 so that each distribution was 10 represented once. The variables in the final model were: relative advantage (normal), 11 organizational size (exponential), privatization (binary), manager gender (binary), ownership type (other), average trip length (other), and peer effects (other). Figure 3 demonstrates the estimated 12 13 decisions of each organization in the network when peer effects are and are not accounted for. 14



15 16 17

Figure 3 Visualization of network without peer effects (Left) and with peer effects (Right)

18 While the effect is subtle due to the visually cluttered network, the peer effect seems to 19 have the strongest impact on CAT adoption in the center clusters of the network. This is intuitive 20 because the majority of the high weight nodes are found in the center clusters, and the densely 21 packed nodes mean that the distance between nodes is very small. We would expect that the 22 influence of the peer effects factor would be strongest in these situations. Note that because the 23 network is 4-dimensional, the 2-dimensional visualization of the network has some small 24 variations that seems to imply that the nodes are moving. However, in the 4-dimensional space, 25 the nodes have a fixed location and distance from one another.

While a snapshot of initial decisions is important, the real purpose of this model is to predict how organizations will act over time as the technology improves. Therefore, we iterate the model to simulate the effect of peer effects on the network over time. For the purposes of this case study, we do not include a method for changing the other factors such as relative advantage, perceived risk, and organizational size over time; peer effect is the only factor which varies over time. This is because the peer effect influence is dependent on the decisions of other organizations in the network, and so updating the decisions of other variables will cause a shift in the peer effect 1 variable. Figure 4 demonstrates the way that the network changes over time as a result of peer

2 effects.



Figure 4 Adoption decisions of organizations over time based on peer effects

6 The primary trend noticeable in Figure 3 is that the number of organizations which 7 completely reject the innovation steadily decrease over time while the number of organizations 8 that choose to partially adopt increases. The number of organizations which fully adopt grows 9 more slowly than partial adoption, and the total number of organizations that choose to test CATs 10 remains relatively steady because the number of organizations moving from "Reject" to "Test" is roughly equal to the number moving from "Test" to "Partial Adoption." Also of note is the fact 11 that the change in decisions based on peer effects diminishes over time, indicating that peer effects 12 13 alone is not likely to be enough to cause widespread acceptance of CATs. Figure 5 shows the 14 visualization of the network at Year 25.



Figure 5 Visualization of network decisions at Year 25

The main insight that can be gathered from Figure 5 when compared to Figure 3 is that the largest organizations are the least likely to change their decisions based on peer effects. This is intuitive because the influence of peer effects for organization n is based on the weight of the peers and the distance between those peers and organization n. Larger organizations will be less influenced by other organizations in their network, and because peer effects were the only modifying factor in Figure 5, the number of small organizations that changed their decision was much greater than the number of large organizations.

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12 CONCLUSIONS AND FUTURE WORK

13 This study lays the methodological groundwork for predicting the adoption rate of 14 innovations by organizations. The concept of peer effects on individual choice is introduced, and 15 a number of key variables from the literature are selected for a discrete choice model. The use of 16 a graph theory model to approximate the peer effect network allows for organizations to be 17 heterogeneous and provides an easily repeatable method for generating these interorganizational 18 communication and competition networks. The proposed methodology provides intuitive results, 19 and the addition of real-world data in the future is expected to yield important information about 20 organizational adoption behavior.

21 Accurate predictions for the market penetration rate of innovations is important for 22 policymakers, manufacturers, and innovators alike. By providing an estimation of the number of 23 CATs that will be operational 5, 10, or 20 years into the future, we will enable policymakers to 24 prepare appropriate legislation and regulations for CAT operations. Manufacturers will benefit 25 from innovation adoption studies by understanding both the level of enthusiasm that innovators feel towards CATs as well as what attributes are perceived as most important. Innovators will be 26 27 able to examine the actions of other innovators to see if they are accurately assessing the potential 28 risks and benefits of the innovation. However, each of these benefits depends on the innovation 29 adoption study being able to accurately represent real-world adoption behavior. Without incorporating peer effects, the model would be ignoring some of the most powerful factors in the
 decision-making process: communication and competition. By developing a methodology that
 incorporates traditional innovation adoption techniques with peer effects, we have generated a
 model that can accurately provide the market penetration rate of innovations.

5 The next step in future work will be to collect real-world data so that we can make 6 meaningful predictions about organization innovation adoption behavior. The purpose of this 7 paper is to develop and test the methodology to be sure that the model behaves in a rational manner. 8 With additional data – and potentially additional variables, if more are discovered to be significant 9 - we will be able to use the model to provide reasonably accurate estimations of organizational 10 networks and their effect on the decision-making process with regards to innovations. Another 11 aspect of the model which certainly deserves further study is whether or not other variables such 12 as relative advantage, perceived risk, and organizational size change significantly over time. It is 13 likely that as an innovation is adopted and further improvements to the technology are made, 14 organizations which previously decided that the innovation was not suitable for them may change their decision. Currently, we have not included a mechanism to allow for the data to evolve over 15 16 time to various scenarios, but future work will need to consider this possibility.

17

18 AUTHOR CONTRIBUTIONS

19 The authors confirm contribution to the paper as follows: study conception and design: 20 Jesse Simpson and Sabyasachee Mishra; data collection: Jesse Simpson; analysis and 21 interpretation of results: Jesse Simpson; draft manuscript preparation: Jesse Simpson and 22 Sabyasachee Mishra. All authors reviewed the results and approved the final version of the 23 manuscript. 24

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