

# Adoption of Natural Gas Vehicles – Estimates for the U.S. and the State of Texas

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*Natural gas vehicles (NGV) have attracted more and more attention from policy makers since natural gas is a clean substitute for traditional fossil fuel that is also readily accessible. In some areas such as the state of Texas, vehicles that do not use traditional fossil fuel (e.g., NGVs) are exempt from paying fuel taxes. Government financial incentives have motivated substantial adoption of NGVs. This paper studies NGV adoption behavior in both U.S. and Texas markets to estimate the dynamics of NGV diffusion. This research employs well-known Bass diffusion models applied to NGV adoption, using data from both the U.S. and Texas. Among several interesting results, we find that NGV adoption through an imitation effect appears to be significant for the U.S. NGV market.*

## INTRODUCTION

Natural gas vehicle (NGV) technologies have gained a stronger presence in U.S. alternative vehicle markets. Within the past few years, counts of NGVs across the US have increased steadily, starting from 23,281 in 1992 to 121,650 in 2011 (Alternative Fuels Data Center 2014). In addition, multiple agencies predict that heavy-duty NGVs in the U.S. will have a penetration rate of 40% or higher by 2050 (National Energy Information Center 2010; National Petroleum Council 2012). For transit buses, a forecast of the US Department of Energy shows that natural gas fuels may garner upwards of 65% of total U.S. transit fuel usage by 2035 (National Energy Information Center 2010). Other studies report growing market penetration trends for NGVs in light-duty and medium-duty U.S. auto markets (National Petroleum Council 2012). Overall, a consensus is emerging that there will be continued growth in the use of NGVs across most U.S. transportation sectors.

In addition, the price spread between conventional and natural gas fuel will be a key economic driver for future NGV adoption in the United States. For decades, the price of natural gas has been about one half or even a third of conventional fuels, namely gasoline and diesel (Alternative Fuels Data Center 2014). Even though greater market penetration of NGVs could drive up natural gas prices, abundant supplies from U.S. domestic shale natural gas production should be able to meet domestic demand for natural gas fuels (U.S. Energy Information Administration 2015). In the meantime, increasing prices for conventional fuels contribute to a continuing price spread between conventional and natural gas fuel (Alternative Fuels Data Center 2014; National Petroleum Council 2012). The potential for cost savings by using natural gas instead of conventional fuels remains a strong incentive for the public and U.S. urban transportation fleets to adopt NGVs.

Environmentally, NGV is also a cleaner fuel option, producing less air pollution and greenhouse gas emissions than conventional fuels. For example, natural gas produces far less CO<sub>2</sub> compared with gasoline and diesel. Natural gas also yields lower levels of NO<sub>x</sub> and sulfur, additional components of greenhouse gases. In highly populated areas, higher adoption rates for NGVs could lead to significant improvements in air quality and a reduction of air pollution, as well as reducing pollution-related diseases and associated social costs (Engerer and Horn 2010; Pasaoglu, Honselaar, and Thiel 2012).

Growth of NGVs could also help the U.S. energy sector reduce dependence on petroleum-based fuels. Transportation fuels generate more than half of energy use in the United States (National Energy Information Center 2010). Furthermore, using U.S. domestically produced fuels reduces the U.S. economy's dependence on major oil and gas producing countries. Natural gas as a fuel could also help mitigate the consequences of growing energy consumption by large oil and gas consuming

countries, such as China and India. Adopting NGVs also can diversify the use of technologies to power vehicles, such as natural gas, propane, electricity, as well as conventional fuels.

There has been a body of qualitative studies predicting an optimistic landscape for NGV adoption in the U.S. auto market. However, to the knowledge of the authors, the potential trajectory of NGV adoption and diffusion has not yet been quantitatively examined. For example, little is known about NGV growth patterns over a longer time horizon. Even those states leading NGV adoption display different growth rates in terms of specific annual market growth. In order to better understand the use and diffusion of NGVs in the U.S. moving forward, we offer that potential NGV technology diffusion within the U.S. as well as key state level markets needs to be quantitatively examined.

It is clear that the diffusion of NGV technologies is strongly conditioned by natural gas prices and the coverage of natural gas refueling infrastructure. Accordingly, a realistic NGV forecast model requires simultaneous assessments of changes in both prices and infrastructure. In fact, a few studies in the extant literature on alternative vehicle technologies examine in detail price and infrastructure effects with respect to a demand forecast model (Park, Kim, and Lee 2011).

This paper will estimate models of the diffusion of NGV technology. These models will also help us to better understand the nature of NGV penetration across both the U.S. and Texas automobile markets. By conducting this analysis, it is our hope to shed some light on the nature of current NGV market growth as well as the future of NGV adoption both in the U.S. and Texas.

## LITERATURE REVIEW

There has been a previous body of literature that studies forecasts for adoptions of various vehicle technologies. Researchers have applied a variety of statistical models to assess or forecast demands for vehicles with conventional and alternative fuel technologies. One stream of vehicle technology adoption research applies time-series or causal relationship modeling techniques.

As an example of the above, Garcia-Ferrer et al. (1997) applied an autoregressive integrated moving average (ARIMA) model to study the evolution of the Spanish automobile industry. Shahabuddin (2009) developed several regression models and used historical data (1959-2006) to forecast US automobile sales. On a much broader scale, Dargay and Gately (1999) applied causation regression modeling techniques to predict worldwide vehicle ownership. Regression modeling research requires inputs of historical socioeconomic data that are often collected from public sources. It should be noted that time-series or causation models have typically only been used to model technology adoption of conventional fuels, i.e., gasoline and diesel. Trends for alternative fuel vehicle technologies (AFVTs) cannot be easily derived from these studies because the shares of AFVTs are small. In new AFVT markets, technology adoption data may not exist or simply be too limited to perform reliable statistical analyses.

Other widely used modeling techniques in this area are known as consumer choice models (Menon and Biswajit 2012). Consumer choice studies use surveys to gather data on respondents' personal characteristics and vehicle technology attributes. In turn, discrete choice models are applied to analyze the survey data and determine the effects of personal characteristics and technology attributes on the market share of each vehicle technology (Lee and Cho 2009). Consumer choice models rely on data from surveys, which usually are expensive to conduct. In addition, surveys are most often cross-sectional, and broader market share forecasts need extrapolations that can lead to imprecise predictions (Potoglou and Kanaroglou 2008).

In the case of sparse data for adoption of new vehicle technologies, multiple diffusion forecast models have been developed in the AFVT adoption literature. Researchers have applied Gompertz, Logistic, Bass, and Generalized Bass (GBass) diffusion models to forecast diffusion rates of AFVTs, e.g., electric vehicles (EVs) and NGVs. All four specifications demonstrate the well-known S-shaped diffusion curve associated with adoption of new technologies, and all have a fixed saturation level

(McManus and Senter 2009). But Gompertz, Logistic, and Bass specifications require only one variable and produce unconditional forecasts (Wilson and Keating 2009), while in contrast, GBass functions allow more explanatory variables into the model, which can help better determine the shape of the S-curve. The following sections highlight those studies applying Bass and GBass models to study technology as well as AFVT diffusions (Park, Kim, and Lee 2011).

### **The Bass Technology Diffusion Model**

Several quantitative studies have applied the classic Bass model (Bass 1969) to estimate market penetration of new technology. The Bass model explains how consumers move from one potential social group to an adopter social group. The salient feature of the Bass diffusion model is the S-shaped market growth for new technologies. Growth rates within the S-shaped diffusion curve are determined by three parameters:  $p$ , the rate of initial adoption by users independent of marketing efforts for the new technology;  $q$ , the imitation rate of technology users, who follow word-of-mouth information in order to decide upon adoption; and  $M$ , the maximum market potential of the new technology.

Chang and Wang (2011) used the Bass diffusion model to forecast growth patterns for Twitter adoption and hashtag diffusion in Taiwan. Heinz et al. (2013) applied the Bass model to study stationary fuel cell diffusion. Their Bass estimates showed that a fuel cell market will reach half of the maximum market size within five years, and after eight years the market will be close to projected full market size. Finally, Becker et al. (2009) utilized the Bass diffusion model to predict the U.S. EV penetrations to 2030. The study predicted that the EV penetration can reach 24% of the U.S. light-duty fleet. The researchers also estimated the reduction of emissions resulting from EV growth.

### **The Generalized Bass Technology Diffusion Model**

Bass et al. (1994) further developed what they called the Generalized Bass (GBass) model of technology diffusion. This specification included not only internal, but also external marketing variables into diffusion estimates. Essentially, Bass et al. (1994) included a mapping function consisting of a mix of marketing variables into the original Bass model. Unlike the basic version, the GBass model incorporates additional variables intended to capture the effects of marketing actions. In turn, these variables may change the shape of the diffusion curve as well as the ultimate market potential estimate (McManus and Senter 2009).

Estimating both Bass and GBass models will generate richer output and provide better insight into the marketing characteristics of the market under study. Examples using the GBass model include Park et al. (2011), who estimated a GBass diffusion model to understand market penetration for Hydrogen Fuel Cell Vehicles (HFCVs) in Korea (Park, Kim, and Lee 2011). In the U.S., researchers have forecast the diffusion processes of Plug-In Hybrid Electric Vehicles (PHEVs) (McManus and Senter 2009), while the same researchers also utilized a GBass approach to estimate PHEV penetration (McManus and Senter 2009).

There are a number of interesting features of these latter studies. First, the critical  $p$ ,  $q$ , and  $M$  parameter values were similar across both Bass and GBass estimates; in fact, the Bass and GBass curves behaved very similarly with the PHEV data. Finally,  $p$  and  $q$  were both significant in the Bass model; whereas in the GBass model, all parameters except  $q$  were statistically insignificant. These insignificant parameters suggest a need to explore additional decision variables that may affect technology diffusion and the growth of alternative vehicle markets.

In summary, among the various technology diffusion estimation techniques, Bass and GBass models allow incorporation of consumer behavior into the model specifications. Moreover, the additional flexibility to include socioeconomic variables in the GBass model gives more

interpretational flexibility to the forecasts. By contrast, Gompertz and Logistic diffusion models do not have simple microeconomic interpretations and, hence, do not generate ready explanations for consumer adoption of AVFTs (Wilson and Keating 2009).

## MODEL DEVELOPMENT

### Bass Model for NGV Diffusion

Bass technology diffusion is driven by the concept that there exists some probability of new adoption of a technology in the marketplace. Specifically, the probability of new adopters for the focal technology (i.e., NGV) that have not already adopted is a linear function of existing adopters of this technology which have adopted it (Bass 1969). The analytic expression is:

$$(1) P(t) = p + (q/M)A(t)$$

$P(t)$  = the probability that an initial NGV purchase (in this case) will be made at  $t$ , given that no purchase has yet been made, is just a linear function of the number of previous buyers (Bass 1969);

$p$  = the coefficient of “innovation,” meaning independent technology adoption without external influences;

$q$  = the coefficient of imitation, meaning adoption following independent or other adopters; or, alternatively, a measure of network influence;

$A(t)$  = the number of previous buyers, where  $A(0) = 0$ ;

$M$  = the total initial purchase of the product over the period of interest (i.e., the life of the product).

Statistically, equation (1) is a hazard function that shows the limiting probability that a potential NGV user who has not adopted before time  $t$  does so at time  $t$ . While  $p$  represents the rate of initial adoption by users independent of marketing efforts for the new technology,  $q$  represents the imitation rate of technology users who follow information from social networks to make decisions about adoption. Intuitively,  $p$  and  $q$  are positive in that independent adopters and follower adopters must coexist in the (AFVT) marketplace. However, the coefficient of  $p$  is likely to be relatively small, meaning less risk-seeking behavior associated with AFVT adoption. The coefficient of  $q$ , in contrast, is expected to be larger than  $p$ , indicating more risk-averse behavior associated with AFVT adoption. Finally, we predict that  $M$ , the maximum market potential of the NGV technology, is going to be positive.

Under these assumptions, the likelihood of a purchase at time  $t$  given that no purchase has yet been made is (Bass 1969):

$$(2) \frac{f(t)}{1-F(t)} = P(t) = p + \left(\frac{q}{M}\right) A(t) = p + qF(t)$$

$f(t)$  = the likelihood of purchase at  $t$

The cumulative possibility of purchase over period  $t = [0, T]$  is;

$$(3) F(t) = \int_0^t f(t) dt, \text{ and } F(0) = 0$$

So we can compute sales at time  $t$ ,  $S(t)$ , as;

$$(4) S(t) = Mf(t) = \left(p + \frac{q}{M} \int_0^t S(t) dt\right) \left(M - \int_0^t S(t) dt\right)$$

In turn, the total number purchasing during the time interval [0, t] is

$$(5) \quad A(t) = \int_0^t S(t)dt = M \int_0^t f(t)dt = MF(t)$$

So the ultimate solution to the Bass model is (Bass 1969):

$$(6) \quad F(t) = \frac{1 - e^{-(p+q)t}}{1 + \left(\frac{q}{p}\right)e^{-(p+q)t}}$$

Meaning that the total number purchasing during the time interval [0, t] is

$$(7) \quad A(t) = F(t)M = M \frac{1 - e^{-(p+q)t}}{1 + \left(\frac{q}{p}\right)e^{-(p+q)t}}$$

**Generalized Bass Model for NGV Diffusion (Bass et al. 1994)**

The updated GBass differential equation describing technology diffusion multiplies the original Bass differential equation by an additional expression,  $x(t)$ . As mentioned,  $x(t)$  is an equation which contains marketing variables associated with the technology diffusion model. In the AFVT literature, a variety of marketing variables have been studied. In our context, sales of NGVs at time  $t$ ,  $S(t)$ , is (Bass et al. 1994):

$$(8) \quad S(t) = \left(p + \frac{q}{M}A(t)\right)(M - A(t))x(t)$$

where

$$(9) \quad x(t) = 1 + \beta_1 \frac{Pt}{P} + \beta_2 \frac{Gt}{G}$$

$\beta_1$  the effect of the price premium for natural gas fuels on NGV adoptions;

$\beta_2$  the effect of the number of natural gas refueling stations on NGV adoptions;

Intuitively,  $\beta_1$  should be negative since higher prices for natural gas fuels are likely to lower NGV demand.  $\beta_2$  is expected to be positive because greater availability of natural gas refueling infrastructure will motivate more NGV demand. Next, let us define the change in the natural gas fuel price premium by:

$$(10) \quad P(t) = \frac{\text{price of conventional fuel} - \text{price of natural gas}}{\text{price of conventional fuel vehicle}}$$

and the change in the number of natural gas stations by:

$$(11) \quad G(t) = \frac{\text{No. of NG refueling station at time } t - \text{No. of NG refueling station at time } (t-1)}{\text{No. of NG refueling station at time } t}$$

So in this case, the solution to our version of GBass model is:

$$(12) \quad A(t) = M \left( \frac{1 - e^{-(p+q)(t + \beta_1 \ln(P(t)) + \beta_2 \ln(G(t)))}}{1 + \left(\frac{q}{p}\right)e^{-(p+q)(t + \beta_1 \ln(P(t)) + \beta_2 \ln(G(t)))}} \right)$$

### Statistical Estimation Methods for Bass and GBass Models.

Several methods have been used to estimate key parameters in the Bass and GBass models. A basic non-linear regression of the equation specification is the most common approach for both the Bass and GBass model specification. With respect to model estimation, we specify here the observational data as a nonlinear combination of parameters and independent variables (Guseo and Dalla Valle 2005). The general objective function used for our non-linear regression is (Greene 2000):

$$(13) \min \sum_1^N (y - f(x))^2$$

$N$  = the total number of pairs of observations and independent variables in the dataset;

$y$  = the vector of observed dependent variables;

$x$  = the vector of independent variables;

$f(x)$  = the model function.

Methods to solve nonlinear regression problems can be tricky and vary from one software package to another. Keeping with prior studies, here we start by using STATA (Version 9) as our non-linear estimation package. The primary reason for doing this is that STATA is well established as an econometric and statistical software and in turn is relatively easy for a researcher to use (McManus and Senter 2009; Popp, Hascic, and Medhi 2011).

## DATA DESCRIPTION

### Data Sources

We collected national and state (Texas) data on NGVs as well as natural gas refueling stations. Several U.S. archival sources were utilized to gather these data. These include the Federal Highway Administration, the Bureau of Transportation Statistics, the U.S. Energy Information Administration (EIA), and the Alternative Fuels Data Center. We also note that the U.S. Department of Transportation (DOT), Department of Energy (DOE), and Energy Information Administration (EIA) publish national and state-specific data on NGVs and refueling stations.

### NGV Penetrations in U.S. National Auto Markets

Table 1 presents the U.S. Census Bureau summary counts of vehicles powered by alternative fuels during the period 2003-2009. The data source is the U.S. DOT (Federal Highway Administration 2014; U.S. Census Bureau 2015). The table shows estimated consumption of vehicle fuels by fuel type. Six primary categories of fuel are listed in the table. These are compressed natural gas (CNG), electric, ethanol 85% (E85), liquefied natural gas (LNG), and liquefied petroleum gas (LPG). Among these, two fuel types can be summarized as natural gas vehicles: CNG and LNG. The total number of CNG vehicles was 114,406 in 2003 and 114,270 in 2009. LNG vehicles increased from 2,640 to 3,176 over 2003 to 2009. In terms of vehicles in use, NGVs comprise a nontrivial market force among the set of alternative fueled vehicles in the U.S. Note that while the total number of NGVs in use has stayed above 117,000 over time, the NGV percentages decreased from 21.92% to 14.21% during 2003-2009.

Table 2 summarizes the data from the Energy Information Administration and shows the number and proportion NGVs compared to the total number of vehicles. The total number of NGVs increased from 117,046 to 121,254 during 2003-2011. Among NGVs, there are significantly more CNG vehicles than LNG vehicles. Finally, starting from 2003, we note that the percentage of NGVs

over all ground vehicles is less than 0.0006%. The percentage remained almost the same over this time, only showing slight fluctuation below a range of .01%.

**Table 1: Alternative Fueled Vehicle Counts, by Fuel Type**

Type of Alternative Fuels	2003	2004	2005	2006	2007	2008	2009
Compressed Natural Gas (CNG)	114,406	118,532	117,699	116,131	114,391	113,973	114,270
Liquefied Natural Gas (LNG)	2,640	2,717	2,748	2,798	2,781	3,101	3,176
Total NGV	117,046	121,249	120,447	118,929	117,172	117,074	117,446
NGV Percentage	21.92%	21.44%	20.34%	18.74%	16.84%	15.09%	14.21%
Electric	47,485	49,536	51,398	53,526	55,730	56,901	57,185
Ethanol, 85 percent (E85)	179,090	211,800	246,363	297,099	364,384	450,327	504,297
Hydrogen	9	43	119	159	223	313	357
Liquefied Petroleum Gas (LPG)	190,369	182,864	173,795	164,846	158,254	151,049	147,030
Other Fuels	0	0	3	3	3	3	3
<b>Total</b>	<b>533,999</b>	<b>565,492</b>	<b>592,125</b>	<b>634,562</b>	<b>695,766</b>	<b>775,667</b>	<b>826,318</b>

Source: US Census Bureau (2015).

**Table 2: NGVs Number and Percentage in the U.S.**

YEAR	CNG	LNG	NGV TOTAL	ALL VEHICLES	CNG (%)	LNG (%)	TOTAL (%)
2003	114,406	2,640	117,046	231,000,000	0.000494	.0000114	0.000506
2004	118,523	2,644	121,167	237,000,000	0.0005	.0000111	0.000511
2005	117,511	2,687	120,198	241,000,000	0.000487	.0000111	0.000498
2006	116,100	2,747	118,847	244,000,000	0.000475	.0000113	0.000487
2007	114,359	2,727	117,086	247,000,000	0.000462	.000011	0.000474
2008	113,940	3,028	116,968	248,000,000	0.000459	.0000122	0.000471
2009	114,237	2,869	117,106	246,000,000	0.000464	.0000116	0.000475
2010	115,817	3,030	118,847	242,000,000	0.000478	.0000125	0.000491
2011	118,168	3,086	121,254	25,300,000	0.000467	.0000122	0.000479

Source: Energy Information Administration (2013).

### NGV Penetration in Texas Auto Markets

In order to estimate the penetration of NGVs in Texas' auto markets, we reviewed vehicle data from several federal datasets (Bureau of Transportation Statistics 2002, 2014; Federal Highway Administration 2014; U.S. Census Bureau 2015; U.S. Energy Information Administration 2013). The U.S. EIA provides data on state-specific alternative fuel vehicle counts. Table 3 shows Texas NGVs' and other alternative vehicles' historical levels and percentages. In 2003, the number of CNG vehicles in Texas was around 6,927, while LNG numbers were about 604 vehicles, so that total NGV numbers were about 7,531 vehicles. The EIA reports that after 2003, the total number of NGVs increased from 7,531 to 11,185 over nine years. We note that CNG vehicles are the main

contributor to increasing NGV penetration. The number of LNG vehicles actually fell over this time. In any case, the CNG vehicle sector still represents around 0.000553 % of all Texas vehicles, a relatively small ratio.

**Table 3: Texas NGV Number and Percentage**

Year	CNG	LNG	NGV TOTAL	ALL VEHICLES	CNG (%)	LNG (%)	TOTAL (%)
2003	6,927	604	7,531	14,888,780	0.000465	.0000406	0.000506
2004	10,160	558	10,718	16,906,714	0.000601	.000033	0.000634
2005	11,376	501	11,877	17,469,547	0.000651	.0000287	0.00068
2006	11,026	550	11,576	17,538,388	0.000629	.0000314	0.00066
2007	10,827	411	11,238	18,072,148	0.000599	.0000227	0.000622
2008	11,032	422	11,454	18,207,948	0.000606	.0000232	0.000629
2009	10,125	315	10,440	18,208,170	0.000556	.0000173	0.000573
2010	11,275	319	11,594	17,193,559	0.000656	.0000186	0.000674
2011	10,845	340	11,185	19,617,055	0.000553	.0000173	0.00057

Source: Energy Information Administration (2013).

In addition, we collected data from the U.S. EIA to calculate the percentage of different types of NGVs in the Texas vehicle market (see Table 4). Here, pickup and van categories comprise the majority of total NGVs. Pickups have approached half of total vehicle numbers, while in contrast, the SUV category occupies the smallest market share of NGVs in Texas.

**Table 4: Different NGV Types in Texas**

Year	Van	Pickup	Truck	Bus	SUV	Other	Total
2003	580	3,240	1,432	476	165	1,034	6,927
2004	1,132	4,210	1,535	780	294	2,209	10,160
2005	999	4,523	1,869	662	219	3,104	11,376
2006	1,778	5,350	985	680	238	1,995	11,026
2007	1,739	4,997	688	769	241	2,393	10,827
2008	1,650	4,557	524	1,133	255	2,913	11,032
2009	1,608	4,458	381	1,345	N/A	2,333	10,125
2010	1,624	4,877	551	1,452	357	2,414	11,275
2011	2,153	4,538	521	1,084	7	2,542	10,845

Source: Energy Information Administration (2013)

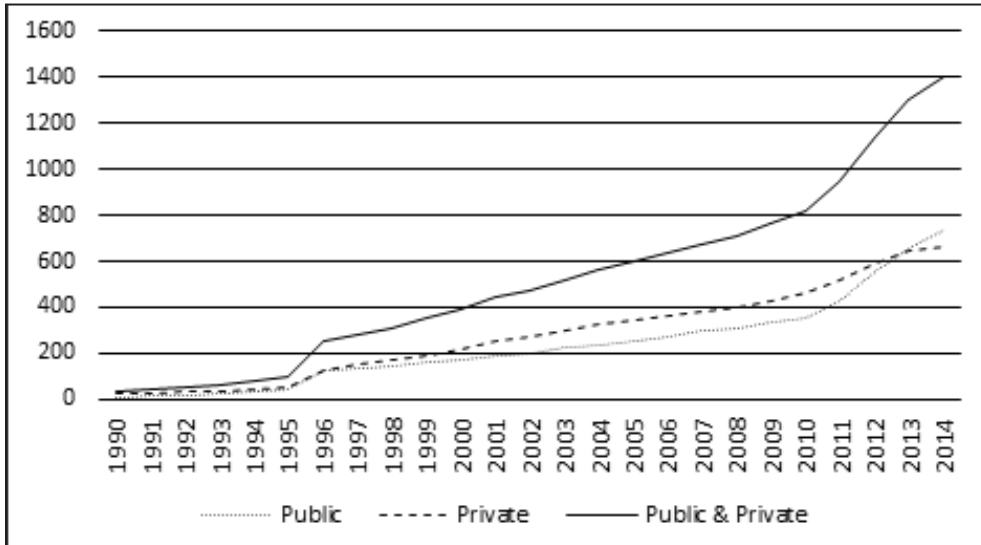
In terms of U.S. natural gas refueling infrastructure, the number of CNG stations reached the 100 station threshold in 1996. Since then, the number of CNG stations has risen. In contrast, U.S. LNG stations display a slower growth rate and only reached 100 stations nationwide in 2014. Public stations and private stations are distinct service groups for NGV refueling infrastructure. Public stations are similar to the widespread gasoline and diesel refueling stations, and the services are open for public NGV adopters. In contrast, private stations are reserved for NGV fleets owned by private or public organizations, such as carriers, businesses, and governments (National Petroleum Council 2012).

By the end of 2013, there were 1,305 CNG stations (657 public stations and 648 private stations) and 88 LNG stations (47 public stations and 41 private stations). By the summer of 2014, there were

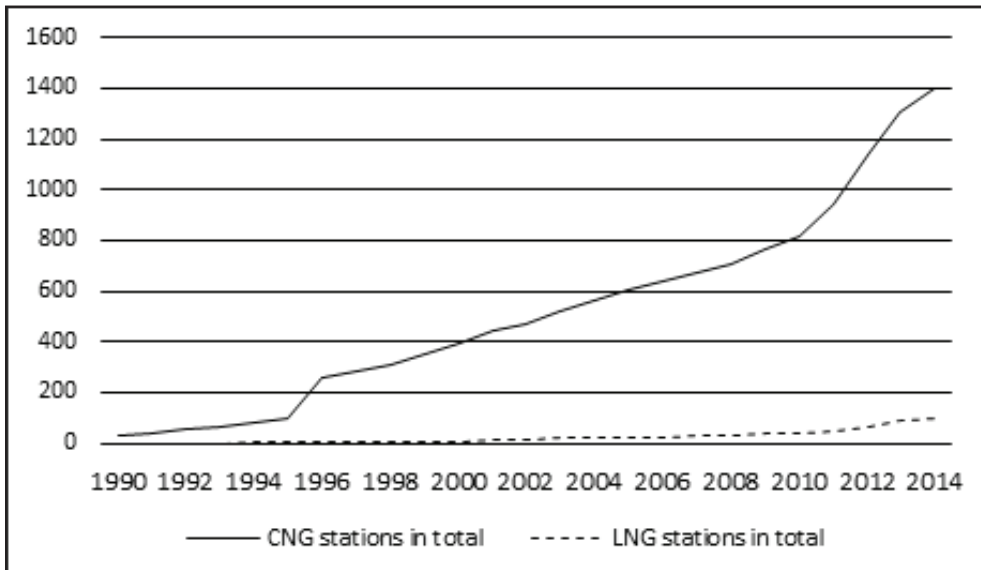


1,399 CNG refueling stations (732 public stations and 667 private stations) and 100 LNG refueling stations (58 public stations and 42 private stations) across the United States. Figure 1 illustrates the growth of CNG stations and the relative distribution between public and private refueling stations over time. Figure 2 shows and contrasts growth rates of both U.S. CNG and LNG stations.

**Figure 1: US CNG Station Growth and Distribution of Public vs. Private Stations**



**Figure 2: Growth in US CNG and LNG Refueling Stations**

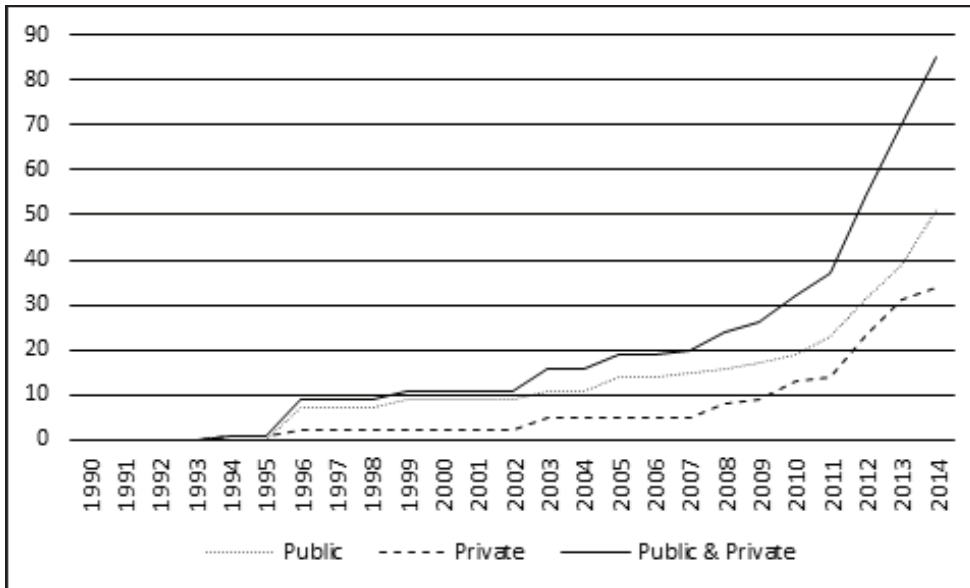


With respect to natural gas refueling stations in Texas, it is worth noting that Texas has never been the largest NGV market in the U.S., in part because of the relatively low prices of gasoline and diesel. By the end of 2013, there were 70 CNG stations (39 public CNG stations and 31 private CNG stations) and 12 LNG stations (eight public LNG stations and four private LNG stations) in Texas. By the summer of 2014, Texas had 85 CNG stations and 13 LNG stations. Among them, there are

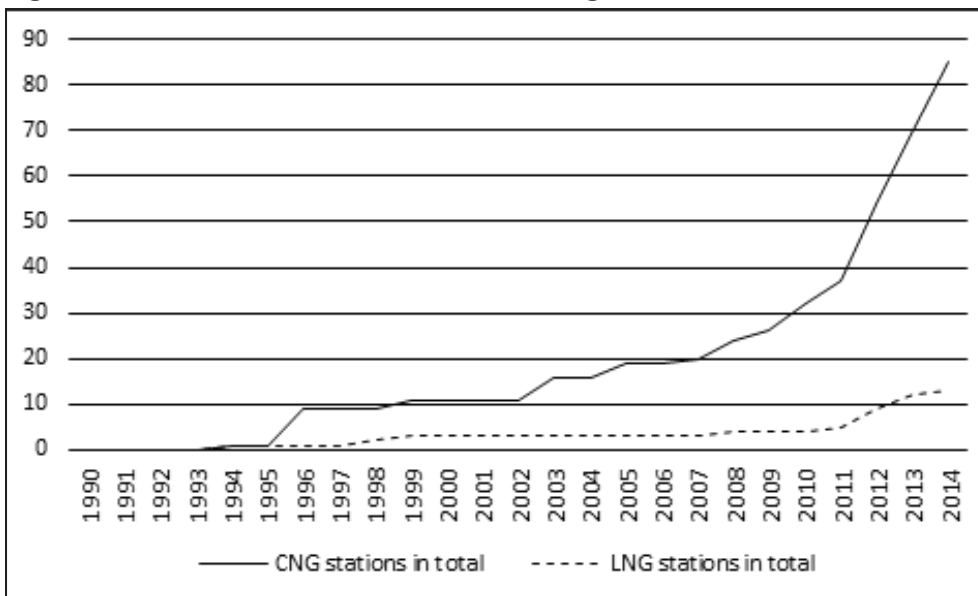
51 public CNG stations and 34 private CNG stations, and nine public LNG stations and four private LNG stations. In other words, 60% of CNG stations and 69% of LNG stations are public stations in Texas.

LNG is mostly used for heavy duty trucks. However, there are more and lighter duty cars using CNG as fuel, as more CNG stations are being built. Figure 3 illustrates the growth of CNG stations in Texas and the distribution of public and private refueling stations over time. Figure 4 contrasts the growth rates of Texas CNG and LNG stations.

**Figure 3: Texas CNG Stations Growth and Distribution of Public vs. Private Stations**



**Figure 4: Growth in Texas CNG and LNG Refueling Stations**



In summary, U.S. NGV adoption has been stable since 2003 at around 117,000 units, by measure of NGV registrations. The percentage of U.S. NGV adoption has remained at .04% or above over this time. For the Texas NGV market, the percentage of NGV adoption is slightly higher than overall U.S. adoption. Texas percentage has remained at .05% or above since 2003. With respect to natural gas refueling infrastructure, although the numbers of natural gas stations in the U.S. and Texas appear to be small, their numbers have been increasing at a steady pace. In particular, private refueling stations have had much stronger growth in recent years in both the United States and Texas markets. Stable NGV adoption and growing refueling infrastructure would seem to indicate that NGVs are slowly growing in fleet importance within AFVT markets.

## MODEL ESTIMATION AND RESULTS

These national and state data sets are used to estimate both Bass and GBass NGV technology diffusion models described earlier. Non-linear regression techniques are applied to estimate the coefficients of NGV technology adoption and diffusion models.

### U.S. NGV Diffusion Model Estimation

**Bass Model Estimation.** As the annual national NGV data distinguish CNG vehicles from LNG vehicles, we can perform Bass-based NGV diffusion estimates for both CNG vehicles and LNG vehicles, respectively. The numbers of CNG and LNG vehicles are combined to get national counts of total NGVs. Time values are assigned in accordance with the years when NGV data were available.

As mentioned, the values for the innovation parameter ( $p$ ) and imitation parameter ( $q$ ) are expected to be positive and significant. Initial values for these parameters are needed to run the Bass modeling on STATA. Referencing related studies by Becker et al. (2009) and McManus and Senter (2009), we initially assign the following values:  $p = .01$  and  $q = .5$ .

Table 5 shows the Bass model estimates for our data on CNG vehicles, LNG vehicles, and total US NGV vehicles. In each model, note that respective  $p$  values are smaller than their corresponding  $q$  values, indicating that for this market imitation effects are stronger than innovation effects. In addition, the  $p$  coefficients are not significant, but all  $q$  coefficients in the models are positive and statistically significant. This finding suggests that potential NGV adopters in the U.S. are risk-averse and will typically commit to this technology purchase based on others' information and experience.

**Table 5: Estimation Results for Parameters in US NGV Bass Models**

Parameters	Total NGVs	CNG Vehicles	LNG Vehicles
<b>m</b>	115341.6 (22.05)***	112399.1 (22.00)***	2973.056 (29.58)***
<b>p</b>	.0750829 (.88)	.076494 (.87)	.0343847 (1.51)†
<b>q</b>	.7856463 (1.92)*	.7982316 (.076)*	.5716242 (3.83)***

\*\*\*  $p < .001$ ; \*\*  $p < .01$ ; \*  $p < .05$ ; †  $p < .10$  (1-tailed tests).  $t$  values in parentheses.

**Generalized Bass Model Estimation.** The GBass model for U.S. NGV penetration includes two additional marketing variables, whose choice was motivated by the relevant literature: natural gas fuel price per GGE (gasoline gallon equivalent) and the number of natural gas refueling stations nationwide. Natural gas fuel price effects are estimated by the coefficient  $\beta_1$ , while natural gas refueling infrastructure effects are evaluated by the coefficient  $\beta_2$ . To determine the initial values of  $p$  and  $q$ , we again refer to Becker et al. (2009) and McManus and Senter (2009) and assign the values  $p = .1$  and  $q = .5$ . We anticipate  $\beta_1$  to be negative and significant since increasing prices have a negative effect on vehicle sales. In contrast,  $\beta_2$  is expected to be positive and significant because a well-developed refueling infrastructure will encourage more NGV adoption.

Again, we utilize non-linear least squares to estimate our NGV GBass models. Table 6 shows the GBass model estimates for CNG vehicles, LNG vehicles, and total U.S. NGV vehicle models. In our three GBass models, respective values of  $p$  are smaller than their corresponding  $q$  values. These outcomes are similar to our basic Bass models in Table 5 and again show imitation effects here are stronger than innovation effects. Moreover, our  $p$  coefficients are not significant, but the  $q$  coefficients in all our GBass specifications are positive and statistically significant, buttressing our findings that this market is characterized by risk-averse purchasing behavior of potential adopters in U.S. NGV markets.

**Table 6: Estimation Results for Parameters in US NGV Generalized Bass Models**

Parameters	Total NGVs	CNG Vehicles	LNG Vehicles
$m$	123941.7 (35.60)***	120757.6 (35.76)***	3107.289 (29.32)***
$p$	.0340352 (.55)	.0344995 (.54)	.0159096 (.36)
$q$	.2701521 (2.00)*	.2685476 (1.96)*	.4131224 (3.25)**
$\beta_1$	-.5722201 (-.15)	-.5275174 (-.14)	-.5328285 (-.22)
$\beta_2$	.6631471 (.71)	.6814265 (.72)	.1553682 (.15)

\*\*\*  $p < .001$ ; \*\*  $p < .01$ ; \*  $p < .05$ ; †  $p < .10$  (1-tailed tests).  $t$  values in parentheses.

The signs of  $\beta_1$ , the coefficient for natural gas fuel price per GGE, are negative. But surprisingly, the coefficients  $\beta_1$  are not statistically significant in all our models. The signs of  $\beta_2$ , the coefficient for the number of NG refueling stations, are positive. But the coefficients  $\beta_2$  are not statistically significant in all specifications. We speculate about these outcomes, which may result from several factors. First, most current NGV adopters are fleet owners, and various governments in the United States have used financial aids to incentivize NGV adoption. Secondly, NGV technologies are estimated to be more environmentally friendly and to generate less emission. As such, natural gas fuel price at this stage may not be a dominant factor for NGV adoption. Regarding the infrastructure effect, fleet owners, as primary NGV adopters, are more likely to build their own refueling facilities to sustain their NGV operations, so that the level of NGV adoption may be independent of the expansion of natural gas refueling infrastructure. In any case, our results are broadly comparable with the prior related results of McManus and Senter (2009), who found that only the imitation parameter was statistically significant.

### Texas NGV Diffusion Model Estimation

**Bass Model Estimation.** Bass models need a certain number of observations to ensure reliable estimation (Balakrishnan 2007). Small samples may lead to a long convergence time, or the model may not converge at all. For this research, the complete data sets for state-specific NGVs, fuel prices, and refueling stations each contain nine observations. Thus for our Texas NGV Bass models, STATA cannot converge. Alternatively, we use tools of MATLAB’s Statistics and Machine Learning Toolbox (also used in recent technology diffusion literature) to run our non-linear regression models on this data (Lin and Lai 2012; Vodopivec and Herrmann 2012). MATLAB utilizes iterative least square estimation methods to estimate non-linear regression coefficients. MATLAB tools enumerate possible initial values to start new non-linear regressions and return a local optimum. The iterative processes continue and eventually identify global optimal estimates (MathWorks 2016a, 2016b).

Once again, in this specification, there are four unknown parameters:  $p$ , the coefficient of innovation;  $q$ , the coefficient of imitation;  $M$ , the maximum market size; and  $Y$ , the start year of the model. We assume here that  $Y$  is at 2003 (the first year in our data set). Non-linear regression estimation in MATLAB requires assigning an initial value for each parameter in the Bass model to

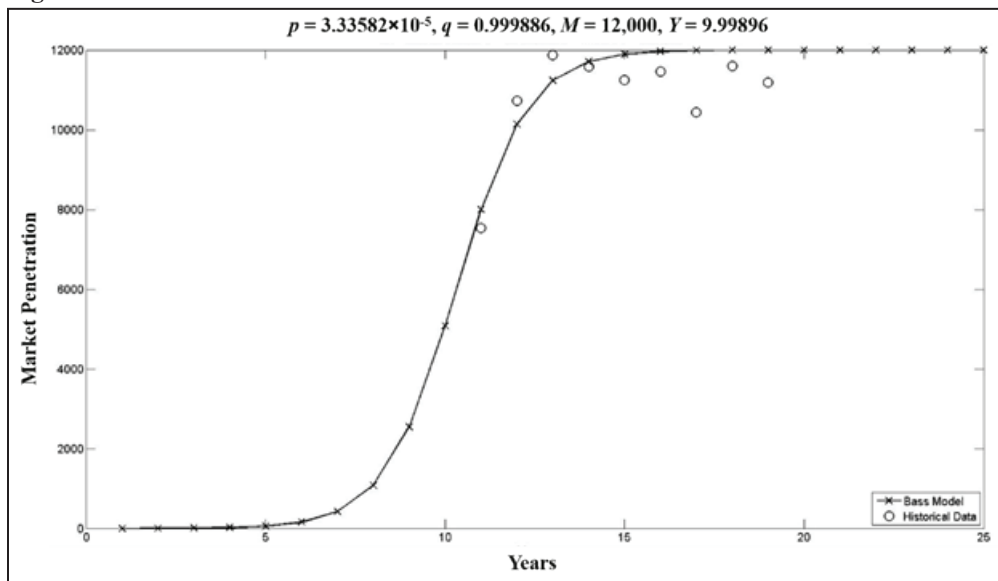
initiate the iterations. In order to avoid bias in conjectures about the initial values of the innovation and imitation coefficients ( $p$  and  $q$ ), maximum NGV market size ( $M$ ), and the start year ( $Y$ ) are assumed to be unknown parameters.

In spite of the small sample size, MATLAB achieves convergence. However, the codes developed by the modeler are not able to generate variances on the coefficients for hypotheses testing. Hence, the regression outputs reported here must be considered as exploratory outcomes. Table 7 summarizes point estimates of the unknown parameters for Texas NGV and CNG vehicle Bass models. Applying the estimates, the formal Bass adoption curves can be derived for both NGV and CNG vehicles' market penetration in Texas. The Bass curves for Texas NGV penetration are shown in Figures 5 and 6 below. The figures indicate the models' approximation (shown as "x" in the figure) and the historical data (shown as "o"), along with the particular S-shape curves derived from the estimates.

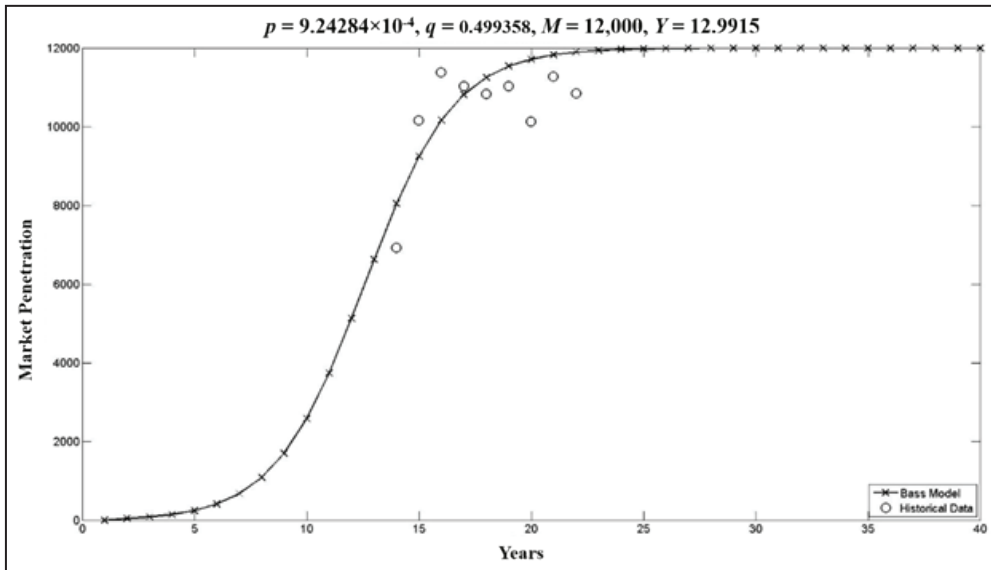
**Table 7: Estimation Results for Parameters in Texas NGV Bass Models**

Parameters	Total NGVs	CNG Vehicles
$M$	12000	12000
$p$	.0000333582	.000924284
$q$	.999886	.499358
$Y$	9.99	12.99

**Figure 5: Estimated Bass Curve for Texas NGV Penetration**



**Figure 6: Estimated Bass Curve for Texas CNG Vehicle Penetration**



## DISCUSSION

Researchers have observed that AFVT sales growth or market penetration reflects technology diffusion, and the nature of this process can be estimated by Bass and/or GBass models. Early AFVT research applied the Bass model to study hybrid electric vehicles diffusion, while Bass/GBass methods were subsequently utilized to forecast the diffusion of newer technologies, such as plug-in hybrid electric vehicles. This research extends Bass and GBass model applications within the modern AFVT literature.

One theme in AFVT diffusion studies is the challenge of data availability. Prior studies were conducted in early stages of AFVT adoption, and sometimes only a few observations exist from available sources. Furthermore, the early stages of technology introduction may cause fluctuations in market penetration due to factors like competitive dynamics, market inertia, technological failures, and so forth (Huo et al. 2012; Paltsev et al. 2011). As a result, the sales data needed to estimate Bass and GBass models may display nontrivial variation, generating insignificant estimates or even model non-convergence. This research also highlights an approach to estimate Bass/GBass models with extreme data constraints.

We use our NGV data to estimate Bass and GBass models of U.S. and Texas NGV diffusion. We find that NGV technologies now seem to be considered somewhat mature in the automobile industry. Adoption of both CNG and LNG vehicles seems to be increasingly common among vehicle fleets and the public.

By using statistical software that accounts for small sample issues, we show the limitations on estimating Bass diffusion models on smaller data sets can be overcome. The complete Texas-specific data set only contains nine observations, and this number is lower than the observational threshold typically used in empirical Bass studies. We use MATLAB and develop an exploratory exercise to illustrate that, by using appropriate software combined with non-linear least square regression tools, both the Texas Bass NGV and CNG vehicle models converge.

Among all U.S. and Texas Bass model runs, the  $p$  and  $q$  parameter estimates are similar. The  $p$  values (innovation factors), are all much smaller than the  $q$  values (imitation factors). The low  $p$  values indicate that very few fleets or the public are likely to invest in such novel vehicle technology in either the U.S. or Texas automobile markets. On the other hand, imitation effects are observed in

NGV penetration, considering our estimated  $q$  values. Our  $q$  value suggests that “word of mouth” continues to be effective in promoting NGVs to fleets and the public. In turn, the estimates of signs and values of  $p$  and  $q$  are consistent with our expectations and those results documented in prior AFVT studies.

The U.S. GBass estimates provide insight into how natural gas fuel prices and available refueling stations affect extant NGV penetration. First, for the three specifications of all NGVs, CNG vehicles, and LNG vehicles, estimates of  $\beta_1$ , the coefficient of the natural gas fuel variable, are similar. The negative sign of  $\beta_1$  suggests that higher natural gas fuel prices will negatively impact the growth of NGVs. In addition, the estimates of  $\beta_2$ , the coefficients of the number of natural gas refueling stations, are positive. This suggests that as more natural gas refueling stations are available to fleets and the public, there should be more adoption of NGVs.

Our estimates of the maximum number of NGV vehicles, represented by the values of the  $M$  parameters, are similar to recent NGV counts in our data. This implies that both the U.S. and Texas NGV markets may have reached a saturation level. These are surprising outcomes given the optimistic statements by NGV proponents who were informally interviewed during the project. Further, our findings appear to be somewhat contradictory to reports of emerging NGV markets that can be found in trade publications.

The discrepancy between our results and the apparent phenomenon of growing NGV markets may be explained by newly introduced bi-fuel engine technologies. Bi-fuel NGV technologies allow drivers to switch between natural gas and a conventional fuel, either diesel or gasoline. Indeed, the primary purpose of bi-fuel vehicles is to avoid the range problem that exists because of a lack of natural gas refueling infrastructure, allowing drivers’ use of conventional fuels when desired or when natural gas fuels are not available.

As per the distinction between various types of electric vehicles (for example hybrid electric vehicles and plug-in hybrid electric vehicles), we offer that dedicated NGV and bi-fuel NGV diffusion processes may need to be analyzed separately. While NGV technologies are similar across the two types of vehicles, certain operational characteristics, i.e., need for maintenance, operational range, vehicle routing and scheduling plans, etc., may vary significantly between dedicated and bi-fuel NGVs. From both the current and potential NGV adopters’ standpoint, dedicated and non-dedicated NGVs look to be considered as essentially different technologies.

## CONCLUDING REMARKS

Proponents of alternative fuels have offered natural gas as a major alternative transportation fuel for the United States in the near future. We know that the price spread between natural gas and conventional fuels, e.g., gasoline and diesel, has been widening over the last decade, meaning that U.S. fleets operating on natural gas can save fuel costs from one-half to two-thirds of conventional fuel costs. Environmentally, natural gas is also a clean-burning fuel. The potential of natural gas fuels to reduce pollutant emissions and greenhouse gases has led to governments increasing funding for NGV adoption, and has also motivated existing fleets to purchase or convert to NGVs.

Furthermore, adoption of NGV technology will also enhance energy independence in the United States by moving away from its traditional reliance on foreign oil and gas imports. The recent growth of domestic oil and gas exploration and production within the United States implies continued reductions in the need for foreign oil and gas. Since the transportation sector has been the largest energy user in the United States, continued growth of NGV adoptions in U.S. fleets as well as the public can help stimulate long-term natural gas production and help maintain a domestic natural gas fuel market.

Interestingly, our results indicate that NGV markets appeared to become saturated around the year 2010. This finding stands in contrast to anecdotal evidence about ongoing NGV adoption. In fact, promotional activities for CNG, LNG, and bi-fuel vehicle technologies were not widely

introduced to either fleets or the public until quite recently. Any increasing adoption of related technology motivated by promotional activities is not likely being captured in our data set.

In addition, newly adopted NGVs are equipped with so-called bi-fuel technologies, which allow drivers to switch between natural gas fuels and CNG or LNG. These bi-fuel NGVs are distinct from traditionally dedicated NGVs, since bi-fuel NGVs have fewer constraints on range and thus more flexibility in routing and scheduling arrangements. These features are similar to hybrid electric vehicles and reduce the risk of operation compared with traditional NGVs. This latter technology may motivate more acceptance among potential NGV adopters, but we do not distinguish between the two NGV engine configurations due to data availability. Future research should collect detailed data to examine whether the market penetrations will vary between dedicated and non-dedicated NGVs.

Finally, it should be noted that the empirical contribution of the present research pertains to the STATA-based model specifications. The MATLAB-based exercise is employed to make it useful for the small set of Texas diffusion data and address the convergence problem in STATA runs. While STATA and MATLAB tools have appeared in technology diffusion literature, it is inconclusive that particular research tools, or newer versions of them, might overcome such shortfalls as estimation convergence with extremely limited data. In our view, future research may perform in-depth assessments regarding the effectiveness of extant research tools to model technology diffusions with data limitations. Furthermore, research that improves the efficiency of algorithms to specify diffusion models using limited data is in order.

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