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A Bass Diffusion Model Analysis: Understanding Alternative Fuel Vehicle Sales

Michael H. Shoemaker
Claremont McKenna College

CLAREMONT McKENNA COLLEGE

A BASS DIFFUSION MODEL ANALYSIS:
UNDERSTANDING ALTERNATIVE FUEL VEHICLE SALES

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PROFESSOR SERKAN OZBEKLIK

AND

DEAN GREGORY HESS

BY

MICHAEL SHOEMAKER

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Abstract

Frank M. Bass developed the Bass Diffusion Model to predict how innovative consumer durable products diffuse through consumer markets. This thesis will use data from 1999-2011 to examine the applicability of the Bass Diffusion Model to the introduction of alternative fuel vehicles (AFVs) in the automobile market. The findings in this thesis indicate the Bass Diffusion Model fit the diffusion pattern exhibited by AFVs well, but failed to accurately forecast diffusion patterns outside a given range of data. This thesis investigates potential reasons for the inaccurate 'Out of Sample Forecast', and gives recommendations for directions of future research on AFV diffusion.

I. <u>Introduction</u>

In 2007, worldwide there were an estimated 806 million cars and light trucks consuming 260 billion gallons of gasoline and diesel (Plunkett Research). According to Bhandari (2007), the United States consumes 370 million gallons of gasoline per day. Pressures to develop alternative fuel vehicles (AFVs) seem to fluctuate with world events and election cycles. How might automobile manufacturers decide whether the cost of introducing a new fuel efficient AFV is justified? Product diffusion models describe the rate and extent to which new products are incorporated into existing consumer markets. This thesis investigates the applicability of the Bass Diffusion Model to the introduction of AFVs in the automobile market. First developed by Frank M. Bass (1969), the Bass Diffusion Model predicts the time and magnitude of newly released product categories' sales peaks. Bass (1969) first fit this model to annual sales data for an array of eleven different consumer durables. Each product category was considered an innovative addition to an already existent market.

To assess the applicability of the Bass Diffusion Model to the introduction of AFVs, the model is fit to a dataset of monthly AFV sales and the resulting statistics are compared to those calculated by Bass (1969). This thesis compares the modeled time and magnitude of peak sales to the actual time and magnitude of peak AFV sales. Additionally, to test the model's predictive capability outside the sample data range, an "Out of Sample Prediction" is conducted using one half of the available data. Subsequently, an "Out of Sample Forecast" compares predicted values generated from the "Out of Sample Prediction" to actual sales figures. As such, the "Out of Sample

Forecast" assesses the Bass Diffusion Model's predictive accuracy outside a given range of sample data.

The results of this analysis indicate the Bass Diffusion Model captures the general trend of AFV diffusion more accurately than it predicts diffusion patterns outside the range of available sample data. Findings of this thesis topic fall under Industrial Organization, and as such are applicable to automobile manufactures interested in predicting the diffusion process of an AFV model. Additionally, model parameters calculated in this thesis can serve as a starting point for automobile manufacturers interested in releasing AFV models. Further research investigating parameter effects when firms enter and exit markets would enhance the corporate applicability of the model's estimation.

This thesis is organized as follows: Section II reviews the literature on diffusion models; Section III details the Bass Diffusion Model and explains the empirical strategy used in this thesis; Section IV describes the process of data organization; Section V reports results of the empirical analysis and discusses potential reasons for imperfect fit; Section VI concludes this thesis; Section VII includes data tables; Section VIII includes figures; Section IX cites relevant references.

II. Review of Literature

The Literature of Diffusion Models

The literature on forecasting sales for the release of new products centers on work introduced by Bass (1969). Bass applied the model to sales data for new releases of eleven different consumer durable products, including electric refrigerators, home freezers, black and white televisions, water softeners, room air conditioners, clothes dryers, power lawnmowers, electric bed coverings, automatic coffee makers, steam irons, and 'recover players'.[1] Using annual time series data for the release of each innovation, the Bass Diffusion Model predicted the magnitude and timing of peak sales with impressive accuracy.

Generally, the Bass Diffusion Model applies to the release of any new innovation in an existing product category. For instance, when first released, electric bed coverings were innovative additions to the bed covering market. Likewise, when power lawnmowers were released they were an innovative addition to the lawnmower market. Subsequent research in the realm of new product diffusion developed more specific applications of the Bass Diffusion Model.

Bass and Norton (1987) extend the Bass Diffusion Model by incorporating the notion that introductions of a new product generation occur before the preceding generation fully diffuses. Drawing from past literature on substitution models, Bass and Norton (1987) explain that sales from each successive generation must come from 1) expanding applications to obtain sales which would not have otherwise gone to earlier generations and/or 2) capturing sales that earlier generations would have seized over the duration of their diffusion process. They used data for successive generations of two basic types of integrated circuits: memory and logic circuits. Data for these specific products was chosen because they were similar goods, both of which employed cutting edge technology. The results Bass and Norton (1987) calculate indicate the developed

[1] 'Recover Players' was likely a typewriter typo for what was meant to be record players.

model yields an accurate forecast ‘conditional on the timing of introduction of successive generations of the technology.’

Krishnan et al. (2000) contribute to the literature on diffusion models by specifying the Bass Diffusion Model at a brand specific level. Krishnan et al. (2000) incorporate the effects that a newly entered brand could have on existing brands’ sales and overall market potential of the product category. To achieve this, Krishnan et al. (2000) use city specific data from cell phone service providers to assess the entrance of a third firm into a market historically defined by two firms. Krishnan et al. (2000) define each city as an individual market, and assess how different formulations of the Bass Diffusion Model fit the data after the third brand entered the market. Specifically, the authors focus on any change in the speed of diffusion within a product category and any change in market potential after the third brand entered the market.

Krishnan et al. (2000) calculate different effects in each of the three markets studied. They report Market 1 experienced an increase in the speed of product diffusion, but no change in market potential. Market 2 experienced an increase in market potential, but no change in the speed of product diffusion. Market 3 experienced an increase in both the speed of product diffusion and the category’s market potential. Krishnan et al. (2000) compare their brand level specification of the Bass Diffusion Model to the original Bass Diffusion Model using *mean absolute percentage error* (MAPE) as a gauge. Krishnan et al. (2000) determine the brand level Bass Diffusion Model to forecast sales more efficiently than the original Bass Diffusion Model for markets with new brand entrants. However, Krishnan et al. (2000) emphasize the brand level Bass Diffusion Model reduces to the original Bass Diffusion Model when all brands’ sales are compiled together and treated as a single entity. As such, Krishnan et al. (2000) explain the Bass Diffusion Model provided a generally good fit to the data, but failed to account for the specific dynamics created by new brands entering a product category. As evidence of this Krishnan et al. (2000) cite the brand level Bass Diffusion Model's MAPE of 3%, as compared to the original Bass Diffusion Model's MAPE of 8%.

Bass et al. (1994) investigate why the Bass Diffusion Model fits without decision variables. An article by Russell (1980) critiques the Bass Diffusion Model for its failure to explain sales contagion effects in relation to fundamental economic variables, namely price. Bass et al. (1994) explain the Bass Diffusion Model has two dimensions, a time domain and a cumulative adoption domain. Consequently, they argue incorporating decision variables capable of changing over time, to represent lagging effects in certain periods, will result in a better fit than the Bass Diffusion Model.

Bass et al. (1994) proceed to refute Russell's (1980) claim by generalizing the Bass Diffusion Model to include decision variables for 'marketing effort' ($x(T)$), 'advertising' (ADV(T)), and 'price' (Pr(T)). Bass et al. (1994) emphasize the incorporation of decision variables is done such that the Generalized Bass Model reduces to the original Bass Diffusion Model. Specifically, Bass et al. (1994) develop the Generalized Bass Model with the intention of it reducing to the Bass Diffusion Model when the incorporated decision variables are assumed to remain constant over time. Bass et al. (1994) calculate the Generalized Bass Model to fit better than the Bass Diffusion Model for the sales data of Room Air Conditioners, Color TVs, and Clothes Dryers used by Bass (1969).[2] Bass et al. (1994) conclude that the Generalized Bass Model will provide a good fit when the Bass Diffusion Model provides a good fit, and that the Generalized Bass Model will provide the same fit if the included decision variable function remains approximately constant (e.g. $x(T)$ is constant).[3]

III. <u>Model and Estimation Strategy</u>

Introduction of Alternative Fuel Vehicles

To the best of the author's knowledge, the introduction of alternative fuel vehicles to the automobile market marks one niche of product diffusion not considered in previous applications of the Bass Diffusion Model. When first released for commercial sale in 1999, alternative fuel vehicles were an innovative addition to the already existent automobile market. As consumer durables, cars as a product category fall under the Bass Diffusion Model's general requirement that product purchases be spread out over time. This requirement enables the model to assume no repeat purchasers within a given period.

When considering which form of the Bass Diffusion Model should be used to estimate the diffusion pattern of alternative fuel vehicles through the automobile market, two important points stand out. First, upon the initial release of alternative fuel vehicles it is unclear consumers had developed a brand-dependent understanding of the alternative

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[2] The Generalized Bass Model maintained the trend of the Bass Diffusion Model. Bass et al. (1994) determine the Sum of Squared Errors (SSE) and Mean Squared Error (MSE) reduce significantly when the Generalized Bass Model is fit to Bass's (1969) data. In the case of Room Air Conditioners for example; the Generalized Bass Model reduced the SSE by 58.10% and the MSE by 27.68%. Improvements of similar proportions characterize the performance of the Generalized Bass Model for both Color TVs and Clothes Dryers.

[3] The authors explain this difference in goodness of fit to be the result of the included decision variables, when the coefficients are statistically significant, explaining deviations in the actual data missed by the Bass Diffusion Model due to its smooth curve.

fuel vehicle market. As such, it is not clear that the model developed by Krishnan et al. (2000) should fit the data better than the original Bass Diffusion Model. It may be that at later points in evolution of the alternative fuel vehicle market, their brand dependent Bass Diffusion Model should be used to fit the dataset analyzed in this thesis. Second, limitations in the author's understanding of the mathematics and potential to access the necessary data to apply the Generalized Bass Model indicate the Bass Diffusion Model to be a more logical starting point for an initial assessment of AFV diffusion.

Bass Product Diffusion Model

Bass (1969) uses sales data to assess the market effects of new product introductions. The model he develops assesses the rationale behind consumer behavior in terms of innovative and imitative behavior, as well as the market potential of the product category. Bass (2004) cites Rogers' (1962) description of the diffusion of innovations to explain the nature of timing in the adoption process. Rogers (1962) explains that adoption can be categorized in two ways; by a 'judge's ratings' method, or by a 'time of adoption' method. Roger's advocates the latter of the two methods because it enables the adoption process to be categorized using normally standardized measures.

Using the categorization method advocated by Rogers (1962), Bass (1969) develops the distinction between the influence of innovation and imitation in the diffusion of new products. What follows is the simple Bass Diffusion Model used in this thesis.

Bass (1969) uses the equation,

$$\boldsymbol{P(T) = p + (q/m)Y(T),} \tag{1}$$

to show the probability of an initial purchase occurring at T, assuming that the consumer made no prior purchase of the innovation, is a linear function of the number of previous buyers.

In this equation, ***P(T)*** is the likelihood of purchase at time T given that no purchase has yet been made; ***p*** is the "coefficient of innovation", a constant representing the probability of an initial purchase at $T = 0$ (because $Y(0) = 0$), and its magnitude represents the importance of innovators in society; ***q*** is the coefficient of imitation; ***m*** is the number of initial purchases of the product; ***q/m*** is a constant; ***Y(T)*** is the number of previous buyers; and thus ***Y(T)(q/m)*** demonstrates pressures acting on imitators as the number of previous buyers increases.

Basic Assumption to Bass Diffusion Model:

1) Over the life of the product there will be *m* initial purchases of the product. Because consumer durables are products consumers purchase infrequently, the unit sales of the product will equal the number of initial purchases for the period of the time interval that excludes replacement sales. The formulation of the model focuses on this portion of the time interval.

Bass (1969) explains the behavioral rationale behind the basic assumptions to be:

A. Preliminary purchases are comprised of both 'innovators' and 'imitators'. The buying influence distinguishes innovators from imitators. Innovators are not influenced by the number of previous purchasers, while imitators are influenced by the number of previous purchasers.

B. The importance of innovators is greater initially, but diminishes monotonically over time.

C. ***p*** will be referred to as the coefficient of innovation and ***q*** as the coefficient of imitation.

Formulating equation (1) as a continuous model and a density function, Bass (1969) shows,

$$[f(T)]/[1 - F(T)] = P(T) = p + (q/m)Y(T) = p + qF(T). \qquad (2)$$

Where *f(T)* is the likelihood of purchase at time *T*, Bass (1969) indicates,

$$F(T) = \int_0^T f(t)dt, \qquad F(0) = 0. \qquad (3)$$

m is the number of purchasers in the period for which the density function was built, and *f(T)* is the likelihood of purchase at time T. Thus,

$$Y(T) = \int_0^T S(t)dt = m \int_0^T f(t)dt = mF(T) \qquad (4)$$

represents the total number of purchasers in the interval (0,*T*) interval. As such, sales at time T is shown as

$$S(T) = mf(T) = P(T)[m - Y(T)] = \left[p + q \int_0^T S(t)\, dt/m\right]\left[m - \int_0^T S(t)dt\right]. \qquad (5)$$

Bass (1969) then expands the two bracketed terms to get the model's basic function,

$$S(T) = pm + (q - p)Y(T) - q/m\,[Y(T)]^2. \tag{6}$$

I formulate the analog of the regression function given in equation (6) as,

$$S_T = x + y(Y_{T-1}) + z(Y_{T-1}^2), \tag{7}$$

where $S(T)$ = sales at time T; $Y_{T-1} = \sum_{t=1}^{T-1} S_t$ = cumulative sales through period T – 1; x estimates pm; y estimates $q - p$; and z estimates $-q/m$.

The steps to solve for the parameter estimates begin

$$q = z(-m). \tag{8}$$

Then substituting q into the y estimate yields,

$$y = z(-m) - p, \tag{9}$$

and

$$p = z(-m) - y. \tag{10}$$

Substituting p into the x estimate yields,

$$x = (z(-m) - y)m, \tag{11}$$

and

$$0 = zm^2 - ym - x. \tag{12}$$

As indicated by equation (12), m must be solved for using the quadratic equation. Using m to solve for the remaining parameters in the model,

$$p = x/m, \tag{13}$$

and

$$q = z(-m). \tag{14}$$

After running regressions with the model specified above, Bass (1969) formulates the time of peak sales (T^*) by solving for $F(T)$ in order to define $f(T)$ in terms of parameters p, q, and m. Using the equality demonstrated in equation (2), Bass (1969) expresses $f(T)$ as,

$$f(T) = [p + qF(T)]\,[1 - F(T)] = p + (q - p)F(T) - q[F(T)]^2. \tag{15}$$

Thus, finding $F(T)$ requires solving the following non-linear differential equation:

$$dT = dF/(p + (q - p)F - qF^2). \tag{16}$$

Bass (1969) reports the solution to be

$$F = (q - pe^{-(T+C)(p+q)})/q(1 + e^{-(T+C)(p+q)}). \tag{17}$$

As per equation (3), $F(0) = 0$. Thus, Bass (1969) evaluates the integration constant, z, and determines F(T) to be:

$$-z = (1/(p + q))Ln(q/p), \tag{18}$$

and

$$F(T) = (1 - e^{-(p+q)T})/(q/pe^{-(p+q)} + 1). \tag{19}$$

Substituting the expression of $F(T)$ from equation (19) into equation (15) and then the first equality of equation (5), Bass (1969) finds

$$f(T) = ((p + q)^2/p)[e^{-(p+q)T}/(q/pe^{-(p+q)T} + 1)^2], \tag{20}$$

and

$$S(T) = \ m[((p + q)^2/p)[e^{-(p+q)T}/\big(q/pe^{-(p+q)T} + 1)^2\big]]. \tag{21}$$

To calculate the peak time of the sales rate in equation (21), Bass (1969) differentiates S,

$$S' = (m/p(p + q)^3e^{-(p+q)T}\big(q/pe^{-(p+q)T} - 1\big))/(q/pe^{-(p+q)T} + 1)^3. \tag{22}$$

Setting this derivative equal to zero and solving for T, Bass (1969) calculates the peak time (T*) to be

$$T^* = \ -1/(p + q)Ln(p/q) = 1/(p + q)Ln(q/p).[4] \tag{23}$$

Substituting equation (23) into equation (22), Bass (1969) establishes

$$S(T^*) = (m(p + q)^2)/4q, \tag{24}$$

and

[4] For an interior maximum to exist the coefficient of imitation must be greater than the coefficient of innovation (i.e. q>p).

$$Y(T^*) = \int_0^{T^*} S(t)dt = m(q-p)/2q. \quad (25)$$

Empirical Strategy

In this thesis, the Bass Diffusion Model is used to estimate the diffusion pattern of AFVs. The raw data consists of monthly sales for the 585 vehicle models sold in the United States from January 1995 to December 2011. Monthly sales were chosen instead of annual sales due to how recently AFVs were released. AFVs were initially released in late 1999, and as such monthly sales figures provide a significantly larger sample size with which to conduct the analysis.

The raw data was then cleaned and organized into five groups, Utility AFV, Passenger AFV, Utility IC, Passenger1 IC, and Passenger2 IC. Subsequently, I created the two additional variables necessary to regress the model, cumulative sales and the square of cumulative sales. [5] For the purpose of this thesis, the two AFV groups were of primary interest. As such, regression analysis was conducted using the Utility AFV and Passenger AFV groups. To conduct this regression, the regression specification shown in equation (7) was created as an analog of equation (6). In the context of this analysis, the specification may also be written as,

$$\widehat{Sales}_T = x + y(CumulativeGroupSales) + z(CumulativeGroupSales^2) + u_i.^6 \quad (26)$$

[5] A detailed report of the data organization process is available in the **<u>Data</u>** section.
[6] As per equation (18), the Z coefficient will always be negative.

"In Sample Predictions" were calculated by regressing the data using the Bass Diffusion Model for all time periods available. Subsequently, the resulting regression coefficients were used to calculate the model's parameters *m*, *p*, and *q*.[7]

"Out of Sample Predictions" were calculated by regressing the model over a predetermined range of time periods. Both groups' "Out of Sample Predictions" were calculated using half of the available months of data. The resulting coefficients were then used to predict values over the entire sample period. "Out of Sample Forecasts" were then conducted by regressing these predicted values upon actual sales figures for each group. The results of this regression give an indication of Bass Diffusion Model's predictive ability outside the range of available data.

An OLS time series estimator was used for each analysis mentioned above. Ideally, the regressions would have controlled for autocorrelation in the data, and the Newey-West estimator appeared to be the appropriate estimator to do so. Unfortunately, the statistical package used for this thesis did not report an R-squared value when the regression was estimated using the Newey-West estimator. For the purpose of comparing my results to those of Bass (1969), obtaining R-squared values was prioritized over controlling for autocorrelation in the data.[8]

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[7] The results of these calculations are included in the **Results** section of this thesis, along with a comparison to results from Bass (1969).

[8] When the Newey-West estimator was used to control for autocorrelation the regression coefficients exhibited higher standard errors and lower t-statistics. Still, all coefficients from the regression of the basic Bass Diffusion Model remained statistically significant.

IV. Data

Data Overview and Cleaning

The data provided by WARDSAuto was categorized by fuel type and vehicle type. The categories created for fuel types were alternative fuel vehicles (AFV) and standard internal combustion engines (IC). The vehicle type categories were defined as utility vehicles (Utility) and passenger vehicles (Passenger). Due to recent evolutions in car design, careful inspection of each automobile model included in the original data was required to categorize vehicle type.

The categorization criteria are as follows: Four door sedan, coup, and compact hatchback vehicles were categorized as 'passenger vehicles', while SUVs, trucks, station wagons, and larger 'crossover' type vehicles were categorized as 'utility vehicles'. In developing these categorization criteria, I considered general divisions in the automobile market, as well as characteristics of the Bass Diffusion Model. Solely considering the nature of the Bass Diffusion Model, it is tempting to categorize alternative fuel vehicles by date of release. Such organization would likely smooth sales trends, but would fail to capture the influence concrete characteristics have on vehicle sales. While 'alternative fuel vehicle' is undoubtedly a distinct product category within automobiles, other categories, such as vehicle size, functional purpose, and price, influence sales in the automobile market. The Bass Diffusion Model explains sales, within distinct product categories, as a function of time and previous purchasers, and as such AFV group categorization criteria must consider vehicle characteristics that influence purchase. By considering these characteristics, the categorization criteria segment the automobile market in a manner that reflects typical decisions motivating the purchase of a new vehicle (i.e. size, functional purpose, and price).[9]

After the data was categorized, each of the five categories was transposed into new spreadsheets; 'Utility AFV', 'Passenger AFV', 'Utility IC', 'Passenger IC 1', and 'Passenger IC 2'. The model's fundamental variables (sales, cumulative sales, and square cumulative sales) were then created for each model. Though time intensive, this data transformation was done so the model could be applied to individual car models, if necessary later on in the analysis. This information is stored in the sheets labeled '*Work Sheet Name* Cum' and '*Work Sheet Name* Cum^2'.

The data used to fit the Bass Diffusion Model was calculated differently. A column was added to total all monthly sales for each of the five categories. These total columns were then copied to the worksheet 'Totals'. Columns were added calculating the cumulative sales and the square of cumulative sales data for *the total sales of each category*.

The next issue pertained to omitting entries capable of distorting the diffusion process explained by Bass (1969). Models released prior to 1995 were omitted to account for sales data which had already 'diffused' significantly before the period in consideration. Inclusion of this data would distort the Bass Diffusion Model's estimation. In the process of omitting automobile models released before 1995 a few trends were noted. First, automobiles released between 1990 and 1995 typically exhibited sales statistics associated with early stages of the diffusion process. This trend

[9] As mentioned in the **Literature Review**, price is not included in this assessment of AFV diffusion in through the automobile market. The Bass Model (1969) does not account for it. Authors such as Russell (1980) and Bass et al. (1994) discuss the importance of decision variables (i.e. price) in the Bass Diffusion Model in the context of the Generalized Bass Model.

raised the question of whether or not to include automobile models with such release dates, and if so, which date to choose as a cutoff? This question was answered on a case by case basis because models which diffuse at faster rates provide shorter intervals to assess the diffusion process.

Another issue regarding potential distortions to the data concerned the initial release, and subsequent recall of electric vehicles in the mid-1990s. GM, Honda, and Nissan were the first to release AFVs, but these Passenger AFV models, the Saturn EV1, Honda EV Plus, and Nissan Altra, were recalled after two years on the market. Discussion concerning the reasons behind the recall ensues to this day, but as it pertains to preparing data for the Bass Diffusion Model such models required exclusion. Had these recalled models been left in the sample, gaps in the data would distort the model's estimation of the diffusion process in question. [10]

Finally, all years prior to the release of each group were removed from the data set. This was intended to prevent null values from skewing the model's results. Had they not been removed, the null values included for years prior to introduction would bias the assessment of the Bass Diffusion Model's applicability to the introduction of AFVs. This would problematically result in R-squared values being incorrectly inflated due to the model's perfect fit for values of zero.

Description of Raw Sales Data

Interestingly, categorizing the data based on the criteria explained in the previous part of this section accounted for trends in the timing of the Passenger AFVs'

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[10] In **Tables**, *Table 8* details which models were in question and what decisions were made.

introductions to the automobile market. From *Table 1* it is apparent the initial release of Passenger AFVs occurred roughly 5 years before the release of Utility AFVs. This delayed release may account for the lack of trends in AFV releases for the Utility group. Careful inspection of Passenger AFV data revealed 3 distinct release periods. As indicated in *Figure 2*, the first period from 1999 to 2002 marked the introduction of AFVs to the automobile market, and included the release of the Toyota Prius and Honda Insight. After a slow first year for both models, Toyota Prius sales increased significantly while Honda Insight sales remained depressed. It is important to note each of the two 'pioneer AFVs' were newly created models. It was not until the next period that major car manufacturers, particularly Japanese ones, began to release hybrid versions of standard issue models.

As indicated in *Figure 3*, the next period clustered with introductions of new Passenger AFV models began in 2003 with the introduction of the hybrid Honda Civic. This was followed by the release of the Honda Accord, Toyota Camry, and Nissan Altima, all with hybrid engines. Models released in the second period experienced substantial success in sales. Sales figures for both the Civic and Camry grew quickly, and as a result the two models became distanced runner-ups to the Prius.[11] Both the Honda Accord and Nissan Altima reported monthly sales figures greater than those of the Honda Insight.[12] The break between introductions of new Passenger AFV models in August 2007 marks the close of the second period clustered with new releases.

[11] As of 2011, the Prius accounted for 62% of Passenger AFV sales, and an even greater percentage earlier on in the diffusion of Passenger AFVs.

[12] Note *Figure 3* includes the Honda Insight for comparison of maximum monthly sales.

As indicated in *Figure 4*, the final period in which new Passenger AFV models were introduced began in 2008 and continued to the end of the sample period. This period is characterized with the most Passenger AFV model releases. Unlike previous periods, multiple new companies entered the retail AFV market during this period. Such companies include Lincoln, Porsche, BMW, Mercedes-Benz, and Hyundai.

The expansion in suppliers of Passenger AFVs was likely motivated by a combination of factors. First, the astronomical sales figures demonstrated by the Prius were likely to have caught the eye of competing automobile manufacturers. If so, companies' desires to establish an early advantage in all market niches would prompt them to release Passenger AFV models. The price of gas and recessionary effects in the US are other factors capable of influencing automobile manufacturers' decisions whether or not to enter the AFV market.[13]

It is important to note this categorization of release periods was not incorporated into the regression analysis conducted in this thesis. Instead, the purpose of this discussion was to identify how Passenger AFV models were released in clusters over the sample period. Additionally, this categorization of time periods could be used to generate the lags necessary to control for autocorrelation if the Newey-West estimator was used to conduct the regression analysis. [14]

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[13] Although not investigated empirically, further discussion of the potential influence high fuel prices and reductions to short term income had on AFV sales is included in the **Results** section of this thesis.
[14] See **Empirical Strategy** section for detailed discussion of regression analysis.

V. **Results**

In Sample Prediction

As indicated in *Table 2* of the **Tables** section, the "In Sample Prediction" for Utility AFVs resulted in an R-squared value of 0.457. As such, roughly 46% of the variation in Utility AFV sales is explained by the model. Coefficient X was calculated to be 3383.054 with a standard error of (-412.72). Coefficient Y was calculated to be 0.031384 with a standard error of (-0.0049). Coefficient Z was calculated to be -8.98E-08 with a standard error of (-1.18E-08). All three coefficients are statistically significant at the 5% level. The resulting values of m, p, and q are 4.36E+05, 7.76E-03, and 3.91E-02, respectively.

The "In Sample Prediction" for Passenger AFVs resulted in an R-squared value of 0.776. As such, roughly 78% of the variation in Passenger AFV sales is explained by the model. Coefficient X was calculated to be 1553.75 with a standard error of (-612.44). Coefficient Y was calculated to be 0.0378975 with a standard error of (-0.0024). Coefficient Z was calculated to be -1.68E-08 with a standard error of (-1.56E-09). All three coefficients are statistically significant at the 5% level. The resulting values of m, p, and q are 2.30E+06, 6.77E-04, and 3.86E-02, respectively.

One important point to consider is the 0.319 difference in R-squared values between "In Sample Predictions" of Passenger AFV sales and Utility AFV sales. This indicates the Bass Diffusion Model explains roughly 32% more of the variation in AFV sales for the Passenger group than for the Utility group. Potential explanations for this R-squared differential include variation in short run income, the implementation of Car Allowance Rebate System, and variation in retail fuel prices.

As indicated in *Figure 5*, Utility AFVs were released in October 2004 and monthly sales peaked in May 2007 at 10,110 units. Additionally, *Figure 5* indicates some of the starkest deviations from the modeled trend occurred prior to the May 2007 peak in monthly sales. The majority of the deviation in this period is above the modeled trend. As such, these deviations may have been the result of issues similar to those reported by Bass (1969) for the case of black and white televisions. If true, such deviations resulted from rapid sales growth in initial periods after the product category's release. As indicated in *Figure 6*, Passenger AFV sales experienced less deviation from the modeled trend in initial periods following introduction. As such, this rationale may explain some portion of the R-squared differential between "In Sample Predictions."

Similarly, Bass (1969) explains deviations from the Bass Diffusion Model's trend occur, in some of the starkest instances, due to variations in short-term income. [15] Applying his intuition to my data, it appears the reduction to income resulting from market instability in the second half of 2007, and the subsequent financial crisis in 2008, has potential to explain the sharp fall in monthly Utility AFV sales between May and September of 2007. This fall in monthly sales, from the absolute maximum to a local minimum, is followed by a downward trend in cumulative sales. The timing of this trend coincides with the start of the subprime mortgage crisis that lead to panic on Wall Street, the Global Financial Crisis, and ultimately the Great Recession. Clearly, further statistical analysis is necessary to determine an empirical relationship, but the Bass (1969) intuition fits contextually and may explain some portion of Utility AFV's low R-squared value.

[15] Bass (1969) explains this to be the reason for the low R-squared value calculated for Home Freezers.

“In Sample Prediction” results for Passenger AFV sales appear to have been similarly affected by the onset of recession in mid-2007. Monthly Passenger AFV sales peaked in May 2007 at 36,823 units sold. Subsequently, monthly sales fell to a local minimum of 17,582 units in January 2008, and then to another local minimum of 11,222 in January 2009. Between these two local minimums, monthly sales of Passenger AFVs rebounded to 34,120 in April 2008. By August 2008, monthly Passenger AFV sales had rebounded from the January 2009 local minimum to a local maximum of 32,829 units. That volatility in monthly Passenger AFV sales continued through the recession implies factors beyond variations in short run income may have influenced Passenger AFV sales.

A potential additional explanation for the volatile deviations in monthly Passenger AFV sales between May 2007 and August 2009 is the initiation of the Car Allowance Rebate System (“Cash for Clunkers”) on July 1, 2009. This policy appropriated federal funding to incent owners of older, less-efficient vehicles to trade them in for newer, more-efficient vehicles. Mian and Sufi (2010) explain the $1 billion initially allocated for the program by Congress was exhausted within the first month of the program. Congress subsequently renewed funding for the program through the authorization of an additional $2 billion. This funding lasted until November 2009, the predetermined duration of the program.

The enactment of such a policy is likely to create an exogenous outward demand shock in the AFV market. Indication of such a shock can be seen in the apparent increase in Passenger AFV sales between the January 2009 and August 2009. While the surge in monthly Passenger AFV sales does not continue through the duration of the CARS program, its stimulatory effect on demand for Passenger AFVs can be seen for the month of July 2009. Mian and Sufi (2010) report the program to have induced a 360,000 unit increase in car sales for the month. Considering the initial $1 billion congressional appropriation required renewal due to substantial participation in the program throughout July 2009, it may hold to reason a majority of demand from initial participants was directed toward Passenger AFV models. If true, the parallel timing of the CARS program and substantial deviations from the modeled trend has potential to explain some portion of the variation in monthly Passenger AFV sales not captured by the model.

A final potential reason for unexplained variation in monthly Passenger AFV sales is retail fuel prices. Although this thesis conducted limited empirical analysis regarding the significance of such an effect, intuition indicates fuel prices should have an effect on demand for fuel efficient transportation substitutes. The limited empirical analysis conducted with fuel prices involved regressing actual sales data of each sample group on retail fuel prices. As indicated in *Table 5*, the resulting R-squared value from the Utility AFV sample regression was 0.00 with a t-statistic of 0.43, while the R-squared value from the Passenger AFV sample regression was 0.72 with a t-statistic of 19.25. As such, it appears changes in retail fuel prices hold greater influence over sales of Passenger AFVs than sales of Utility AFVs.

The indication of no relationship between Utility AFV sales and retail fuel prices is likely the result of the trend exhibited by the group after the sales peak. After the May 2007 peak Utility AFV sales followed a downward trend. While Utility AFV sales declined during this period retail fuel prices increased. This post-peak period accounts for much of the poor fit denoted by the R-squared value of 0.00. *Table 6* reports results from the regression of actual sales on retail fuel prices for the periods prior to each group's respective sales peak. For the Utility AFV group the R-squared value of the regression was 0.62 with a t-statistic of 6.93, and for the Passenger AFV group the R-squared value was 0.80 with a t-statistic of 18.81. As such, the post-peak deviation in trends between Utility AFVs and retail fuel prices seems to have contributed to the nonexistent relationship shown by the 0.00 R-squared value from the regression reported in *Table 5*.

Figure 9 and *Figure 10* depict the relationship between fuel prices and monthly AFV sales, with quantity sales measured on the left y-axis and retail fuel price measured on the right y-axis. *Figure 9*, comparing Utility AFV sales and retail gas prices, indicates Utility AFV sales peaked roughly one year before retail fuel prices peaked at $4.11 per gallon in July 2008. The subsequent fall in fuel prices coincides with the continued decrease in Utility AFV sales. A clear counterargument to this proposed explanation is the failure for monthly Utility AFV sales to rebound when retail fuel prices rose to $3.96 per gallon in March 2011. The validity of this counterargument would be enhanced by analysis indicating Utility AFVs' decreased variable costs resulting from fuel efficiency do not outweigh the increased fixed cost associated with the purchase of Utility AFV models.

Similarly, changes in fuel price have potential to explain a portion of the model's unexplained variation in monthly Passenger AFV sales. Referring to *Figure 10*, this rationale appears particularly salient when considered in the time frame assessed previously; from the May 2007 absolute maximum to the August 2009 local maximum. The largest change in retail fuel price, between July 2008 and December 2008, coincides with periods containing the largest deviations from the modeled Passenger AFV sales trend. Similarly, this period was marked by reductions in income associated with the onset of recession in mid-2007. As mentioned previously, the proposed rationales for unexplained variation by the model are merely conjectures based on intuition and limited regression analysis. Claiming empiricism to the nature of relationships discussed in this section would require a more robust dataset which takes into account factors associated with the economic downturn of 2007 - 2009. As this dataset was not obtained for the stated purpose of this thesis, in depth empirical analysis of the rationales proposed is outside the scope of this thesis.

Out of Sample Prediction and Forecast

The regression results reported for the "Out of Sample Prediction" in *Table 2* are the coefficients and goodness of fit measures calculated from the regression that used half of the available observations. Thus, the coefficients are important as they will determine the model's goodness of fit when compared to actual sales, but the R-squared values measure the model's goodness of fit for the "Out of Sample Prediction". As such, the R-squared values provided in *Table 2* are not indicative of the out of sample prediction's goodness of fit with actual data.[16]

The "Out of Sample Prediction" for Utility AFVs resulted in an R-squared value of 0.379. As such, roughly 38% of the variation in Utility AFV sales is explained by the model for the sample period October 2004 to May 2008. Coefficient X was calculated to be 2607.794 with a standard error of (-608.8). Coefficient Y was calculated to be 0.0578705 with a standard error of (-0.014). Coefficient Z was calculated to be -2.04E-

[16] For discussion of such goodness of fit measures refer to the "Out of Sample Forecast" portion of this section below.

07 with a standard error of (-5.99E-08). All three coefficients are statistically significant at the 5% level. The resulting values of m, p, and q are 3.23E+05, 8.07E-03, and 6.59E-02, respectively.

The "Out of Sample Prediction" for Passenger AFVs resulted in an R-squared value of 0.891. As such, roughly 89% of the variation in the Passenger AFV sales is explained by the model for the sample period December 1999 to December 2005. Coefficient X was calculated to be 198.354 with a standard error of (-304.04). Coefficient Y was calculated to be 0.0564275 with a standard error of (-0.00623). Coefficient Z was calculated to be -4.20E-08 with a standard error of (-2.10E-08). Coefficients Y and Z are statistically significant at the 5% level. The resulting values of m, p, and q are 1.35E+06, 1.47E-04, and 5.66E-02, respectively.

Table 4 reports results of the "Out of Sample Forecast". This forecast was conducted by regressing the predicted values generated from the "Out of Sample Prediction" on the actual sales data for each group over the entire sample period. Thus, the R-squared values in *Table 4* apply to the "Out of Sample Forecasts" graphed in *Figure 7* and *Figure 8*. *Table 4* indicates this analysis resulted in an R-squared value of 0.364 for Utility AFVs and an R-squared value of 0.016 for Passenger AFVs.

Interestingly, the R-squared values calculated for Passenger AFVs went from 0.891 in the "Out of Sample Prediction" to 0.016 in the "Out of Sample Forecast". This reversal of R-squared values makes more sense when considering the nature of the modeled fit depicted in *Figure 8*. The "Out of Sample Prediction" R-squared value indicates the model captured much of the variation in Passenger AFV sales between December 1999 and December 2005, while the "Out of Sample Forecast" R-squared value indicates the predicted model captures very little of the variation over the entire sample period.

Inspection of *Figure 8* indicates the forecast failed to capture variation in Passenger AFV sales after January 2008. The "Out of Sample Prediction's" time period ended before Passenger AFV sales began to demonstrate significant volatility, around mid-2007. As such, the parameters estimated in the "Out of Sample Prediction" do not incorporate the variation present in the data from mid-2007 onward. This reason likely contributed to the steep decrease in sales modeled by the "Out of Sample Forecast" after the predicted peak in September 2007. Actual monthly Passenger AFV sales remained roughly between 10,000 and 30,000 units during this time period. This difference between the forecasted trend and actual data undeniably contributed to the low R-squared value for the Passenger AFV "Out of Sample Forecast."

The "Out of Sample Forecast" for Utility AFVs modeled actual Utility AFV sales surprisingly well. The differential between "In Sample Prediction" and "Out of Sample Forecast" R-squared values is 0.093. As such, the "In Sample Prediction" captures roughly 9% more of the variation in actual Utility AFV sales than was captured by the "Out of Sample Forecast".

A potential explanation for this low differential is the time period for which the "Out of Sample Prediction" was conducted. The "Out of Sample Prediction" used data from October 2004 to May 2008. Thus, as indicated in *Figure 7*, the "Out of Sample Prediction" included data past the actual sales peak in July 2007. Additionally, this "Out of Sample Prediction" included actual data for months exhibiting significant variation. Thus, the actual sales peak and most stark variations in sales are incorporated into the coefficients, and resulting model parameters, estimated by the "Out of Sample Prediction". As such, the Utility AFV "Out of Sample Forecast" accounted for significantly more variation in monthly AFV sales than the Passenger AFV "Out of Sample Forecast". Nevertheless, both forecasts predict complete diffusion too early, and as such predict negative monthly sales in later periods. Thus, the Bass Diffusion Model's capability to forecast AFV sales outside a given sample range remains in question.

Comparison of Bass (1969) vs. Shoemaker (2012)

Table 9 reports the goodness of fit measures calculated by Bass (1969). The regressions these R-squared values are calculated from are comparable to those I calculated in the "In Sample Prediction" section of *Table 2*. Comparison of these two tables indicates the Bass Diffusion Model provided similar goodness of fits for the Bass (1969) products and AFVs. From *Table 9,* Bass (1969) reports R-squared values between 0.077 and 0.953. The average R-squared value reported in *Table 9* is 0.812. *Table 2* indicates the Passenger AFV "In Sample Prediction" yielded a 0.776 R-squared value. This R-squared value is only 0.036 away from the average of the R-squared value reported by Bass (1969). The R-squared value reported for the Utility AFV "In Sample Prediction" is more similar to the R-squared value reported by Bass (1969) for Home Freezers than the average. Thus, the Bass Diffusion Model predicts Passenger AFV's diffusion pattern more accurately than it does Utility AFV's diffusion pattern.

Table 3 reports the predicted and actual values for the time and magnitude of the sales peak. For comparison, predicted and actual peak values for seven of the eleven products assessed in Bass (1969) were reported alongside predicted and actual peak values calculated in this thesis. Reviewing the results of Bass (1969) reveals the Bass Diffusion Model predicted both the time and magnitude of the sales peak quite accurately.

The results calculated in this thesis reveal the Bass Diffusion Model underestimated the peak magnitude and overestimated the peak period for both AFV groups. “In Sample Prediction” of Utility AFV sales indicates the model’s expected peak time was period 34.5 and expected peak magnitude was 6,125 units. The actual peak time was period 31 and actual peak magnitude was 10,110. In the case of the Passenger AFV “In Sample Prediction”, the model predicted peak time to be in period 103 and predicted peak magnitude to be 22,926 units. The actual peak time occurred in period 89 and actual peak magnitude was 36,823 units.

Table 3 indicates the “Out of Sample Prediction” estimated peak time to be in period 28 and peak magnitude to be 6,711 units for Utility AFV sales. The comparable analysis for Passenger AFV sales estimated peak time in period 105 and peak magnitude to be 19,151 units. Actual peak time and magnitude remains the same for both AFV groups. Thus, the “In Sample Prediction” for Passenger AFVs yielded better estimations for peak time and magnitude than those developed by the “Out of Sample Prediction”. For Utility AFVs, the “Out of Sample Prediction” estimated values of peak time and magnitude closer to those observed in the actual data than the “In Sample Prediction”. While the Bass Diffusion Models’ estimations of peak time and magnitude were roughly correct, they were much further from actual values than the estimations reported by Bass (1969).

The model's general fit for "In Sample Predictions", "Out of Sample Predictions", and "Out of Sample Forecasts" can be explained by the similar nature of coefficient and parameter values calculated in both analyses. As indicated by equation (18) in the **Model and Estimation Strategy** section above, the expected sign of the Z coefficient must be negative for the model to successfully predict diffusion patterns. *Table 2* demonstrates negative Z coefficients for each analysis. Similarly, X and Y coefficients were similar in relative magnitude as compared to those calculated by Bass (1969). Thus, the resulting parameter values for *m*, *p*, and *q* estimated the time and magnitude of peak sales fairly accurately.

VI. Conclusion

The purpose of this thesis was to investigate the applicability of the Bass Diffusion Model to the introduction of AFVs in the automobile market. Monthly data for all US car sales between 1995 and 2011 was refined to fit the analog used to estimate the Bass Diffusion Model. The refinement and categorization process created the two AFV groups assessed in this thesis. Results from the empirical analysis conducted indicate the Bass Diffusion Model fit the general trend of AFV diffusion well for both groups.

The model's estimation of time and magnitude of the AFV sales peak was not as accurate as those presented by Bass (1969). Nevertheless, careful inspection of the regression results indicated a number of factors may have limited the model's overall goodness of fit. These factors include reductions in short term income caused by recessionary economic cycles, exogenous demand shocks for AFVs created by the CARS program, and variation in fuel prices.

This thesis also addressed the Bass Diffusion Model's predictive capability during time periods outside the available sample of data. Results of this inquiry varied by group, but in general the Bass Diffusion Model predicted the diffusion pattern after the sales peak inaccurately. Specifically, both "Out of Sample Forecasts" conducted in this thesis predicted steeply sloped decreases during the second half of the diffusion process. As such, both "Out of Sample Forecasts" predicted a premature end to the diffusion process, and consequently negative sales in later periods. The poor performance of "Out of Sample Forecasts" is likely the result of "Out of Sample Predictions'" failure to incorporate periods with the largest deviations into coefficient calculations used to conduct the "Out of Sample Forecast." Future research on AFV diffusion patterns will likely produce the data necessary to determine appropriate Bass Diffusion Model parameters for the AFV market.

As mentioned in the introduction to this thesis, growing demand for transportation exerts significant pressure on the current system in place. The analysis of AFV diffusion patterns conducted in this thesis will likely prove useful for automobile manufacturers faced with the decision of whether or not to release an AFV model. That this thesis finds the Bass Diffusion Model applicable in estimating the diffusion of AFVs implies future research incorporating effects of both decision variables and brand dependent diffusion will enhance the corporate applicability of this analysis.

VII. Tables

Table 1: Summary Statistics

Variable	Period Covered	Observations	Mean	Standard Deviation	Minimum	Maximum
Utility AFV	October 2004 - December 2011	87	4,539.14	1,933.32	894.00	894.00
Utility AFV Cumulative		87	215,678.30	127,244.70	1,130.00	394,905.00
(Utility AFV Cumulative)^2		87	6.25E+10	5.24E+10	1.28E+06	1.56E+11
Passenger AFV	December 1999 - December 2011	145	12,144.37	9,248.65	17.00	36,823.00
Passenger AFV Cumulative		145	5.60E+05	5.66E+05	17.00	1.76E+06
(Passenger AFV Cumulative)^2		145	6.33E+11	8.84E+11	289.00	3.10E+12
Utility IC	January 1995 - December 2011	204	283,885.40	150,225.20	177.00	625,718.00
Passenger IC 1		204	127,892.10	66,422.28	2,350.00	269,479.00
Passenger IC 2		204	60,283.82	32,215.56	827.00	137,415.00
Retail Fuel Prices UtilityAFV	October 2004 - December 2011	87	2.81	0.57	1.75	4.11
Retail Fuel Prices PassAFV	December 1999 - December 2011	145	2.31	0.77	1.13	4.11

Table 2: Results of Regression Analysis

Coefficient	X	Y	Z	R- squared Value	m	p	q
<u>In Sample Prediction</u>							
Utility AFV	3383.054**	0.031384**	-8.98E-08**	0.457	4.36E+05	7.76E-03	3.91E-02
	(-412.72)	(-0.0049)	(-1.18E-08)				
Passenger AFV	1553.75**	0.0378975**	-1.68E-08**	0.776	2.30E+06	6.77E-04	3.86E-02
	(-612.44)	(-0.00244)	(-1.56E-09)				
<u>Out of Sample Prediction</u>							
Utility AFV	2607.794**	0.0578705**	-2.04E-07**	0.379*	3.23E+05	8.07E-03	6.59E-02
	(-608.8)	(-0.014)	(-5.99E-08)				
Passenger AVF	198.354	0.0564275**	-4.20E-08**	0.891*	1.35E+06	1.47E-04	5.66E-02
	(-304.04)	(-0.00623)	(-2.10E-08)				

* R-squared value for out of sample regression, for R-squared values assessing the out of sample prediction's fit with actual sales see Table 4.

** denotes statistical significance at the 5% level

Table 3: Comparison of Results

Product	(q/p)	Predicted Peak Period (T*)	Actual Peak Period**	Predicted Peak Magnitude S(T*)	Actual S(T*)
Bass (1969)					
Electric Refrigerators	82.4	20.1	Interrupted by War	2.2E+06	Interrupted by War
Room Air Conditioners	40.2	8.6	7	1.8 E+06	1.7 E+06
Black & White TVs	9.0	7.8	7	7.5 E+06	7.8 E+06
Home Freezers	9.4	11.6	13	1.2 E+06	1.2 E+06
Clothes Dryers	20.7	8.1	7	1.5 E+06	1.5 E+06
Record Players	26.3	4.8	5	3.8 E+06	3.7 E+06
Power Lawnmowers	36.7	10.3	11	4.0 E+06	4.2 E+06
Shoemaker (2012)					
In Sample Prediction					
Utility AFV	5.0	34.5	31	6,125	10,110
Passenger AFV	57.0	103.0	89	22,926	36,823
Out of Sample Prediction					
Utility AFV	8.2	28.4	31	6,711	10,110
Passenger AFV	384.2	104.9	89	19,151	36,823

** The first time sales equal or exceed $p\,m$ is defined as the first period

Table 4: Results of Out of Sample Forecast

Regression: Actual Sales on Fitted Values*	R-squared Value
Sample Group	
Utility AFV	0.364
Passenger AFV	0.016

* Fitted values were generated from Out of Sample Prediction

Table 5: Results of Fuel Price Regression

Regression: Actual Sales on Retail Fuel Prices*	R-squared Value	Fuel Price T-Statistic
Sample Group		
Utility AFV	0.00	0.43
Passenger AFV	0.72	19.25

*Regressed over entire sample period

Table 6: Results of Fuel Price Regression

Regression: Actual Sales on Retail Fuel Prices*	R-squared Value	Fuel Price T-Statistic
Sample Group		
Utility AFV	0.62	6.93
Passenger AFV	0.80	18.81

*Regressed from introduction to sales peak

Table 7: Sales Velocity Statistics

Sample Group	Cumulative Sales at Monthly Peak	Duration (Months)	Ratio (Cumulative Sales / Duration)
Utility AFV	167,787	31	5412.49
Passenger AFV	627,449	89	7049.99

Table 8: Models in question and subsequent decisions executed in *Thesis Data Sheets - Exclusive* file:

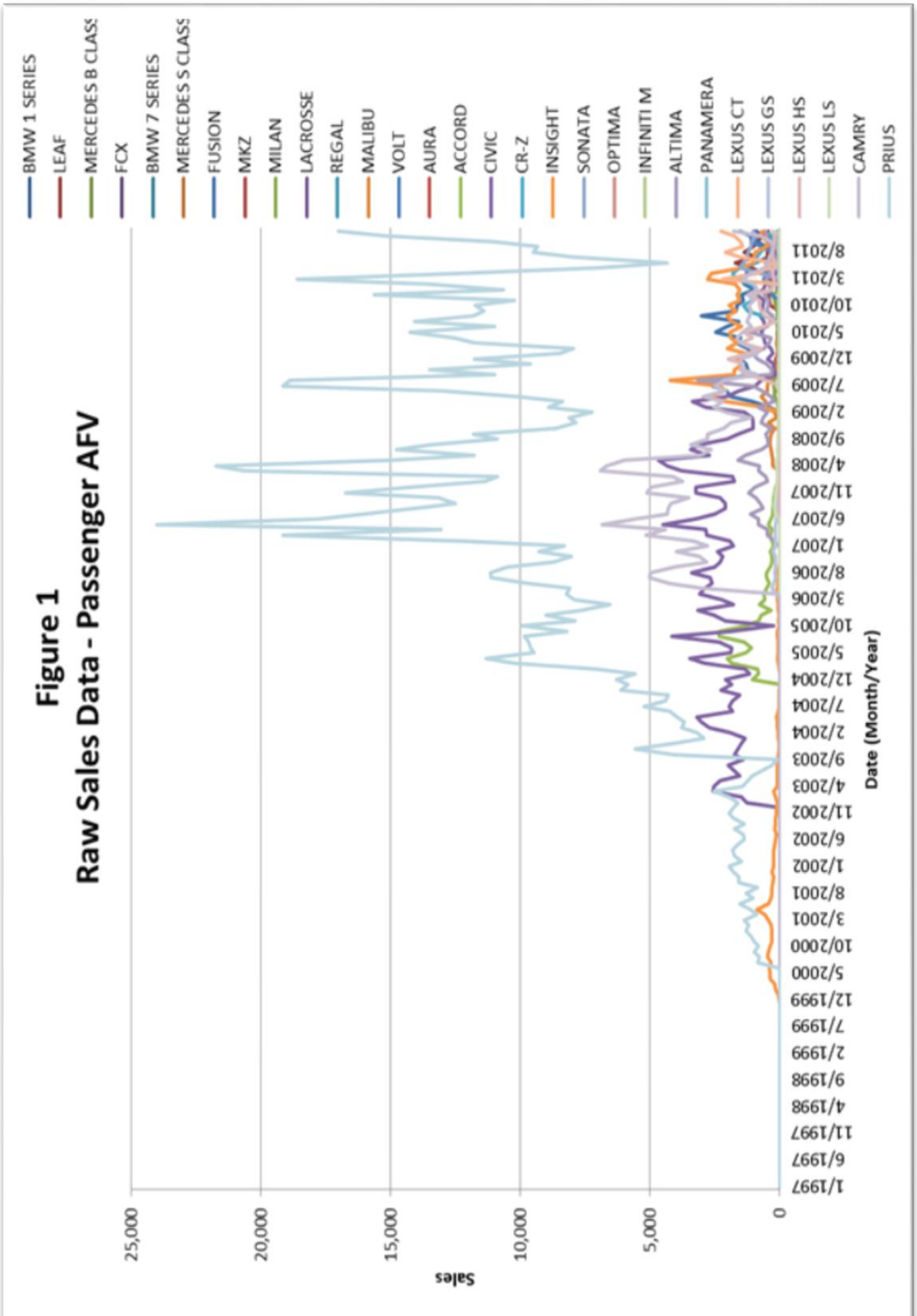
Decision	Vehicle	Release Date	Standard Vehicle	Alternative Fuel Vehicle
Included	Audi A4	1994	x	
	Chrysler Sebring	1995	x	
	Dodge Stratus	1995	x	
	Nissan 200SX	1995	x	
	Nissan Altima	1993	x	
	Subaru Outback	1995	x	
Excluded	Saturn EV1	1997		x
	Honda EV Plus	1997		x
	Nissan Altra	1999		x

Table 9: Forecasting Accuracy of the Model for Eleven Consumer Durable Products**

Product	Period Covered	R-squared
Electric Refrigerators	1926-1940	0.762
Home Freezers	1947-1961	0.473
Black & White TVs	1949-1961	0.077*
Water Softeners	1950-1961	0.920
Room Air Conditioners	1950-1961	0.900
Clothes Dryers	1950-1961	0.858
Power Lawnmowers	1949-1961	0.898
Electric Bed Coverings	1950-1961	0.934
Automatic Coffee Makers	1951-1961	0.690
Steam Irons	1950-1961	0.730
Record Players	1953-1958	0.953
Average	-	**0.812**

* The low 'explained' variance for this product is accounted for by extreme deviation from the trend in two periods.
**Reproduced from Bass (1969).

VIII. Figures



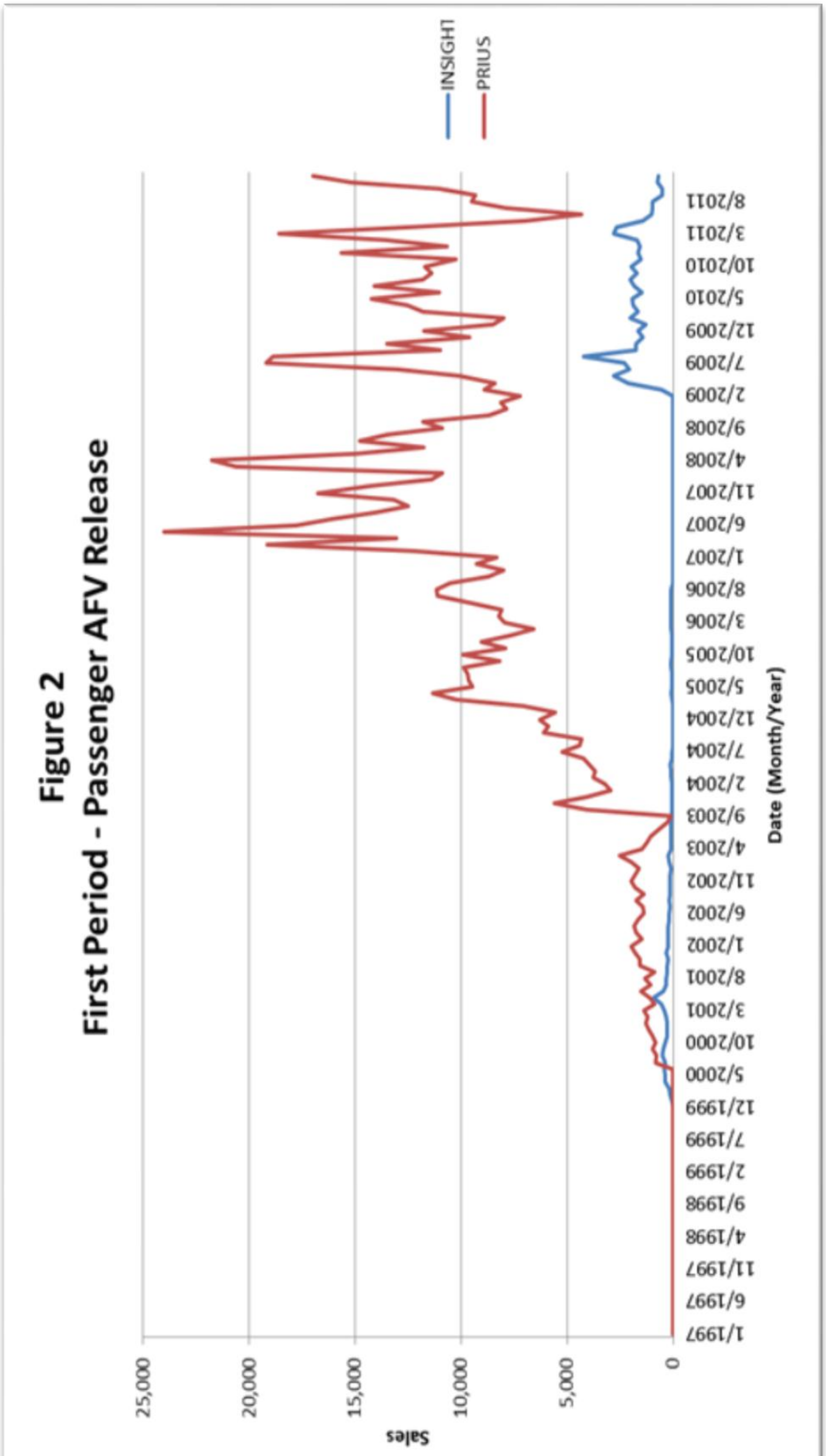


Figure 2
First Period - Passenger AFV Release
Sales
25,000
20,000
15,000
10,000
5,000
0
Date (Month/Year)
1/1997
6/1997
11/1997
4/1998
9/1998
2/1999
7/1999
12/1999
5/2000
10/2000
3/2001
8/2001
1/2002
6/2002
11/2002
4/2003
9/2003
2/2004
7/2004
12/2004
5/2005
10/2005
3/2006
8/2006
1/2007
6/2007
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8/2011
INSIGHT
PRIUS

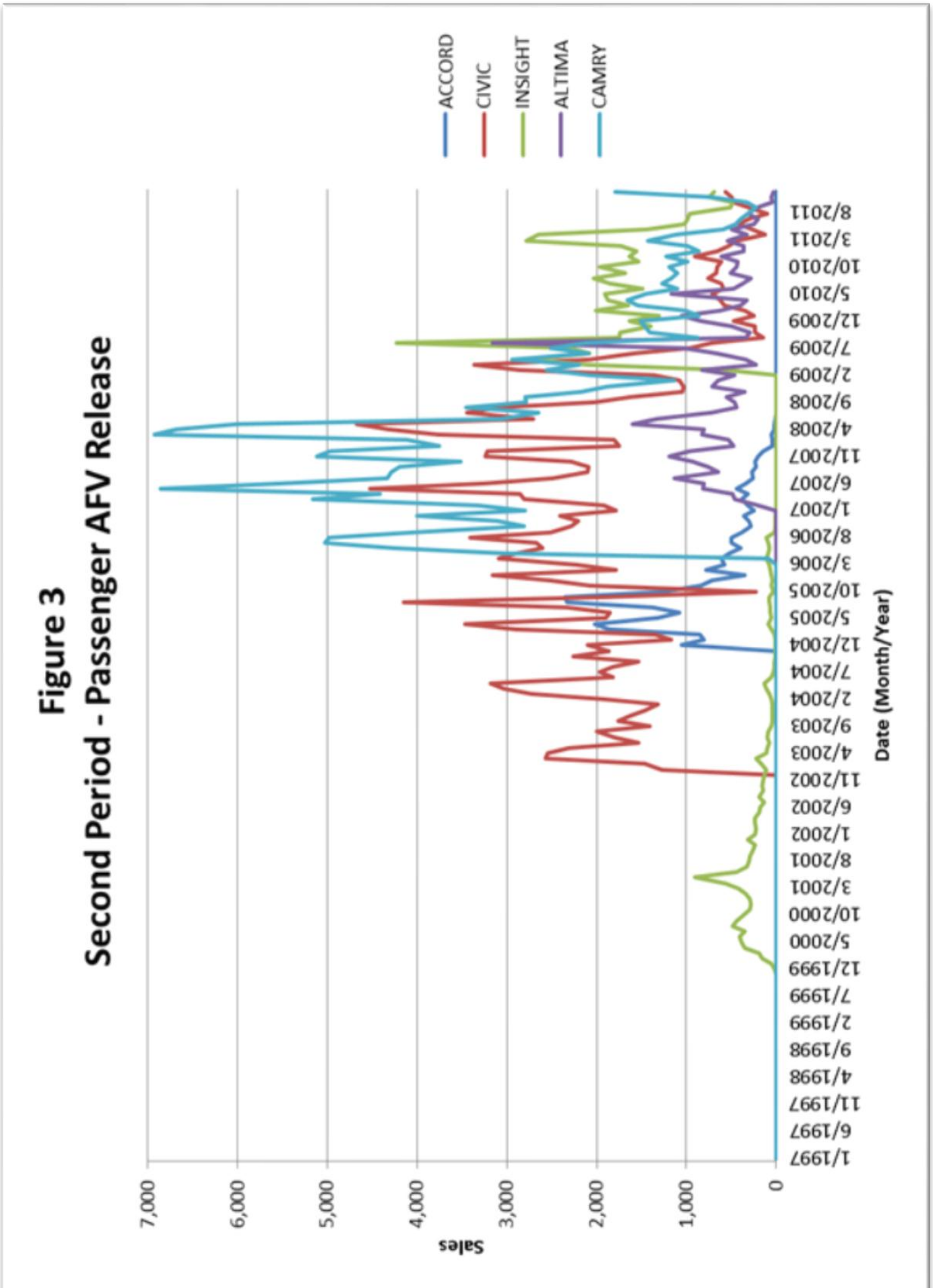
Figure 3
Second Period - Passenger AFV Release
ACCORD
CIVIC
INSIGHT
ALTIMA
CAMRY
Sales
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
1/1997
6/1997
11/1997
4/1998
9/1998
2/1999
7/1999
12/1999
5/2000
10/2000
3/2001
8/2001
1/2002
6/2002
11/2002
4/2003
9/2003
2/2004
7/2004
12/2004
5/2005
10/2005
3/2006
8/2006
1/2007
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10/2010
3/2011
8/2011
Date (Month/Year)

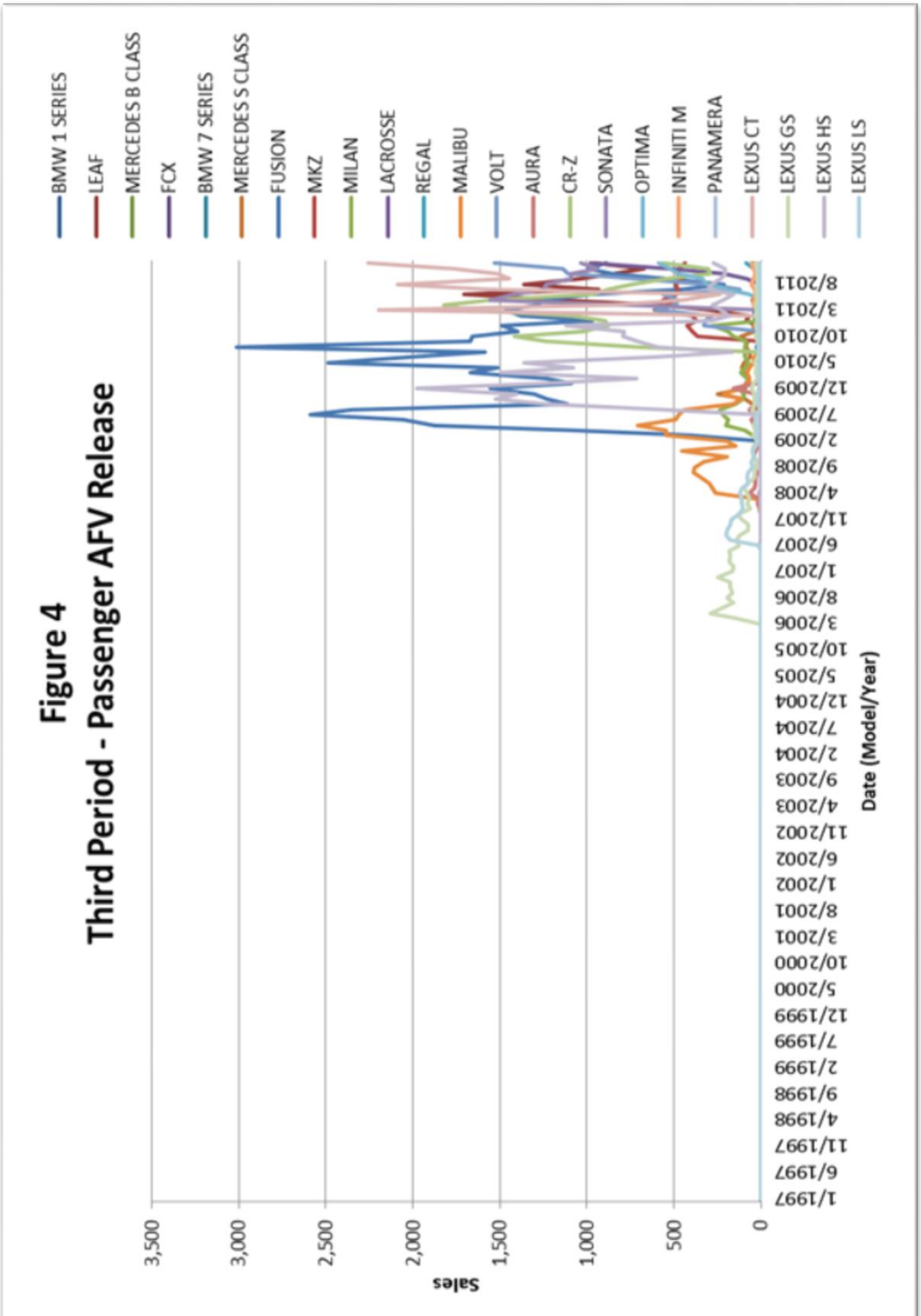
Figure 4
Third Period - Passenger AFV Release
Sales
3,500
3,000
2,500
2,000
1,500
1,000
500
0
Date (Model/Year)
1/1997
6/1997
11/1997
4/1998
9/1998
2/1999
7/1999
12/1999
5/2000
10/2000
3/2001
8/2001
1/2002
6/2002
11/2002
4/2003
9/2003
2/2004
7/2004
12/2004
5/2005
10/2005
3/2006
8/2006
1/2007
6/2007
11/2007
4/2008
9/2008
2/2009
7/2009
12/2009
5/2010
10/2010
3/2011
8/2011
BMW 1 SERIES
LEAF
MERCEDES B CLASS
FCX
BMW 7 SERIES
MERCEDES S CLASS
FUSION
MKZ
MILAN
LACROSSE
REGAL
MALIBU
VOLT
AURA
CR-Z
SONATA
OPTIMA
INFINITI M
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LEXUS LS

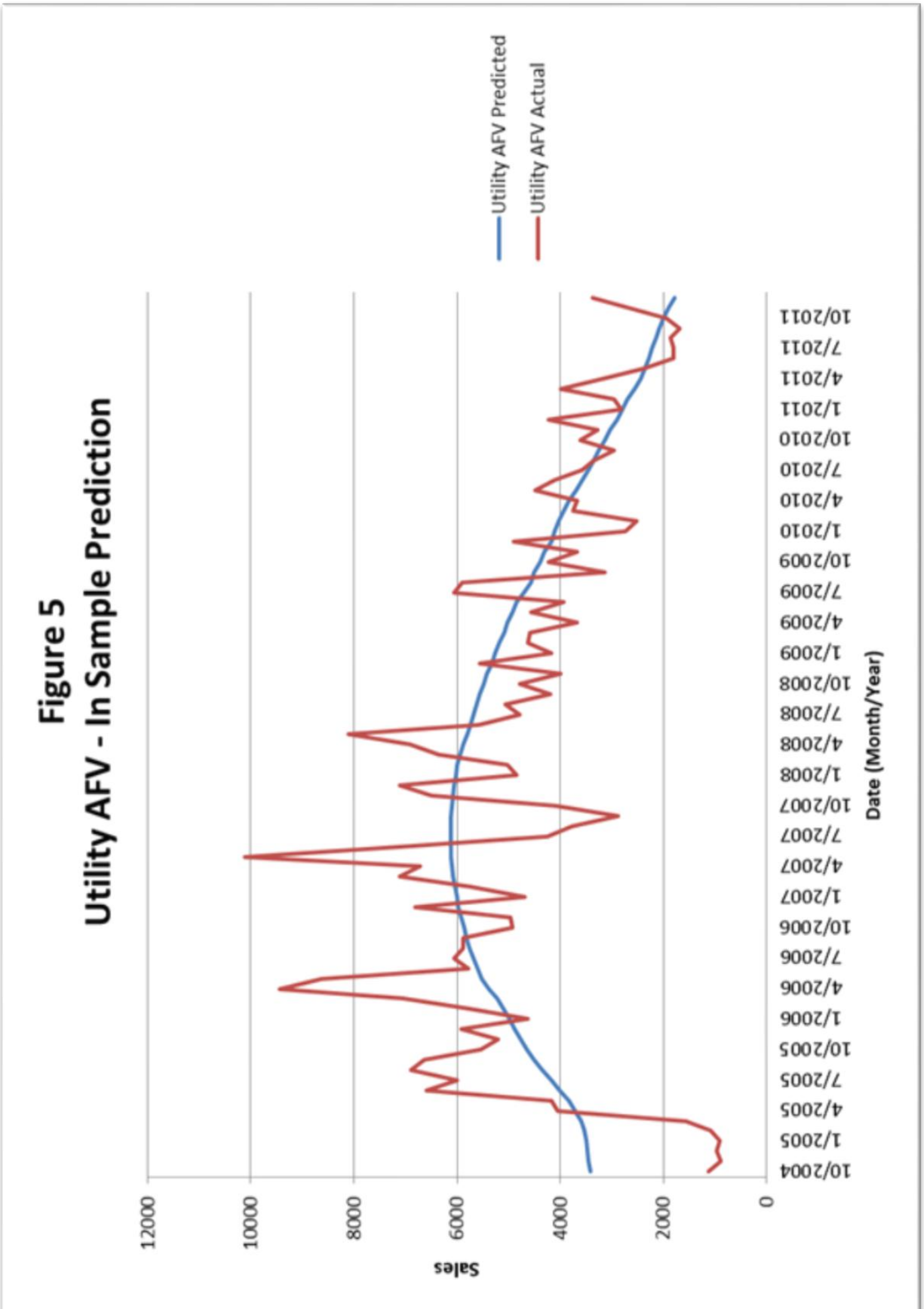
Figure 5
Utility AFV - In Sample Prediction
Sales
12000
10000
8000
6000
4000
2000
0
10/2004
1/2005
4/2005
7/2005
10/2005
1/2006
4/2006
7/2006
10/2006
1/2007
4/2007
7/2007
10/2007
1/2008
4/2008
7/2008
10/2008
1/2009
4/2009
7/2009
10/2009
1/2010
4/2010
7/2010
10/2010
1/2011
4/2011
7/2011
10/2011
Date (Month/Year)
Utility AFV Predicted
Utility AFV Actual

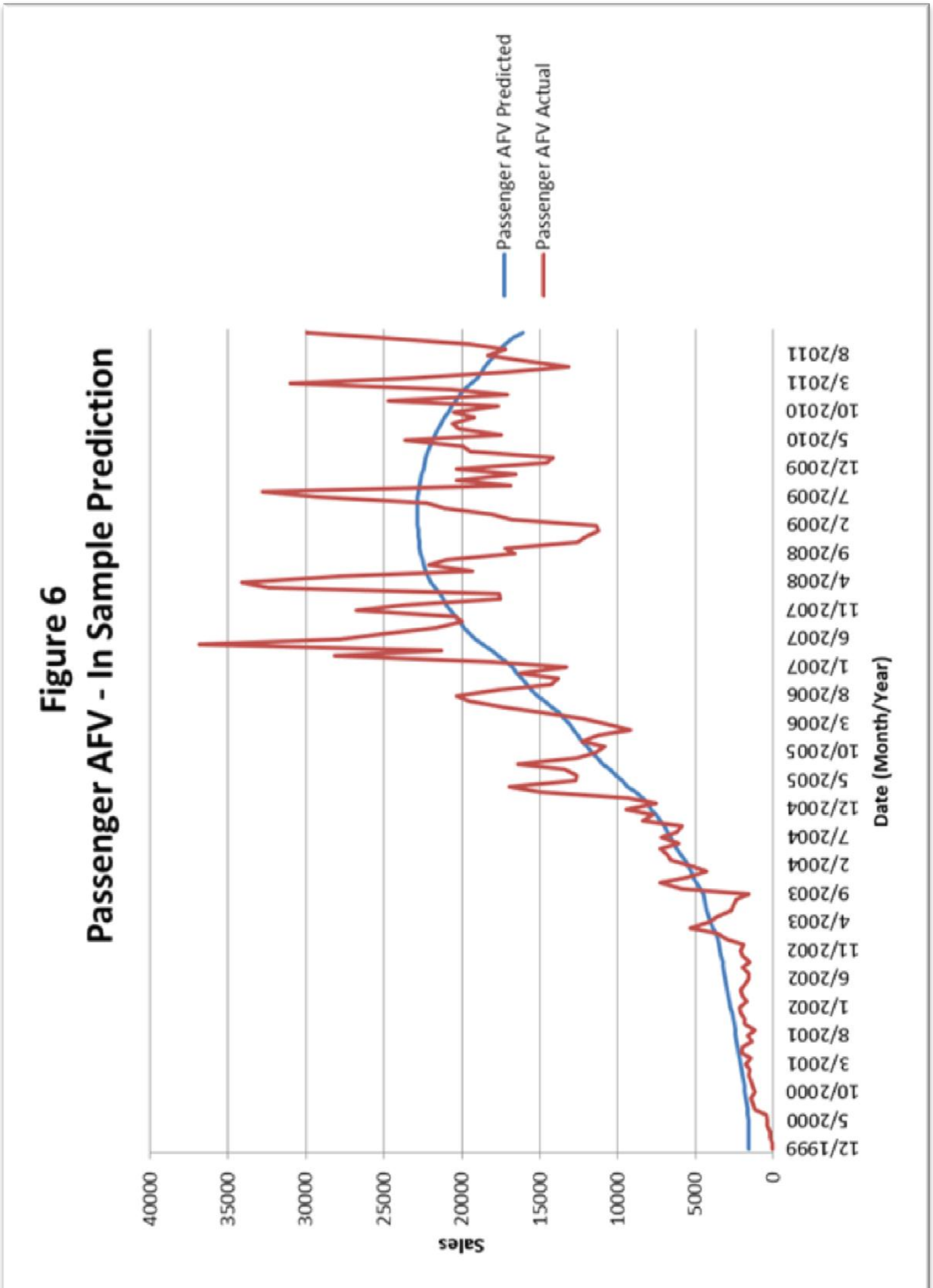
Figure 6
Passenger AFV - In Sample Prediction
Passenger AFV Predicted
Passenger AFV Actual
Sales
40000
35000
30000
25000
20000
15000
10000
5000
0
12/1999
5/2000
10/2000
3/2001
8/2001
1/2002
6/2002
11/2002
4/2003
9/2003
2/2004
7/2004
12/2004
5/2005
10/2005
3/2006
8/2006
1/2007
6/2007
11/2007
4/2008
9/2008
2/2009
7/2009
12/2009
5/2010
10/2010
3/2011
8/2011
Date (Month/Year)

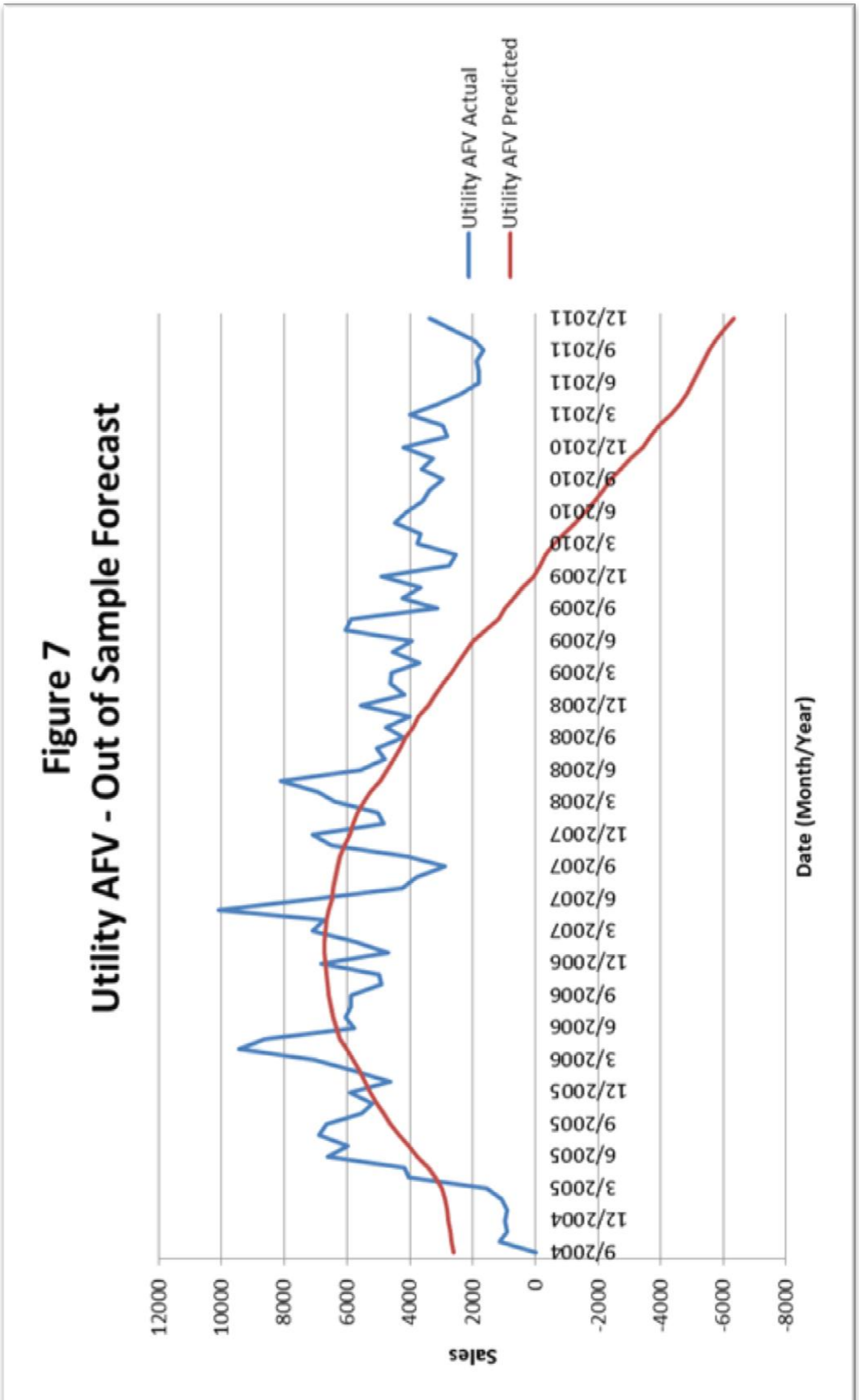
Figure 7
Utility AFV - Out of Sample Forecast
Utility AFV Actual
Utility AFV Predicted
Sales
Date (Month/Year)
12000
10000
8000
6000
4000
2000
0
-2000
-4000
-6000
-8000
9/2004
12/2004
3/2005
6/2005
9/2005
12/2005
3/2006
6/2006
9/2006
12/2006
3/2007
6/2007
9/2007
12/2007
3/2008
6/2008
9/2008
12/2008
3/2009
6/2009
9/2009
12/2009
3/2010
6/2010
9/2010
12/2010
3/2011
6/2011
9/2011
12/2011

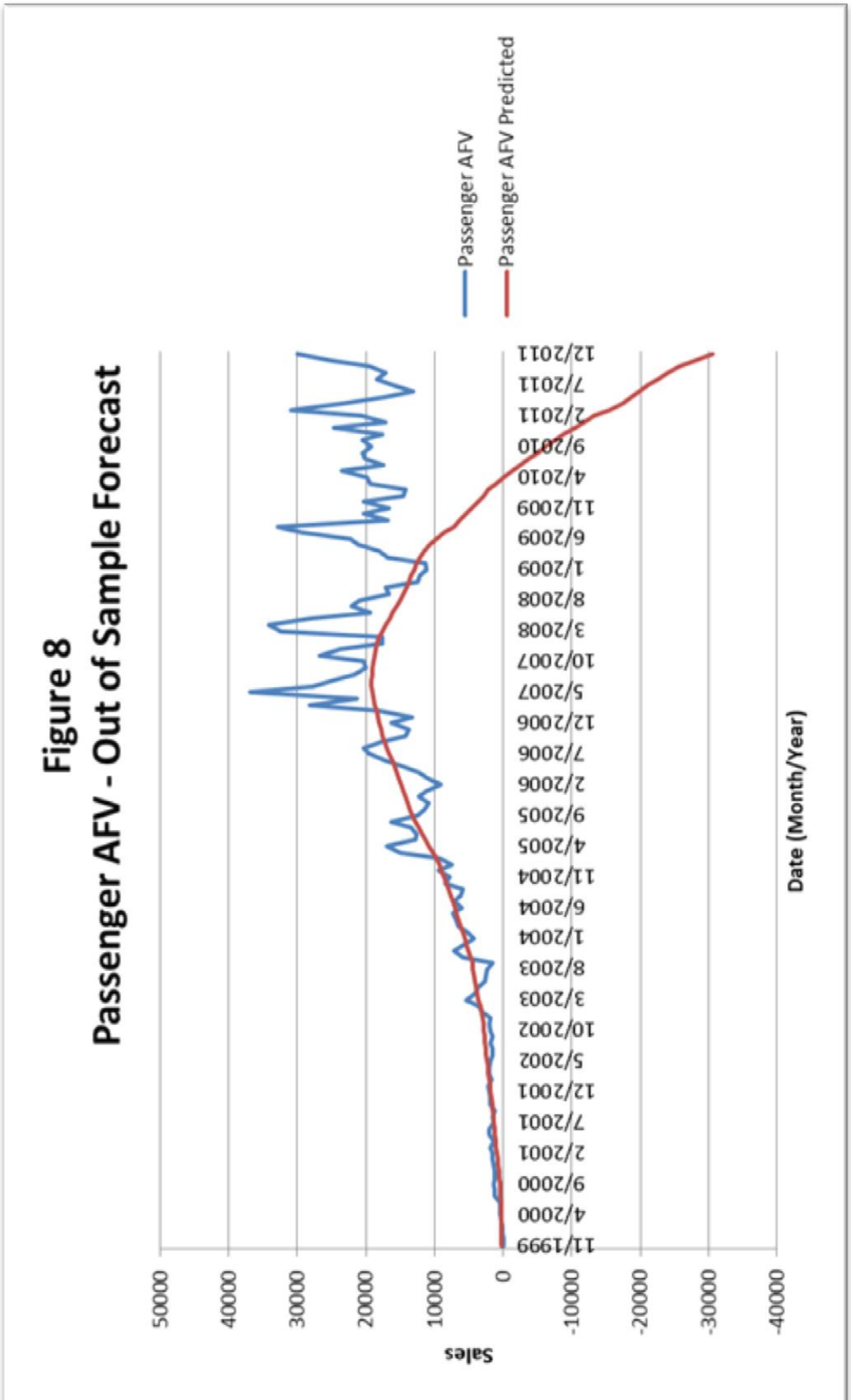

Figure 8
Passenger AFV - Out of Sample Forecast

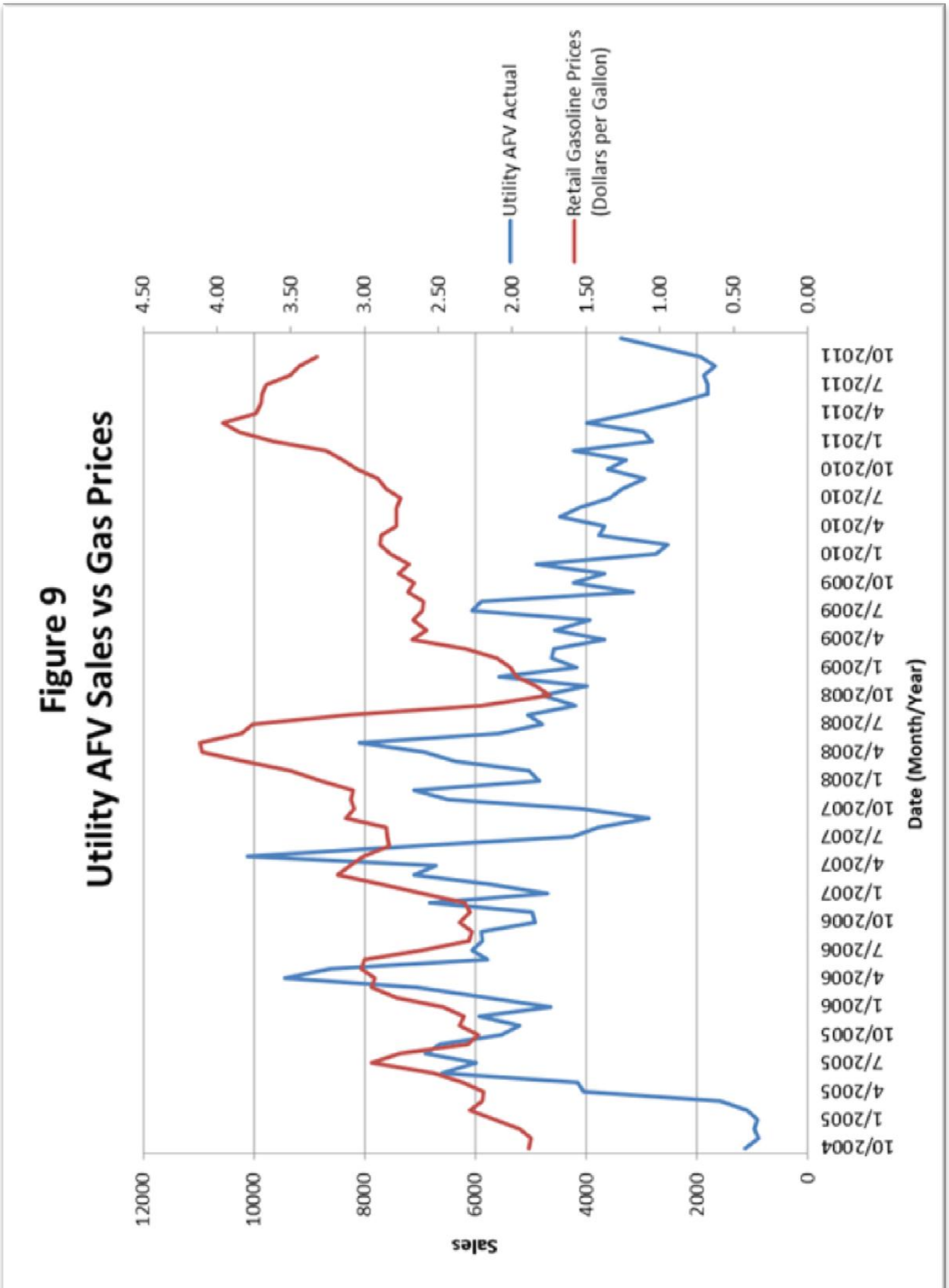
Figure 9
Utility AFV Sales vs Gas Prices
Sales
12000
10000
8000
6000
4000
2000
0
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
10/2004
1/2005
4/2005
7/2005
10/2005
1/2006
4/2006
7/2006
10/2006
1/2007
4/2007
7/2007
10/2007
1/2008
4/2008
7/2008
10/2008
1/2009
4/2009
7/2009
10/2009
1/2010
4/2010
7/2010
10/2010
1/2011
4/2011
7/2011
10/2011
Date (Month/Year)
Utility AFV Actual
Retail Gasoline Prices (Dollars per Gallon)

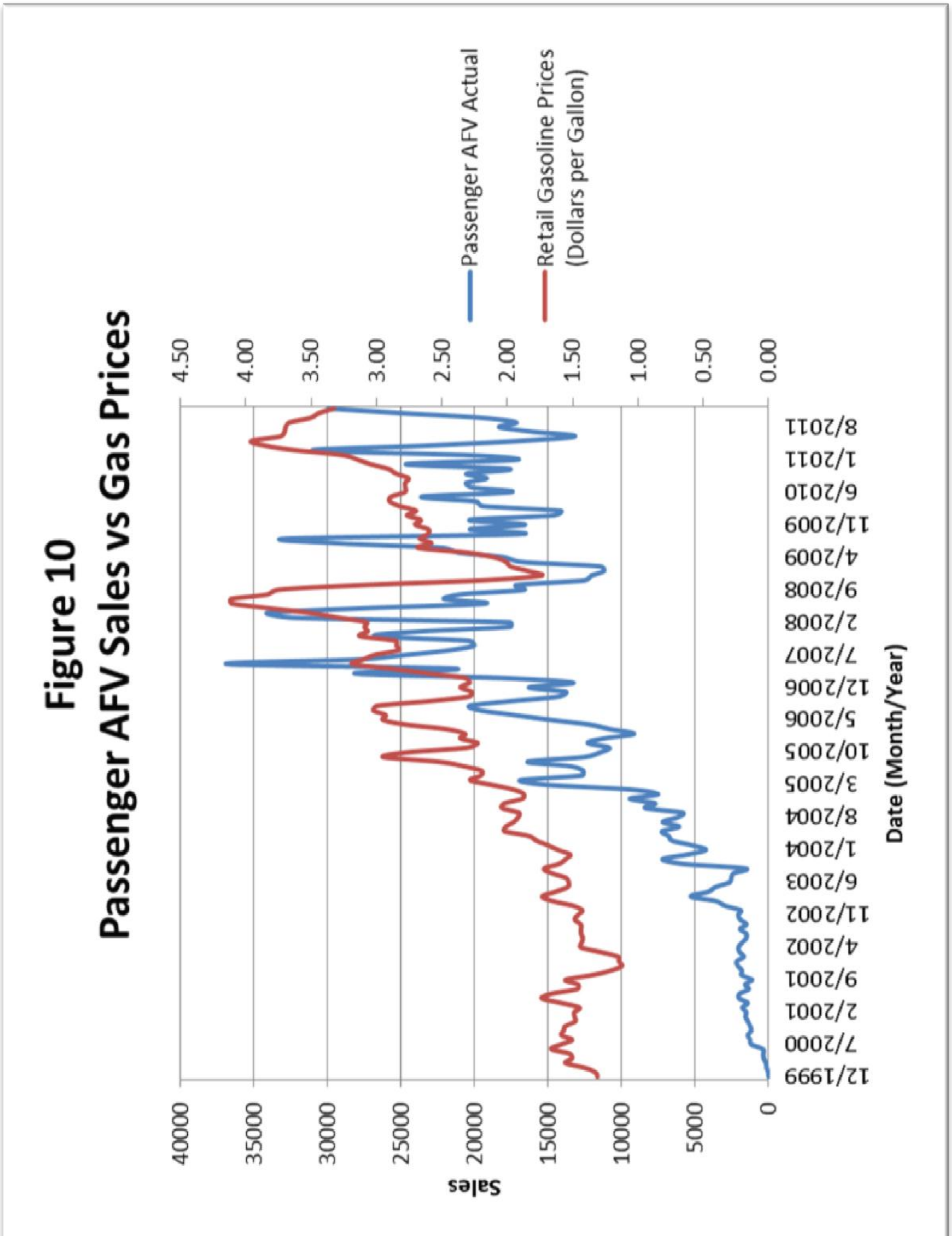
Figure 10
Passenger AFV Sales vs Gas Prices
Passenger AFV Actual
Retail Gasoline Prices (Dollars per Gallon)
Sales
40000
35000
30000
25000
20000
15000
10000
5000
0
4.50
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
12/1999
7/2000
2/2001
9/2001
4/2002
11/2002
6/2003
1/2004
8/2004
3/2005
10/2005
5/2006
12/2006
7/2007
2/2008
9/2008
4/2009
11/2009
6/2010
1/2011
8/2011
Date (Month/Year)

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