AN INVESTIGATION OF THE IMPACTS OF ECONOMIC CONDITIONS ON VEHICLE MILES TRAVELED: A VECTOR ERROR-CORRECTION APPROACH

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ABSTRACT

In this paper, we estimate the long-run gasoline price and income elasticity of VMT for the period 2000-2008. Most of the previous studies use the very common classes of time series methods that are the autoregressive integrated moving average (ARIMA) models. We advance the analytical framework to include a vector error-correction (VEC) regression technique that overcomes several limitations of ARIMA models. We find that long-run gasoline price elasticity to VMT ranges from -0.31 to -0.88, and income elasticity ranges from 0.18 to 0.49.

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1. INTRODUCTION AND LITERATURE REVIEW

Vehicle miles traveled (VMT) is the total number of miles traveled by personal vehicles in a given period of time on the road network (Energy Information Administration). Analysts extensively use the VMT data not only in transportation related areas including highway planning and management, but also in estimating congestion, air quality, resources allocation and expenditure, and potential gas-tax revenues, all of which have important implications for U.S. energy policy and national security. With America's energy independence as one of the top-priorities of president-elect Barack Obama, the amount of travel and consumption of gasoline by American households has become a critical issue.

Several authors and policymakers have investigated gasoline demand, VMT and fuel efficiency since the Organization of Arab Petroleum Exporting Countries' oil embargo in 1973 (Dahl, 1986). Researchers (e.g., Greene, 1992; Jones, 1993; Schimek, 1996) have modeled VMT as a function of income, fuel prices and fuel efficiency as time series data. The studies show income and fuel prices to have a significant influence on the amount of travel demanded, and cumulatively travel demand changes with any of various economic indicators. Myriad of studies have been conducted investigating the price and income elasticities of gasoline demand too. Dahl and Sterner (1991) estimate a typical short-run price elasticity of gasoline demand of -0.26 and an average short-run income elasticity of gasoline demand of 0.48. Espey (1998) determines a median short-run price elasticity of -0.23 and a median short-run income elasticity of 0.39.

Kayser (2000) investigated the role of household characteristics on gasoline demand using Panel Study of Income Dynamics data. Small and Van Dender (2007) use simultaneous aggregate demand model based on time series data from 1966 to 2004. Their analysis showed a decrease in short-run elasticity of VMT to fuel prices from -.045 during the 1966-2001 period to -.022 during 1997-2001 time period. Finally, Hughes, *et al.* (2006) compared the price and income elasticities of gasoline demand in two periods from 1975 to 1980 and 2001 to 2006. The common theme that emerges out of these studies is that consumers are not very reactive to changes in the price of gasoline, at least in the short run.

However, recent changes in vehicles miles driven confirm a change in people's travel behavior in fear of a prolonged energy shock and economic uncertainty. A new study by the Congressional Budget Office (2008) uses an econometric model to examine the scope and intensity of consumers' responses (in terms of trip frequencies, speeds and vehicle stock) to the increasing trend in gasoline prices that began in 2003. A more recent study by Farmers Insurance Company (2008) uses time series ARMA model to quantify impact of gas prices, income and the price of an alternate travel mode on amount of driving with respect to recent changes.

Given the recent economic downturn and energy crisis, reckoning the potential impacts to travel behavior is not as clear-cut as it initially appears since responses to these changes have changed over time. It can still be argued that higher gas prices have had minimal impact on driver behavior and thus on VMT but the recent data, especially from year 2004 to year 2008, is more conclusive towards significant travel behavior shifts. During the one-year period between November 2007 and October 2008, the VMT was 100 billion miles lower as compared to the prior period. These changes are indeed attributed to price spikes but economic uncertainty has played a significant role in altering people's travel behavior.

We have relied on time series modeling techniques in order to test these relationships. Time-series modeling accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation). Most of the previous studies use the very common classes of time series methods that are the autoregressive integrated moving average (ARIMA) models, developed by Box and Jenkins (1994). The traditional approaches of detrending and differencing of non-stationary time series data are not robust because they are sensitive to short-term noise components and are not possible with stochastic trends. The intricacy of the interrelationships involved may not be fully understood unless the methodical tools employed in a time series analysis account for the “dynamics” of the association within a temporal “causal” framework (Masih and Masih, 1995). This necessitates the use of dynamic time-series modeling within temporal “causal” framework that permits the coexistence of both short-run and long-run forces that drive the cyclical influences in the variables.

In this study, we analyze the long-run price and income elasticities using system-based cointegration techniques. A benefit of cointegration analysis is that through their dynamic counterpart vector error-correction models (VECM), the dynamic co-movement among variables and the adjustment process toward long-term equilibrium may be studied. The following sections provide a brief explanation of study variables and the hypothesized relationships, followed by the study methodology and empirical results.

2. STUDY VARIABLES

Recent drastic changes in VMT have necessitated the revision of gasoline demand and income elasticities. In this study, we explore the changes in travel behavior (as captured by change in VMT) from year 2000 to year 2008 (till September). From 2000 to 2004, variations in fuel economy have undoubtedly taken place; nevertheless, since 2004 the structural changes have become quite dramatic. Monthly rate of change in VMT is the dependent variable in our study. Of the many factors, several variables are commonly chosen in models to predict VMT i.e. vehicle stock, number of households (function of population size), number of licensed drivers, income, fuel prices, fuel efficiency, and other economic indicators to name a few. In our time-series model we have restricted the number of variables to:

$$\text{VMT} = f(\text{GP, DI})$$

where VMT is the rate of change in vehicles miles travelled in the US. GP and DI denote gas price, and personal disposable income, respectively. These variables are selected because of their frequent fluctuations and to capture the effect of gas prices on VMT in a long run. These variables are presented in Table 1. The monthly time-series were taken from various sources and all variables are converted into natural logarithms, as shown in Table 1.

Table 1: Summary of Variables and Data Sources

Variable	Description	Source
LnΔVMT	Natural logarithm of monthly rate of change in VMT	Energy Information Administration Monthly Energy Review
LnY	Nature logarithm of personal disposable income	Monthly data release from U.S. Bureau of Economic Analysis
LnGP	Nature logarithm of gas price	Monthly Traffic Volume Trend Report from U.S. DOT

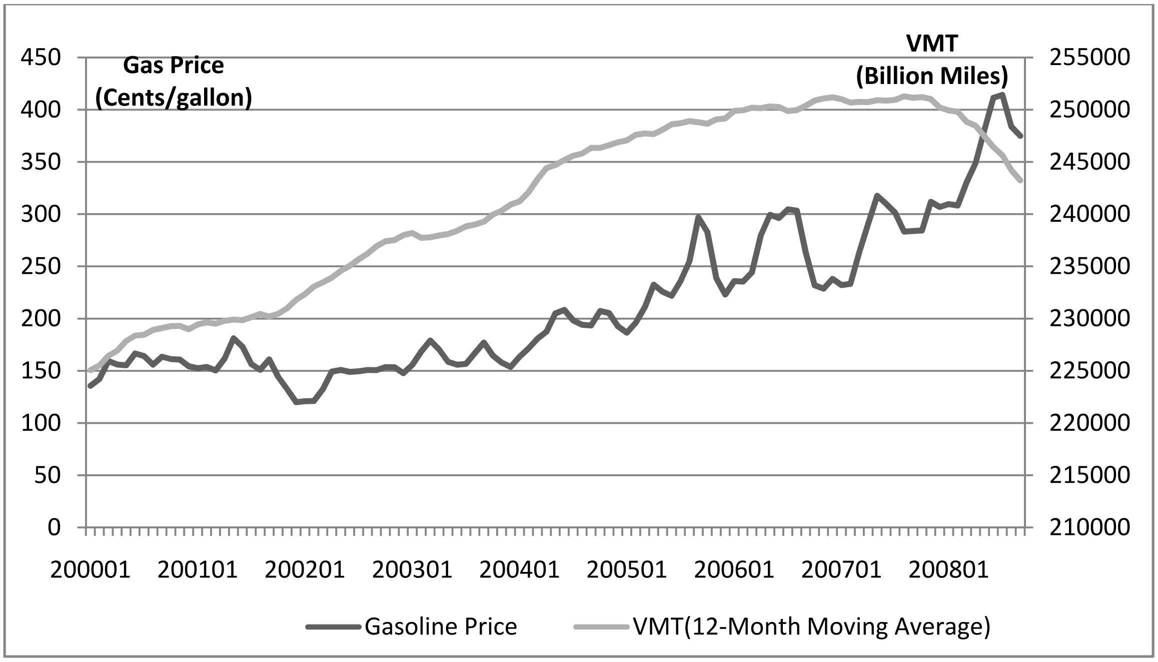
Change in VMT

As happened during 1970s crisis, the U.S. population appears to have made long-lasting changes to their behavior, mainly by decreasing discretionary driving and taking fewer trips. However, there are subtle differences in people's behavior between 1970s and now. Statistics from the late 1970's to early 1980's indicate that people across the United States simply started driving less (Stevens, 1980). An interesting result observed from our analysis suggests that VMT did not go down abruptly when fuel prices hit $4 per gallon. The behavior actually began to change around 2005 when price started closing in around $2 per gallon. The VMT rise flattened out for almost a period of two years. Finally, starting from year 2008 the VMT started falling after a long period of price instability (see Figure 1). Therefore, in this study, we try to capture the change in travel behavior (and VMT) from year 2000 to year 2008.

Gas Prices

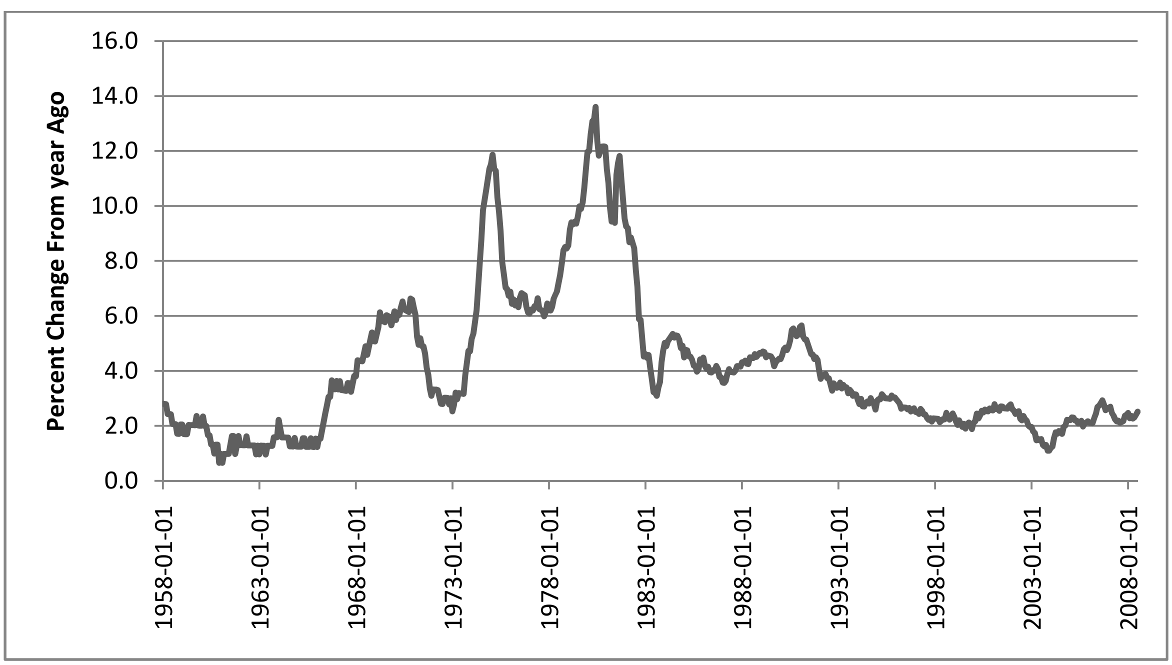
Beginning in 2001 until the fourth-quarter of 2008, crude oil prices worldwide have been increasing, reversing a decade long average decline. Between 2001 and 2006, the average increase between years was equal to $9.24 (2007 dollars) per barrel. In 2007 the rate of increase slowed, but as of May 2008, the average price increased by $32.26 per barrel and continued creeping higher (EIA, 2008). Soaring gasoline prices had helped drive up overall U.S. consumer prices during past two years, but as per a recent Bureau of Labor Statistics report (see Figure 2), core prices (less food and energy) remained quite stable at a rate below 3% for almost 12 consecutive years. As it is related to VMT, one cannot ignore the rising consumers' expenditure on energy and food. Households are spending more than ever on these items as a percentage of their income. In 2001, an average household paid $1,279 on fuel purchases for transport and remitted $1,532 for household services, a difference of about $250. By contrast, in 2006, the average household spent as high as $2,227 on fuel purchases for transport (up nearly $960 per household from year 2001) and $1,913 for household utilities. The trend is same for 2007 and the gap between transport cost and household services cost may get even worse by the end of 2008. Based on these statistics, it can be argued that, drivers are facing a real choice between transportation and non-discretionary spending.

Figure 1: VMT Growth vs. Gas Prices (2001-2008)



Source: Monthly Energy Review, U.S. Energy Information Administration & Traffic Volume Trend Reports, Federal Highway Administration

Figure 2: Consumer Price Index for All Urban Consumers, Less Food and Energy

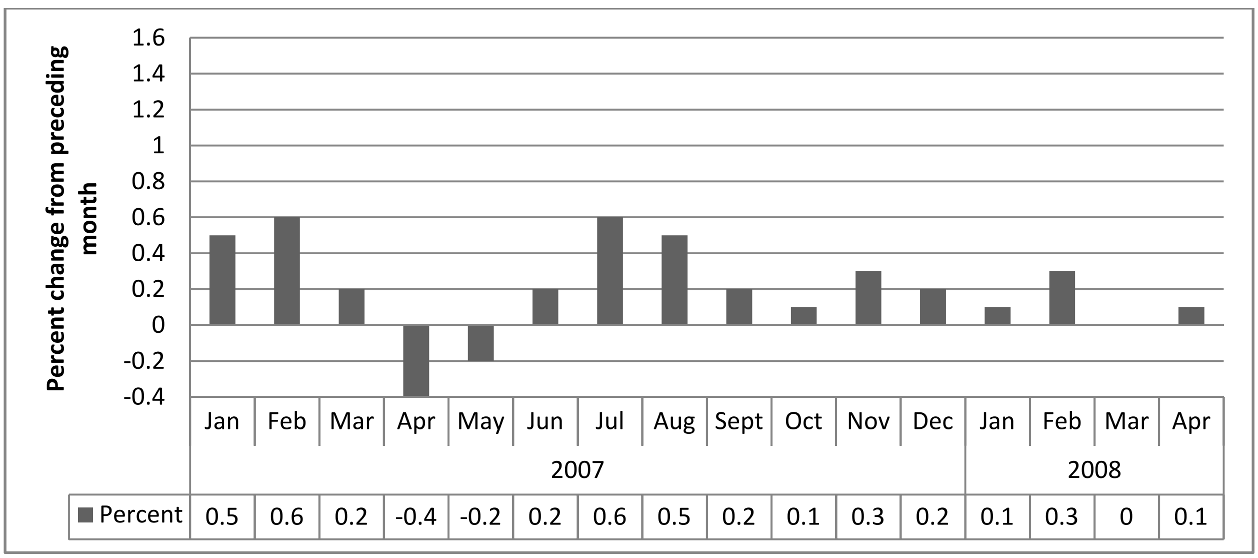


Source: U.S. Department of Labor, Bureau of Labor Statistics

Personal Disposable Income

According to the Bureau of Economic Analysis' 2004 Annual Energy Review VMT is better correlated with disposable income than prices (4). As indicated in Figure 1, the annual VMT had flattened out around 2004. This can be related to the real per-capita disposable personal income, which has also experienced very slow growth since that time. In February 2008, the Bureau of Economic Analysis reported that even with large end-of-year bonuses, the average real disposable income per capita rose only 0.3% (see Figure 3), and was below levels reached in March 2007 (5). Thus, we expect the coefficient of disposable income to have a positive sign and a decrease in overall VMT with decrease in disposable income.

Figure 3: Real Disposable Personal Income



Source: Bureau of Economic Analysis, National Economic Accounts

3. MODEL AND EMPERICAL RESULTS

In this paper we analyze the long-run behavior of VMT in US using system-based cointegration techniques. Cointegration methods deal with the problem of spurious regression among non-stationary time series. In simple words, two variables are defined to be cointegrated if a linear combination of them is stationary and thus have a long-term, or equilibrium, relationship between them. We use Johansen's (1988, 1991) vector error-correction model (VECM) which is used to modeling multivariate integrated data where more than one cointegration equation is expected. A similar approach based on Engle and Granger's (1987) two-step error-correction model may also be employed in a multivariate context but the VECM gives more efficient estimators. Campbell and Perron (1991) and Gonzalo (1994) recommended use of the full information maximum likelihood estimation model which permits testing for cointegration in a whole system of equations in one step and without necessitating a specific variable to be normalized. The Johansen's approach also negates the assumptions of requiring endogenity or exogenity of the variables. The VECM takes the following functional form:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{t=1}^{p-1}(\Gamma_i \Delta y_{t-i}) + \mathrm{v} + \delta t + \varepsilon_t \qquad (1)$$

where y_t is a *K X 1* vector of *I*(1) variables and Δ denotes first differences. p is a lag structure. $\alpha\beta' y_{t-1}$ and $\sum_{t=1}^{p-1}(\Gamma_i \Delta y_{t-i})$ are the vector autoregressive component in first differences and error-correction components, respectively, in levels of Equation (1). This approach estimates Equation (1) subject to the hypothesis that $\alpha\beta'$ has reduced rank *0 < r < K*, where α and β' are both *K X r* matrices of rank *r*. α depicts the speed of adjustment parameters i.e. speed of error-correction mechanism, and β represents the cointegrating vectors. A larger α implies a faster convergence toward long run equilibrium. Γ_i.....Γ_{p-1} are *K X K* matrices of parameters depicting short-term adjustments among variables across *K* equations at the pth lag. v is a *K X 1* vector of constants, while εt is a *K X 1* vector of disturbances, with zero mean.. The constant v implies a linear time trend and δt denotes a quadratic time trend in the levels of data. The v and δt terms allow the model to include a constant or a linear time trend for the differences without allowing for the higher order trend that is implied for the levels of the data.

Step 1: Unit Roots Tests

Many macroeconomic time series behave like random walks, and thus in estimating the VECM, we first check for stationarity and unit roots through performing the Augmented Dickey-Fuller (ADF) test on the variables in levels and first differences. The pth order ADF test statistic for y_t variable is specified by the *t*-ratio of β in the ordinary least squares regression (OLS) of:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \sum_{j=1}^{p} (\zeta_j \Delta y_{t-i}) + \varepsilon_t \qquad (2)$$

where α captures trend and ε_t is assumed to be an identically and independently distributed (i.i.d.) random variable. The variables that are integrated of the same order can be cointegrated, and the results of the unit root tests decide the variables which are integrated of order one, *I*(1). In simple words, the *I*(1) variables attain stationarity after the first differencing. So, we check our study variables through this technique for unit roots to verify their stationarity. The null hypothesis is that a variable is stationary in first difference against the alternative that it is not. Table 2 shows the results of ADF test with a maximum lag structure of 12. The ADF test statistics for all the variables show that we cannot reject the null hypothesis, and we conclude that all the variables in first differences are stationary. As such the variables are integrated of order one and can be cointegrated.

Table 1: Augmented Dickey-Fuller Test for Unit Root

Variables	Test Statistic	1% Critical	5% Critical	10% Critical	p-value
Ln ΔVMT	-1.655	-3.523	-2.897	-2.584	0.4546
LnGP	1.004	-3.521	-2.896	-2.583	0.9943
LnY	1.323	-3.521	-2.896	-2.583	0.9967

*Ln ΔVMT, LnGP, and LnY are rate of growth of VMT, actual price of gasoline in cents, and actual per capita disposable income. All data are converted to natural logs.

Step 2: Estimation of Cointegrating Vectors

The next step in the process is to specify the lag structure in the model and estimating the number of cointegrating equations. The Akaike information criterion (AIC) and Schwartz Bayesian criterion (SBC) are the two most commonly used multivariate forms to decide the lag length. The AIC and SBC are model selection criteria developed for MLE techniques. For minimizing AIC and SBC, we minimize the natural logarithm of the residual sum of squares adjusted for sample size, *T*, and the number of parameters included, *n*. They are given as:

$$AIC = T\ \ln(\text{residual sum of squares}) + 2n;$$

$$SBC = T\ \ln(\text{residual sum of squares}) + n\ln(T)$$

Given our relatively small sample size, we construct VECMs with truncated lags of *p*=2 *to p*=12. The model with the lowest AIC was the one for *p*=12, and with the lowest SBC was the one for *p*=11. We select the lag structure of 12 as it best meets our model-selection criteria.

Next, we want to determine the number of cointegrating vectors (*r*), which indicates the dimension of conintegrating space. The rank of $\pi = \alpha\beta'$, which will give the order of integration, *r*, is determined by two test statistics: the Johansen's "trace" statistic, and his "maximum eigenvalue":

$$\lambda_{max} = -\mathrm{N}\ln(1 - \lambda \mathrm{r}_{r+1})$$

and

$$\lambda_{trace} = -\mathrm{N}\sum_{i=r+1}^{m}\ln(1 - \lambda \mathrm{r}_{i})$$

where N is the number of observations and λr is the estimated eigenvalue. The number of maximum cointegrating relationships (long-term equilibrium) is based on the λ_{trace} tests, while the critical values for the λ_{max} test can be found in Osterwald-Llenum (1992).

Table 4A reports the results and 5% critical values (CV) of the λ_{trace} for *p*=12. The trace statistics at r = 0 of 45.0362 and at r = 1 of 16.1375 exceeds their critical values; we reject the null hypotheses of no, and one or fewer cointegration equations respectively. In contrast, since the trace statistic at r = 2 of .0107 is less than its critical value of 3.84, we cannot reject the null hypothesis of two or fewer cointegrating equations. Thus, we conclude that there are two cointegrating vectors, or *r* = 2. The eigenvalue shown in the last line of the table calculates the trace statistics in the preceding line. Similar results are obtained using the critical values (CV) of the λ_{max} test (Table 5). In case of more than one cointegrating vector, we select the first eigenvector based on the largest eigenvalue.

Table 4: Johansen Tests for Cointegration[a]

A) ***Results and critical values for the λ_{trace} test***

Maximum Rank	Parameters	Eigenvalue	Trace Statistic	5% Critical Value
0	99	.	45.0362	24.31
1	104	0.26957	16.1375	12.53
2	107	0.16079	0.0107*	3.84
3	108	0.00012		

B) ***Results and critical values for the λ_{max} test***

Maximum Rank	Parameters	Eigenvalue	Max Statistic	5% Critical Value
0	99	.	28.8988	17.89
1	104	0.26957	16.1267	11.44
2	107	0.16079	0.0107*	3.84
3	108	0.00012		

** Statistically significant at 5% level;*

a. Maximum number of lags = 12 month.

Step 3: Estimation of Coefficients and Adjustment Responses

The cointegrating vector with the largest eigenvalue is $\beta' = (1.00, -0.00339, 0.005946)$. Table 5 shows the coefficient estimates and summery statistics for the cointegrating vector. Rewriting the cointegrating equation, we get a long-run relationship between VMT, gas prices and personal disposable income as:

$$\ln(\Delta VMT) = 0.0033 \times \ln(Income) - 0.0059 \times \ln(Gas\ Price) + \varepsilon$$

where ε is a first-order stationary error term. As shown in the table, the coefficient of ΔVMT is normalized to 1, while coefficients of Gas Price and Income are both with the expected signs and statistically significant at 1% level. This confirms our hypothesis of VMT to decrease with the soaring gas prices, as well as declining personal disposable income.

Table 5: Vector Error-Correction Model

beta	Coefficient	Std. Error	z	P>|z|	95% Confidence Interval	
Ln ΔVMT	1	.	.	.	.	.
LnY	-0.00339	0.000792	-4.28	0.000	-0.00494	-0.0018
LnGP	0.005946	0.001436	4.14	0.000	0.003131	0.00876

Furthermore, the model simulation also shows when gas price increase by 1%, VMT changing rate will decrease by 0.0059%, which indicates that the actual VMT will decrease by 0.6%. This means that long-run price elasticity of gasoline demand is -0.59. The estimated long-run price elasticity ranges from -0.31 to -0.88. The gas price elasticity of VMT suggests that drivers make the largest adjustment within one year of a price change by reducing VMT. Using the same approach, we get that long-run income elasticity of VMT as 0.33. The income elasticity ranges from 0.18 to 0.49.

As explained above, the coefficients of the speed of adjustment indicate the pace at which the variables will respond to a shock in the system and fall back to long run equilibrium. As shown in Table 6, the adjustment coefficient of ΔVMT is statistically significant at 1% level and the coefficient of disposable income is significant at 10% level. This implies that when an exogenous shock occurs, Ln ΔVMT and LnY variables respond to bring the system back to equilibrium as pointed by the significance of their speed of adjustment coefficients. The magnitude of the parameters signifies a rapid adjustment to disequilibrium by the two variables, being faster in the case of the LnΔVMT (-5.71)

Table 6: Adjustment Coefficient

alpha	Coefficient	Std. Error	z	P>|z|	95% Confidence Interval	
Ln ΔVMT	-5.71181	1.366217	-4.18	0	-8.38954	-3.0341
LnY	1.759851	0.944117	1.86	0.062	-0.09058	3.61029
LnGP	4.001415	4.299937	0.93	0.352	-4.42631	12.4291

4. DISCUSSION

Estimation of long-run gas price elasticity of VMT in this study is -0.59, and ranges from -0.31 to -0.88. In simple words, if there is a permanent increase of gas price from $3.00 to $4.00 per gallon, the VMT would be reduced by about 19.6% in the long run (.59 times 33 percent), holding everything else equal. Our estimate of long-run gas price elasticity is slightly higher than recent studies indicating consumers responded fairly strongly to higher prices for 2000-2008 period. For example, Small and Van Dender (2007) report -.37 as the long-run price elasticity of gasoline across all states over the 39-year period (1966-2004). However, Puller and Greening (1999) found similar gas price elasticity (i.e. -.69) using a two-equation regression model.

The results indicate that the people have made long-lasting changes in their travel behavior in relation to escalating gas prices as happened in 1970s. Figure 1 also confirms this shift in travel behavior. From 2007, gasoline price encountered an enormous increase from $2.32 to $4.14 per gallon and moving average of VMT started to decrease around October 2007. It shows that drivers in US are not unwilling to change their driving behavior; instead, the stimulation was not great enough. From this study, we can conclude that if gasoline price reaches a threshold point and last for long enough, people’s driving behavior could be changed.

A second important finding in this paper is that income is less elastic to VMT than gas price than previously reported. The long-run income elasticity came out to be quite low at 0.33 and ranges from 0.18 to 0.49. The studies based on 1980s and 1990s values by Sterner (1991) and Dahl (1995) estimate the average value of long-term income elasticities as 1.21 and 0.72 respectively. Overall, previous studies have shown that the long-run income elasticities vary from .2 to greater than unity. Therefore, our findings fall within in those limits but points out that income elasticity of gasoline demand is significantly more inelastic in this decade than in previous ones.

One hypothesis for this is that as income has grown; consumer's budget surplus has increased, which lead consumers to be less sensitive to income growth. In other words, if disposable income is higher than some critical level, even though gas price is rising, consumer may not significantly reduce their travel to meet their changing budget. However, the changes in gas price and economic downturn have been drastic enough to see large reduction in consumers' travel in order to save money. Therefore, the next step in our investigation will be to determine the critical levels in the indicator variables at which consumers' reduce their travel to compensate for reduced budget surplus in an economy in recession. Also, we intend to add more macro-economy indicators, such as consumers' confidence, to generate a behavioral simulation in further research. In addition to disposable income helping explain the difference in travel behavior, the related concept of discretionary income could also shed light on the subject.

5. SUMMARY AND CONCLUSIONS

In this paper we estimate the long-run gasoline price and income elasticity to VMT for the period from 2000 to 2008. We advance the analytical framework to include a VEC regression technique that overcomes several limitations of ARMA models. We find that long-run gasoline price elasticity to VMT ranges from -0.31 to -0.88, and income elasticity ranges from 0.18 to 0.49. The result suggests that consumer is more sensitive to gas price than in previous period. The study also reveals that income has less influence on people's driving behavior than gas price. The reasons could be sufficient budget surplus or economic uncertainty.

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