Draft: Effect of gasoline prices on VMTs (Vehicle Miles Travelled): An exploratory analysis of Northern Virginia traffic based on granger causality

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ABSTRACT

From the 2nd quarter of 2007 onwards through much of the 2008, U.S. consumers experienced an unprecedented hike in gasoline prices. It is believed that this may have changed the travel demand behaviour resulting in less vehicular travel traffic. For example, the U.S. DOT's monthly statistics at the state and national level have shown a net decline of more than 100 billion Vehicle Miles Travelled (VMT) in 2008 compared to 2007. The U.S. DOT statistic is based on a few thousand locations spread across more than tens of thousands of miles of road network. In other words, while such measurements when aggregated to national level may be representative of the travel demand at the national level, it is difficult to gauge how VMTs change at the regional and sub-regional level due to changes in regional gasoline prices.

In this paper we propose a novel approach based on a simple but powerful concept of Granger causality. This unique approach will help determine whether the relationship between gasoline prices and VMTs is characterized by simultaneity or there exists a direction of causality such that increased gasoline prices result in reduced VMTs. In the later case, the extent to which VMTs respond to gasoline prices will be determined. For this purpose we use weekly traffic counts on major traffic corridors in the Northern Virginia region as a proxy for the VMTs and determine their relationship with the regional weekly gasoline prices based on the Granger causality. The weekly traffic counts are computed based on actual vehicle counts collected at vehicle sensors throughout the year on major corridors in the Northern Virginia road network. For the first time, we evaluate data from Reversible High Volume Occupancy (RHOV) lanes. The study results are presented through a series of tables, charts and maps.

Keywords: Granger causality, econometrics, VMT, ADMS

INTRODUCTION

The second half of 2007 through much of 2008, the U.S. experienced an unprecedented rise in gasoline prices. For the first time since 1984, the U.S. DOT's monthly traffic trend statistics at the national level showed a net decline of over 100 billion VMTs (Vehicle Miles Travelled) in 2008 compared to 2007 (Figure 1). If one looks at the VMT percent change by month, there have been just 30 months between 1984 and 2009 when there was a month to month decline in the VMTs. What is interesting is that, 18 of these have occurred between the later half of 2007 and 2009, a span of only a little over 30 months and the longest continuous month to month decline of almost a year. It appears that the decline in VMTs was in response to rising gasoline prices.

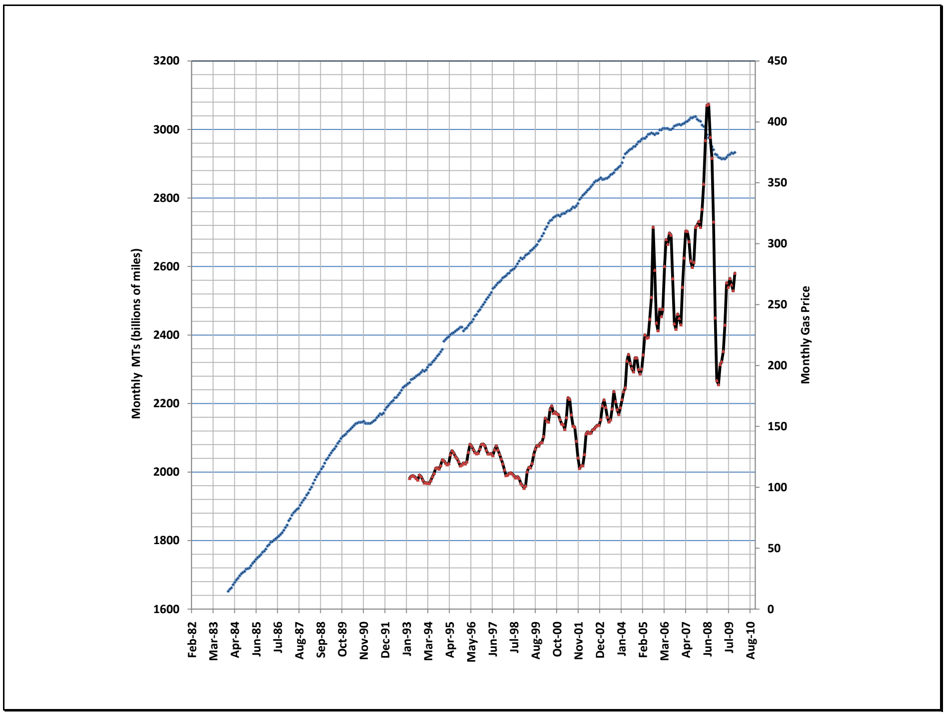

Figure 1 – US monthly traffic volumes and monthly gas prices

If this is the case then it is of interest to see whether there was a similar response at the regional/local level. Further, developing a methodology for investigation this phenomenon at the local regional level through a case study would then enable research into the regional variation across sub-national regions. Such a study would be important because it would enable a way to test for factors that contribute to such variation and thus provide an explanation for such variation and consequently identify possible policy levers that might be used for related transportation management goals.

There is a vast and growing amount of literature that explores how fuel prices affect travel demand. Long term elasticities of highway gasoline and automobile travel demand have been explored in detail based on national level panel data by Schimek (1996). Burger and Kaffine (2008) have studied the relationship between highway speeds and gasoline prices (2008) for the Los Angeles freeway systems. While very interesting work on short term elasticities of travel demand and fuel prices has been carried out by Dahl, 1995; Dargay, Gately, 1997; Goodwin, Dargay and Hanly, 2004; Schiffer, Stinvorth, Milam, 2005. Bomberg and Kockelman researched the change in travel behaviour in response to a gasoline price hike in 2005 based on a survey of few hundred Austin, TX residents (TRB, 2007). A comprehensive meta-analysis of gasoline demand in relation to travel has been studied by Espey (1998). Small and Dender in 2007 studied the fuel-travel demand connection for Europe while a Congressional Budget Office[1] (CBO) study reported on the relationship between gasoline price and travel demand in the U.S. While our current research effort follows in the tradition of this research here are at least two aspects where our research differs. Our current efforts use the novel technique from econometrics called granger causality (Granger citation) to discover whether there is a causal relation between gasoline prices and traffic volumes and if one exists then the magnitude by which change in gasoline price affects change in traffic volume. For this purpose we use sub-regional traffic volumes on major traffic corridors of Northern Virginia portion of Washington D.C. Metropolitan region (Figure 2) and regional gasoline prices covering the time period between January 01, 2004 and December 31, 2009.

The next few parts of the paper describe the study region, data and methodology. Preliminary results of the analysis based on *granger causality* are presented for the relationship between gasoline prices and traffic volumes on I-95 RHOV (Reversible High Occupancy Vehicle), the I-95 South (I-95S) and I-95 North (I-95N) as well I-66 West (I-66 W) and I-66 East (I-66 E) bound vehicular traffic. Although the google search index based on the results of search for variations of the term “gasoline”, “cheap gasoline”, “gasoline price” etc was used in this preliminary analysis, the current exploratory analysis does not use the google search index.

[1] http://www.cbo.gov/ftpdocs/88xx/doc8893/01-14-GasolinePrices.pdf

STUDY REGION

The Northern Virginia portion of the Washington D.C. Metropolitan area consists[2] of 4 counties and five cities and has two major traffic routes, interstate I-95 and interstate I-66, the Capitol Beltway and I-395. Much of the traffic on I-66 consists of local and commuter traffic from the western suburbs while I-95 has both the local/commuter traffic from southern suburbs and interstate personal and commercial traffic.

Interstate I-66 runs east-west and consists of both the East-bound (I-66 EB) and West-bound (I-66 WB) lanes as well as HOV (High Occupancy Vehicle) lanes. This study covers 13 miles in both directions. I-95 runs roughly north-south and consists of North-bound (I-95 NB) and South-bound (I-95 SB) lanes that carry not only the local and commuter traffic but also serves as the major route for the interstate travellers moving along the US Northeast Corridor. On the other hand I-95 also has dedicated RHOV lanes that mainly serve local and commuter traffic.

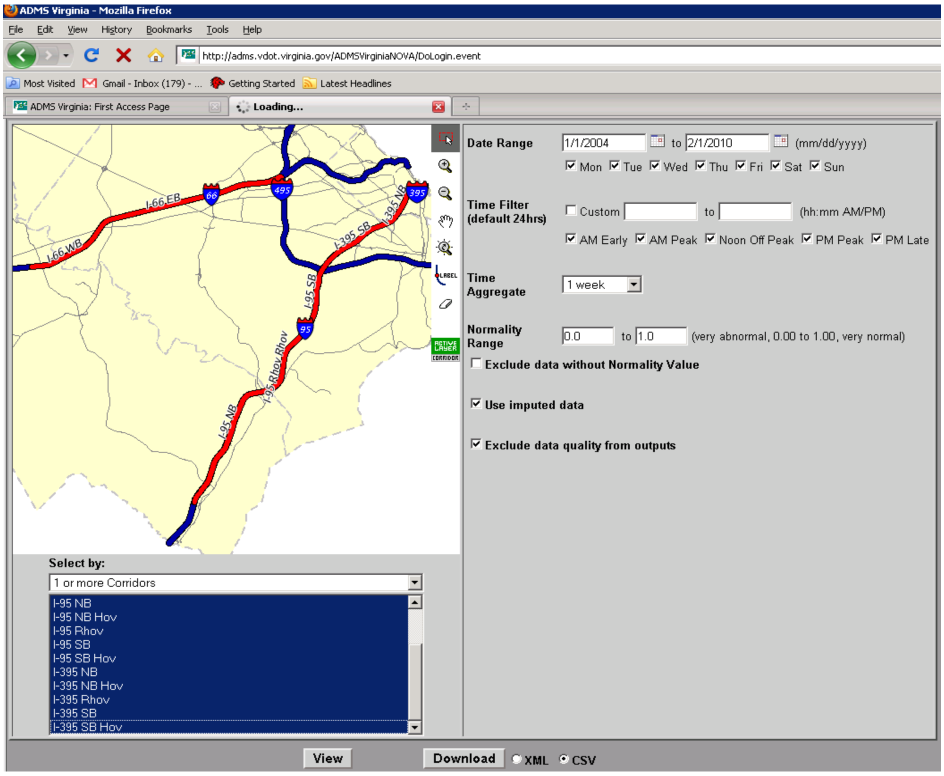

Figure 2 – Study region (Image source: Virginia DOT's website http://adms.virginia.dot.gov)

[2] Arlington county, Fairfax County, Loudoun County, Prince William County and cities of Alexandria, Falls Church, Fairfax, Manassas and Manassas Park.

DATA

All of the weekly traffic volume data was extracted from Virginia DOT's ADMS (Archived Data Management System) website (http://adms.vdot.virginia.gov/ADMSVirginia/). The weekly data covers January 2004 through January 2010, nearly 315 weeks. The data was extracted for each of the major corridors and by the direction of traffic (east and west on I-66 as well as north and south on I-95 and RHOV). The data for I-395 and I-395 RHOV portions was not used because of the noisy data with quite a few weeks when there is not data for the weekly traffic. Each of the traffic corridors consists of dozens of traffic count sensors that collect traffic counts at the minute time interval. The ADMS archived weekly data also collected via the road-side traffic sensors that was aggregated across all sensors to generate the weekly traffic count data for I-66 EB, I-66 WB, I-95 NB, I-95 SB and RHOV (Figure 3).

Weekly gas prices data for the mid-Atlantic region was extracted from the U.S Dept of Energy's Energy Information Administration (EIA) website (http://tonto.eia.doe.gov/dnav/pet/pet_pri_gnd_dcus_r1y_w.htm) and covers the same time period, January 2004 through January 2009. The weekly google search index also covers the same time period.

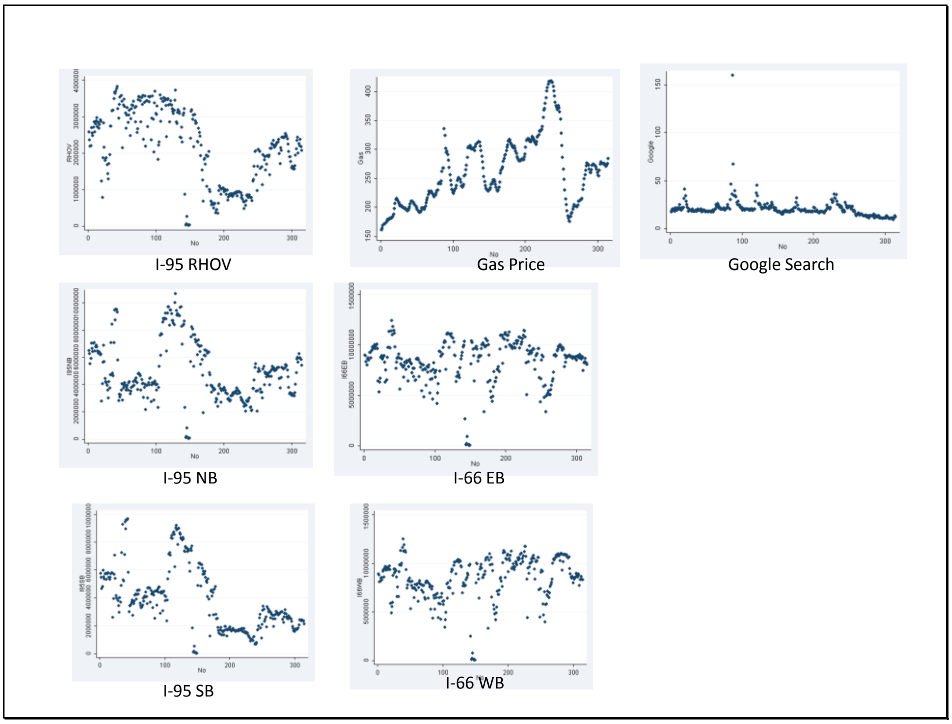

Figure 3 – Traffic volumes and Gas price scatter charts

METHODOLOGY

We used granger causality [Granger, 1997], [Kulkarni,Haynes, Stough, 2010] and [Mur and Paelinck 2009] to carry out two way regression with joint F-tests between the weekly traffic counts and the weekly gas prices with their respective lags. Below is a description of the Granger causality regression and the respective F-tests.

Granger Causality

Given two variables *x* and *y* moving in tandem over a period of time, then one can use Granger causality to determine if:

1. *x* causes *y* or $x \to y$
2. *y* causes *x* or $y \to x$
3. Or that casual direction cannot be determined, i.e., both *x* and *y* change simultaneously.

The idea behind causality is that if *x* causes *y* and that *y* does not cause *x*, and *x* occurs before *y.* Hence the lagged values of *x* are significantly related to the values of *y*.

$$y_t = c_0 + \sum_{i=1}^{n} c_i y_{t-i} + \sum_{j=1}^{m} d_j x_{t-j} \qquad (1)$$

and the lagged values of *y* are NOT significantly related to *x*:

$$x_t \neq a_0 + \sum_{i=1}^{n} a_i x_{t-i} + \sum_{j=1}^{m} b_j y_{t-j} \qquad (2)$$

Where *t*, *t-i*, *t-j* denote time; with index *i* Є [1,*n*] and j Є [1,*m*] denoting time lags from t, such that $n \geq\leq m$. The constants are denoted by a_0 and c_0 while a_i, d_i, represent coefficients of components of vector X at time *t-i* and *t-j* respectively. b_j, c_j are coefficients of components of Y at time *t-j* and *t-i* respectively. Note that vectors X and Y are of equal length and equations (1) and (2) show how components of vectors X and Y relate to each other.

In the third case, they occur simultaneously and hence do not cause each other. The direction of causality can be determined by carrying out two way linear regressions and evaluating them with F-test/joint F-tests in case of an independent variable with more than one lag.

Traffic volumes and gasoline prices

The traffic volume data on I-66, I-95 as well I-95 RHOV and gas price data was subjected to preliminary analysis to determine its spread with auto-correlation and cross-correlations.

Auto-correlation analysis helps to determine how the time data series behaves for different time lags while the cross-correlation analysis helps determine the amount of information between two different variables.

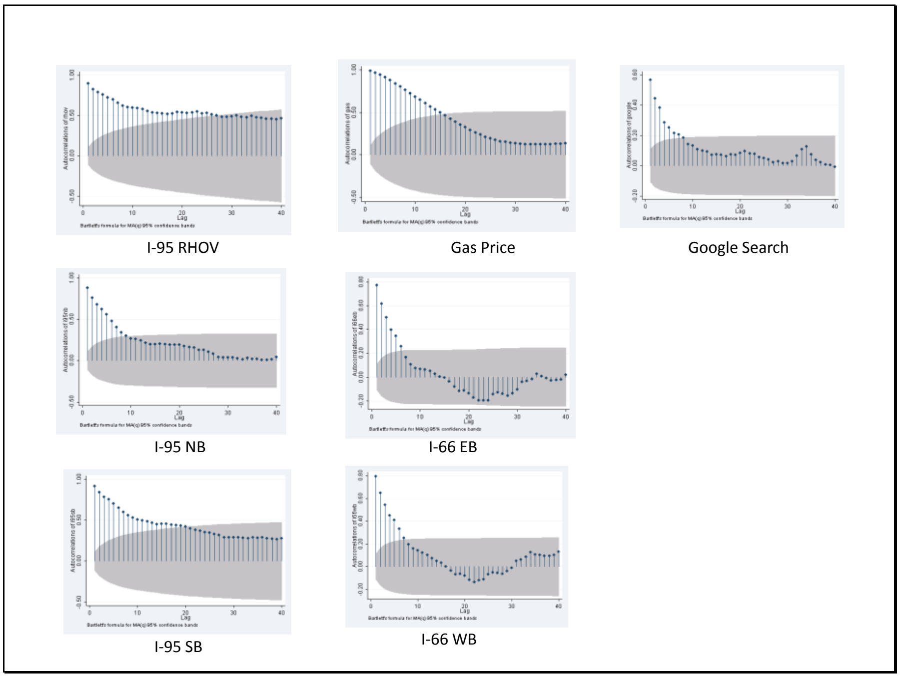

Figure 4 – Auto-correlations

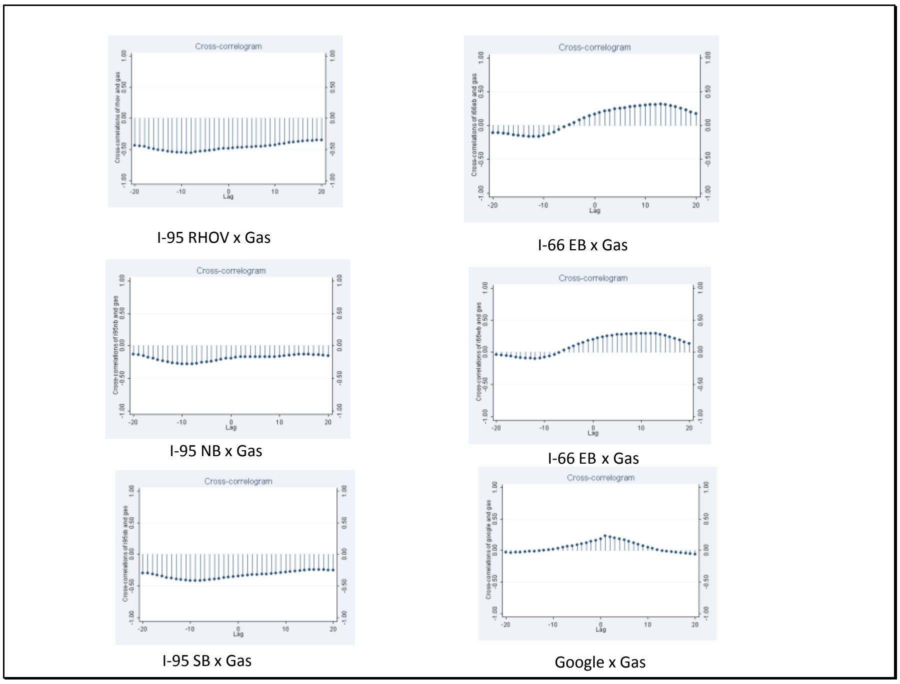

Figure 5 – Cross Correlations

Figures 4 and 5 show the results of auto-correlation and cross-correlation analysis. In the later case traffic volumes on different parts of northern Virginia roads were cross-correlated with gas prices. A preliminary analysis shows that I-66 traffic appears to have very little cross-correlation with gas prices.

Next we carried out “granger causality” regressions and F tests using many different weekly lags for traffic on RHOV, I-95 NB, I-96 SB, I-66 EB, I-66 WB and the weekly gasoline prices. The time period for the analysis was all the weeks between January 2004 to January 2010, a total of 315 observations.

For each of these bi-variate regression models consisting of X and Y, it is assumed that the dependent variable (X) is determined (caused) by the independent variables represented by the lagged values of X and Y. This is our *forward granger regress*ion model. Similarly, the dependent variable Y is determined (caused) by the independent variables represented by the lagged values of X and Y. This is our *inverse granger regression* model. The F tests outputs helped determine the direction of causality. Note that if there were more than one lagged variable of either X or Y, then the joint F tests were carried out.

First the traffic variable was used as a dependent variable and regressed with independent variables consisting of the lagged traffic variable and the lagged gasoline price. Next the gasoline price was treated as a dependent variable and regressed against the independent variables consisting of the lagged traffic and lagged gasoline price variable. The list of variables is shown in Table 1. The direction of causality, if one existed, was inferred based on the F tests. All test statistics were determined at 95% confidence interval. Table 1, below shows the list of variables.

RHOV.Lt = RHOV (Reversible High Occupancy Vehicle) with lag of 1 time period of t = 1, 2, 3..., n-1
I95NB.Lt = I-95 North-bound traffic with lag of t = 1, 2, 3..., n-1
I95SB.Lt = I-95 South-bound traffic with lag of t = 1, 2, 3..., n-1
I66EB.Lt = I-66 East-bound traffic with lag of t = 1, 2, 3.., n-1
I66WB.Lt = I-66 West-bound traffic with lag of t = 1, 2, 3..., n-1
GAS.Lt = Gasoline price with lag of t = 1, 2, 3... , n-1
n = number of observations associated for n time periods

Table 1. List of variables. In each case a variable without Lt stands for t = 0. For eg., RHOV, I95NB, I95SB, I66EB, I66WB, GAS.

Traffic on I-95 RHOV (Reversible High Occupancy Vehicle)

Table 2 shows the results of regressing the dependent variable RHOV traffic against one time period lagged values each of RHOV and Gasoline price, the independent variables. While Table 3 shows the output when Gasoline price is treated as the independent variable and the one time period lagged values each of RHOV traffic and Gasoline prices as the independent variables. One can infer from the small coefficient of RHOV and the F-test (at

95% confidence interval) of Table 3, as compared to Table 2, that the traffic volumes in each week are determined (caused) by traffic volume and gasoline prices of the preceding week.

Gasoline -> RHOV			
Variable	beta	s.e beta	t
RHOV.L1	0.87	0.03	30.75
GAS.L1	-1152.79	484.85	-2.38
Constant	587257.90	166185.50	3.53

Observations	314
Adj R-square	0.81
Root MSE	440000.00
F (1,311)	5.65
Prob > F	0.02
Mean RHOV	2155157.00

Table 2. Gasoline price (Gasoline) “granger” causes (predicts) traffic on I-95 RHOV.

RHOV -> Gasoline			
Variable	beta	s.e. beat	t
RHOV.L1	2.03E-07	4.70E-07	0.43
GAS.L1	9.89E-01	0.01	122.32
Constant	2.73E+00	2.77	0.99

Observations	314
Adj R-square	0.98
Root MSE	7.29
F (1,311)	0.19
Prob > F	0.67
Mean GAS	260.28

Table 3. I-95 RHOV traffic does not “granger” cause (predicts) gasoline price.

F-tests output points to: Gasoline Prices “granger cause” RHOV while RHOV does not “granger cause” Gasoline prices.

Traffic on I-95 NB (North Bound)

Tables 4 shows the output of the bivariate, forward granger regression model where the north bound traffic on I-95 NB was regressed against the one time period lagged values of I-95 NB traffic and two lagged time periods of gasoline prices. Note that the test statistic with just one time period lagged values of I-95 NB and GAS at 0.05 level of significance was 1.16, compared to 2.71 shown in Table 4. In addition, the test statistics in the case of single lag “inverse regression” at 0.05 significance level was 1.56, thereby making the direction of causality indeterminate. However, the main reason for not using the single lag model was that the p values for t-stat at 95% confidence interval were large, namely 0.399 for the constant term and, 0.291 for the I-95 NB.

Gasoline -> I-95 NB			
Variable	beta	s.e beta	t-stat
I95NB.L1	0.87	0.03	31.83
GAS.L1	14870.01	7811.66	1.90
GAS.L2	-16035.29	7789.05	-2.06
Constant	936026.70	318691.20	2.94

Observations	313
Adj R-square	0.78
Root MSE	1000000.00
F(2,309)	2.71
Prob > F	0.07
Mean I95 NB	4921916.00

Table 4. Gasoline price "granger" causes (predicts) I-95 NB traffic.

I-95 NB - > Gasoline			
Variable	beta	s.e. beta	t-stat
I95NB.L1	9.9E-08	1.7E-07	5.7E-01
GAS.L1	1.49	0.05	30.21
GAS.L2	-0.50	0.05	-10.21
Constant	3.13	2.01	1.56

Observations	313
Adj R-square	0.99
Root MSE	6.31
F(2.309)	0.33
Prob > F	0.56
Mean GAS	260.28

Table 5. Traffic on I-95 NB does not "granger" cause (predicts) gas price.

Output of the joint F-tests point to: Gasoline Prices "granger cause" traffic on I-95 NB and not the vice versa.

Traffic on I-95 SB (South Bound)

Tables 6 and 7 show the output of the bivariate forward and reverse granger regression models for I-95 SB (South bound) traffic and gasoline prices. Just as it was for I-95 NB, we used gasoline with two lags and a single lag for I-95-SB. The coefficient for I-95 SB is just a tad bit higher (0.89) compared to 0.87 for I-95 NB. Also, the F-test statistic at 0.05 level of significance is much higher (3.45) than that for I-95 NB (2.71), while the t-test statistic for inverse granger regression at 0.05 significance level is smaller for I-95 NB (0.19) compared to I-95 SB (0.33).

Gasoline -> I-95 SB			
Variable	beta	s.e. beta	t-stat
I95SB.L1	0.89	0.02	37.91
GAS.L1	13076.12	6977.20	1.87
GAS.L2	-14639.90	6963.67	-2.10
Constant	768967.00	290803.20	2.64

Observations	313
Adj R-square	0.8451
Root MSE	8.90E+05
F(2,309)	3.45
Prob > F	0.033
Mean I95 SB	3833050

Table 6. Gasoline price "granger" causes (predicts) I-95 SB traffic.

I-95 SB -> Gasoline			
Variable	beta	s.e. beta	t-stat
I95SB.L1	1.33E-08	1.68E-07	0.08
GAS.L1	1.49	0.05	30.26
GAS.L2	-0.50	0.05	-10.25
Constant	3.70	2.05	1.8

Observations	313
Adj R-square	0.99
Root MSE	6.31
F(1,309)	0.01
Prob > F	0.94
Mean GAS	260.28

Table 7. Traffic on I-95 SB does not "granger" cause (predicts) gasoline price.

Output of the joint F-tests point to: Gasoline Prices "granger cause" traffic on I-95 SB and not the vice versa.

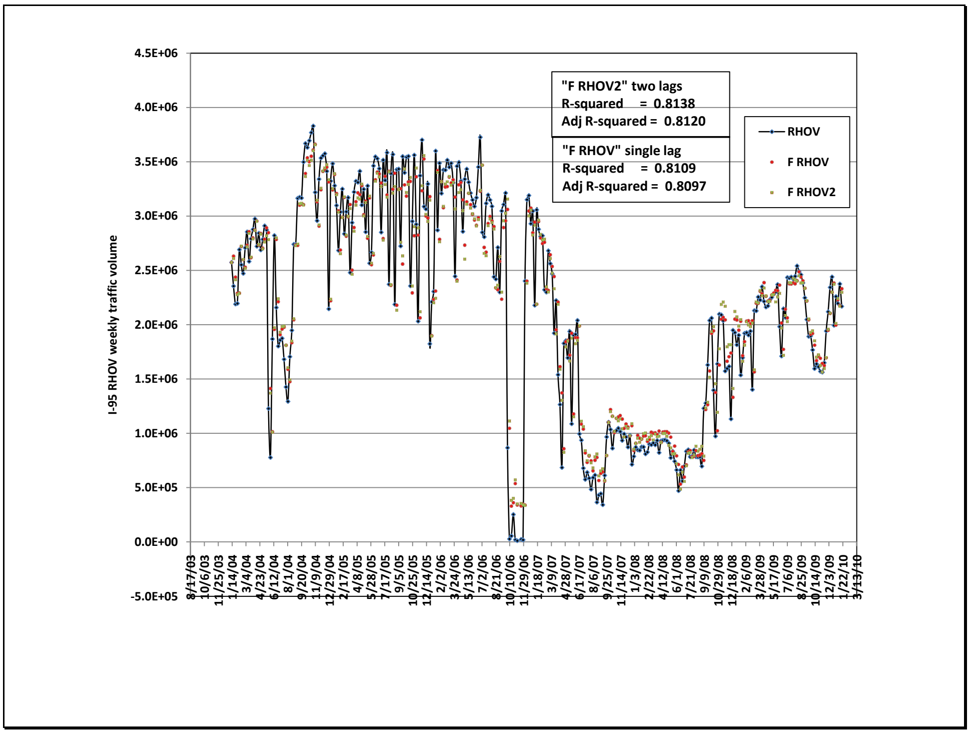

Figure 6 – I-95 RHOV actual and predicted traffic volumes

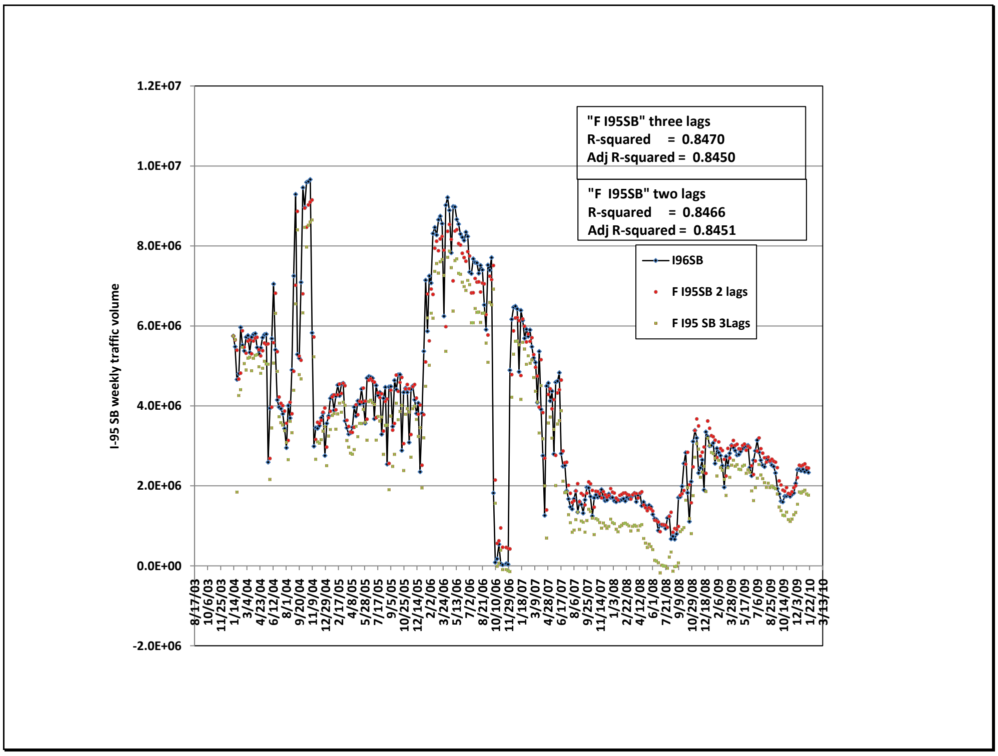

Figure 7 – I-95 SB actual and predicted traffic volumes

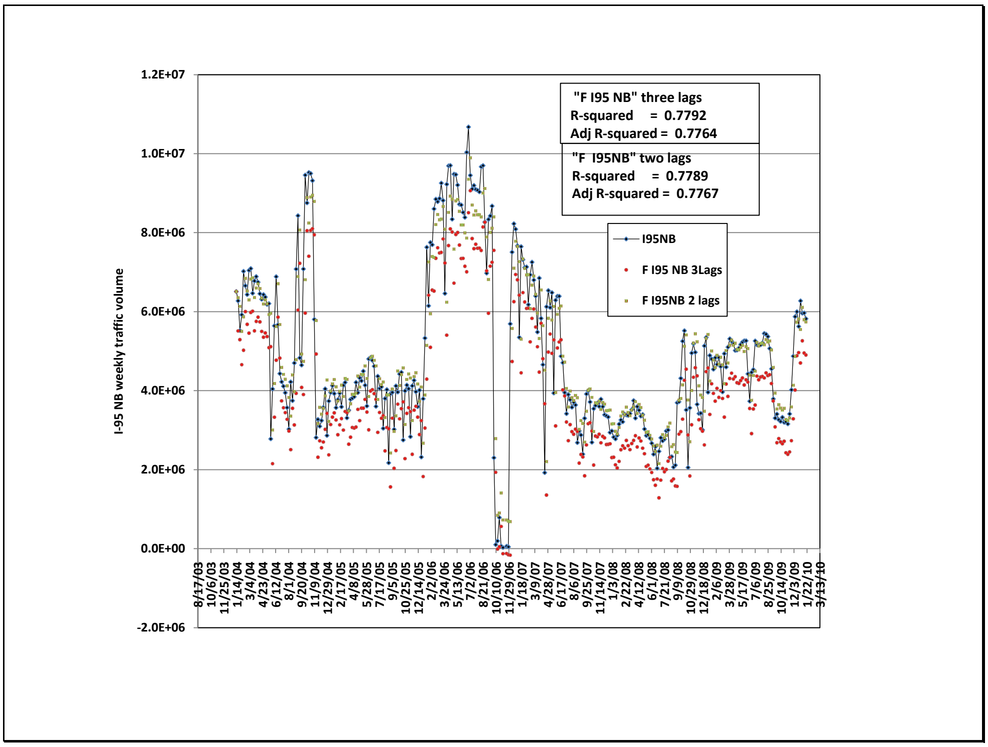

Figure 8 – I-95 NB actual and predicted traffic volumes

It should be noted that the F-test statistics for both I-95 NB and SB at 0.05 significance level are smaller than that for RHOV. It may be that I-95 RHOV carries mostly local and commuter traffic while I-95 SB and NB, in addition to local and commuter traffic also serve as conduits for the interstate traffic. In fact I-95 is a major interstate serving traffic needs along the U.S. east-coast. Figures 6, 7 and 8 show I-95 traffic volume and predicted traffic volume based on one and two lags of gasoline prices for I-95 RHOV and I-95 NB, I-95 SB respectively.

Traffic on I-66 EB (East Bound) and WB (West Bound)

The east and west bound traffic on I-66 serves mostly western suburbs of the Virginia part of the Washington D.C metropolitan area and thus carry much of the local and commuter traffic. Unlike I-95 RHOV the results from the Granger causality analysis were mixed, in the sense that traffic on these roads is not very sensitive to changes in gasoline prices, at least not at the price levels seen during the price hikes of 2007 and 2008 or for the duration of the period of the high peak.

There may be other factors such as the western suburbs being relatively more affluent compared to suburbs to the south along I-95. It may also be the case that a metro light rail runs parallel to I-66 and thus offers people living in the western suburbs an alternative to travelling by road only. Addressing these alternative explanations are beyond the scope of our current paper but will be dealt with in our future research.

The preliminary analysis of the granger regression and F-tests are provided below in Tables 8 through 11. The models with single and two lags of gasoline were not used because the p values for t-statistic at 95% confidence interval were very high.

Traffic on I-66 EB (East Bound)

Gasoline -> I-66 EB			
Variable	beta	s.e beta	t-stat
I66EB.L1	0.74	0.04	19.86
GAS.L1	28918.08	12110.77	2.39
GAS.L2	-21296.1	20795.51	-1.02
GAS.L3	-7049.53	12188.99	-0.58
Constant	1968819	435436.7	4.52

Observations	312
Adj R-square	0.60
Root MSE	1.30E+08
F(3,307)	3.19
Prob > F	0.02
Mean I66 EB	8341924

Table 8. Gasoline price “granger” causes (predicts) I-66 EB traffic.

I-66 EB -> Gasoline			
Variable	beta	s.e. beat	t-stat
I66EB.L1	4.45E-07	1.74E-07	2.55
GAS.L1	1.41	0.06	25.02
GAS.L2	-0.31	0.10	-3.22
GAS.L3	-0.11	0.06	-2
Constant	1.03	2.02	0.51

Observations	312
Adj R-square	0.99
Root MSE	6.21
F(1,307)	6.53
Prob > F	0.01
Mean GAS	260.28

Table 9. Traffic on I-66 EB “granger” cause (predicts) gasoline price.

Traffic on I-66 WB (West Bound)

Gasoline -> I-66 WB			
Forward	beta	s.e beta	t-stat
I66WB.L1	0.77	0.04	21.29
GAS.L1	25890.28	12342.83	2.1
GAS.L2	-18738	21183.5	-0.88
GAS.L3	-6285.38	12372.72	-0.51
Constant	1713868	427851.2	4.01

Observations	312
Adj R-square	0.63
Root MSE	1.40E+06
F(3,307)	2.51
Prob > F	0.07
Mean I66 WB	8426571

Table 10. Gasoline price “granger” causes (predicts) I-66 EB traffic.

I-66 WB -> Gasoline			
Forward	beta	s.e. beat	t-stat
I66WB.L1	3.80E-07	1.65E-07	2.31
GAS.L1	1.41	0.06	25
GAS.L2	-0.31	0.10	-3.18
GAS.L3	-0.12	0.06	-2.11
Constant	1.62	1.95	0.83

Observations	
Adj R-square	0.9884
Root MSE	6.22
F(1,307)	5.32
Prob > F	0.02
Mean GAS	260.28

Table 11. I-66 EB traffic "granger" cause (predicts) gasoline price.

It appears that in the case of I-66 EB and WB traffic, granger causality shows simultaneity, i.e., the granger causality works in both directions. In other words lags in gasoline price and traffic volume seem "granger cause" (predict) each other.

CONCLUSIONS AND FUTURE RESEARCH

Granger causality is a useful tool to test direction of causality in the case of two or more time varying data series. Our aim in this paper was to figure out how traffic at the regional and sub-regional level responded to changes in regional gasoline price. For that purpose we used granger causality to determine the direction of causality. Following are the findings for different traffic corridors of the Northern Virginia region.

- Gasoline Prices "granger cause" RHOV while RHOV does not "granger cause" Gasoline prices.
- Gasoline Prices "granger cause" traffic on I-95 NB (I-95 SB) and not the vice versa.
- Gasoline Prices "granger cause" traffic on I-95 SB and not the vice versa.

From our analysis it appears that the traffic on I-95 corridor indeed responded to changes in changes in gasoline price. Traffic on RHOV responded to gasoline prices changes with a lag of just one week, while the traffic on I-95 North bound and South bound corridor responded with a mixed result of lag of two weeks. Based on the output the weekly traffic on I-95 corridors (Tables 2, 4 and 6) is mainly determined by previous week's traffic and delayed response of one to two weeks to gasoline prices. The actual and predicted traffic volumes are shown in Figures 6, 7 and 8.

On the other hand, the I-66 WB and SB traffic appears to be insensitive to changes in gasoline prices over the range experienced during the study period. It may be that higher gasoline prices will result in significant increases in demand elasticity but not at the levels of those experienced during the peaks seen in '07 and '08. In that case greater increase in gasoline prices would potentially "granger cause" traffic on both East and West bound I-66. However, as pointed out earlier there may be other factors, such as availability of alternate modes of transportation (light rail) and higher income levels of users making the western suburbs and the traffic on I-66 less sensitive to higher gasoline prices than those experienced to date.

Our future research will try to examine other factors that may "granger cause" traffic on I-66 and seek to develop a statistics that measures traffic response to gasoline price changes at the sub-regional level. Also it may be that all of these time series data have to be smoothed using various smoothing techniques before a granger causality method to determine sensitivity to gasoline price changes is fully valid. The future research will also try to examine the sub-regional elasticities of road traffic and gasoline prices.

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APPENDIX

Sample Dataset

No	Date	RHOV	I95NB	I95SB	I66EB	I66WB	Gas	Google
1	1/12/2004	2573045	6509596	5747483	8944253	8880340	160.1	17
2	1/19/2004	2354716	6274684	5480299	8906541	8805185	163.7	19
3	1/26/2004	2188628	5522692	4659844	8282192	8101368	167.8	20
4	2/2/2004	2194988	5923064	4807256	7998976	8164083	170.3	20
5	2/9/2004	2690588	7021667	5963989	8605936	8472968	171.5	20
…								
230	6/9/2008	470144	2389728	1180630	5017336	4409298	401	32
231	6/16/2008	660308	2583454	1158515	9475666	9496385	406.5	31
232	6/23/2008	560286	2034819	883370	8281565	8976256	412.1	35
233	6/30/2008	696625	2464223	1018747	9090295	9625289	416.7	28
234	7/7/2008	833645	2808290	1008906	9891370	10021353	416.7	25
235	7/14/2008	848370	2730151	1017762	9325164	10003955	417.1	25
236	7/21/2008	782647	2773835	932683	9116176	10454842	418.1	24
237	7/28/2008	788031	2980392	1197663	9253291	10133756	417.6	24
238	8/4/2008	845305	3003474	1237023	9435322	10585992	414.9	22
239	8/11/2008	782308	2307746	671788	9639709	10831190	407.9	23
240	8/18/2008	780080	2330226	737636	9545099	10470755	400.8	21
…								
308	12/7/2009	2342962	5874378	2404741	8631069	8926277	274.8	10
309	12/14/2009	2439631	5999857	2406269	8798921	8792470	274.3	11
310	12/21/2009	1993071	5627043	2378349	7411588	7733696	275.3	11
311	12/28/2009	2258716	6274571	2413085	8217452	8328307	272.7	11
312	1/4/2010	2196148	5960439	2354003	8312824	8371711	270.6	9

RHOV = Reversible High Occupancy Vehicle lanes
I95NB = Interstate 95 North Bound
I95SB = Interstate 95 South Bound
I66EB = Interstate 66 East Bound
I66WB = Interstate 66 West Bound
Gas = Gasoline Price in Cents
Google = Google Search index for "gas price", "gasoline" etc.