Gas Prices and Hybrid Electric Vehicle (HEV) Sales

Ange Olson
The College of William and Mary

Abstract: This paper aims to establish whether or not there is a relationship between HEV sales and gas prices in the US through the use of a Vector Error Correction Model, given that there exists a cointegrating relationship between the variables of interest. The VECM indicates that there is no significant relationship between gas prices and HEV sales in the short run or long run, differing greatly from the results generated from the DOLS model suggesting short and long run effects of a 1% increase in gas prices to be roughly .5%. However, even with the DOLS model, there is very little evidence of a relationship post-2013. This suggests that for policymakers trying to incentivize HEV usage, gas prices may not be a great incentivizing force.

I. Introduction

The purpose of this paper is to determine if there is a link between gas prices and Hybrid Electric Vehicle (HEV) sales over time and, if so, what the short-term and long-term effects of an increase in the price of gas might mean for HEVs. It has been argued that gasoline prices and the adoption of HEVs have a relationship[1] with the idea that as gas prices are lower, HEV sales/usage will go down, and when gas prices are high, the opposite. Not only has this been echoed in academic literature but in the press as well. In 2015, The New York Times wrote "In 2012, with gas prices soaring, an owner could expect a hybrid to pay back its higher upfront costs in as little as five years. Now, that oft-calculated payback period can extend to 10 years or more."[2] Whether or not this relationship does actually hold could have major consequences for policy makers arguing that a gas tax might increase HEV sales and usage; and if so, by how much?

To further delve into the question of the relationship between gas prices and HEVs, this paper is organized as follows: First, I outline the theory behind testing for a relationship between HEV sales and gas prices and explain why I believe a Vector Error Correction Model (VECM) is the best model. Then, I describe the data used in analysis and its source. Next, I present the VECM results and lastly, I conclude with a summary of my motivation and findings.

II. Theory and Methodology:

At a basic level, HEV sales are a measurement of demand for Hybrid Electric Vehicles.
Economic theory tells us that demand is a function of the price of a good, income, and the price of a related good—a substitute or complement. It is the latter part of this equation that I am aiming to focus on; that is, how

[1] Diamond, 2009
[2] Ulrich, 2015

much of the demand for HEVs can be explained by the availability and price effectiveness of substitutes and not by price of the good and income of the consumer. Namely, if accounting for the trend of total cars sold in the US, do gas prices have an effect on HEV sales?

In theory, if two cars are exactly the same minus the fact that one is a Hybrid and the other is not, there will be a price premium for the Hybrid version. However, if the savings at the pump make up for this premium, a rational consumer would either be indifferent or would potentially opt for the Hybrid version, since the positive externalities (fewer CO_2 emissions, the intrinsic feeling of helping the environment) are not reflected in the sale price of the good yet still add value to the car. What I aim to study isn't necessarily demand of HEVs in and of itself but the trend in HEV sales given the trends in related goods. Given that I hope to look at trends, time series analysis is best suited for this analysis. The function of interest is, therefore:

$$\Delta X = f(\Delta G, \Delta C, \Delta S, \Delta X_{t-1})$$

Where X = HEV sales, G = gas prices, C = total car sales, and S = usage of substitutes and other factors included in a cost/benefit analysis. In my preliminary work I modelled this with Dynamic OLS and VAR models. However, finding evidence of cointegration between the trends studied, I decided to look into expressing the model as a Vector Error Correction Model (VECM). It can be assumed that if all variables increase over time, then we could expect there to be some underlying trend that directs their movement. In the case of various modes of transportation, it makes logical sense that since transportation generally exhibits inelastic demand, the forms of transportation should be related to one another. So, we could also expect the following:

$$\begin{aligned} \Delta C &= f(\Delta G, \Delta X, \Delta S, \Delta C_{t-1}) \\ \Delta S &= f(\Delta G, \Delta C, \Delta X, \Delta S_{t-1}) \\ \Delta G &= f(\Delta G, \Delta C, \Delta X, \Delta G_{t-1}) \end{aligned}$$

Based on these functions, it is easy to see a VEC system of the kind below:

$$\begin{aligned} \Delta X_t = {} & \beta_{x0} + \beta_{xx}\Delta X_{t-1} + \beta_{x1}\Delta C_{t-1} + \beta_{x2}\Delta S_{t-1} + \beta_{x3}\Delta G_{t-1} \ldots + \beta_{x(k-3)}\Delta X_{t-n} + \beta_{x(k-2)}\Delta C_{t-n} \\ & + \beta_{x(k-1)}\Delta S_{t-n} + \beta_{xk}\Delta G_{t-1} + \delta_x v_1 + \varepsilon_t^x \end{aligned}$$

$$\begin{aligned} \Delta C_t = {} & \beta_{10} + \beta_{1x}\Delta X_{t-1} + \beta_{11}\Delta C_{t-1} + \beta_{12}\Delta S_{t-1} + \beta_{13}\Delta G_{t-1} \ldots + \beta_{1(k-3)}\Delta X_{t-n} + \beta_{1(k-2)}\Delta C_{t-n} \\ & + \beta_{1(k-1)}\Delta S_{t-n} + \beta_{1k}\Delta G_{t-1} + \delta_1 v_1 + \varepsilon_t^1 \end{aligned}$$

$$\begin{aligned} \Delta S_t = {} & \beta_{20} + \beta_{2x}\Delta X_{t-1} + \beta_{21}\Delta C_{t-1} + \beta_{22}\Delta S_{t-1} + \beta_{23}\Delta G_{t-1} \ldots + \beta_{2(k-3)}\Delta X_{t-n} + \beta_{2(k-2)}\Delta C_{t-n} \\ & + \beta_{2(k-1)}\Delta S_{t-n} + \beta_{2k}\Delta G_{t-1} + \delta_2 v_1 + \varepsilon_t^2 \end{aligned}$$

$$\begin{aligned} \Delta G_t = {} & \beta_{30} + \beta_{3x}\Delta X_{t-1} + \beta_{31}\Delta C_{t-1} + \beta_{32}\Delta S_{t-1} + \beta_{33}\Delta G_{t-1} \ldots + \beta_{3(k-3)}\Delta X_{t-n} + \beta_{3(k-2)}\Delta C_{t-n} \\ & + \beta_{3(k-1)}\Delta S_{t-n} + \beta_{3k}\Delta G_{t-1} + \delta_3 v_1 + \varepsilon_t^2 \end{aligned}$$

Where v_1 is a cointegrating vector if it can be shown that there is only one cointegrating vector.

III. Data and Sources

Data for mass transit ridership, vehicle miles travelled (VMT), and total vehicle sales come from FRED. Gas price data comes from the EIA, and HEV sales come from HybridCars' *Hybrid Market Dashboard*, a series of monthly articles and statistics detailing trends and sales of HEVs. Data for this analysis is monthly, from January 2006 through June 2018 for 150 observations. Mass transit ridership and VMT are used here to capture the effect of substitutes and factors in a cost-benefit analysis a consumer might be using to guide their purchase; if mass transit usage is high, we might expect traditional vehicle usage to be lower. If fewer miles are travelled, the possible benefits of buying a hybrid car are less.

Table I. Summary Statistics

Variable	Mean	Min.	Max.	Standard Deviation
Gas prices (US$ per gallon)	2.89954	1.721	4.051	.5750405
Vehicle Miles Travelled (millions)	3028182	2945065	3215643	81971.09
HEV Sales	29312.22	12714	53020	8384.038
Transit Ridership (thousands of unlinked trips)	860738.7	746114	993437	46018.04
Total Car Sales (millions)	15.36389	9.223	18.44	2.516811

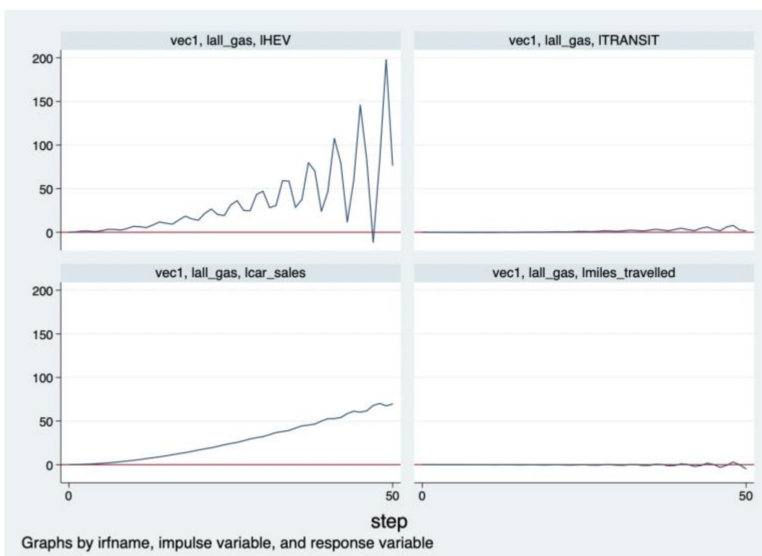
Source: Author's calculations

IV. Analysis and Results

First, I tested to see if the series of the variables listed in Table I are indeed nonstationary and found tha with the exception of transit ridership, all variables are I(1) in levels and I(0) in first differences (data not shown). Using a Dynamic OLS model with two lags each[3] I find the short run elasticity of demand for HEVs based on gas price to be .544763 and the long run elasticity of demand to be .5084131, both statistically significant at the $\alpha = 0.05$ level. However, I believe this estimate to have issues for two reasons: 1.) I find evidence of a structural break in HEV sales and the relationship between HEV sales and gas prices after Sept. 2013, where after this date gas prices seem to have no statistically significant effect on HEV sales and the series is no longer I(1)[4]. Restricting the DOLS model I find that post-September 2013, the short run and long run elasticities drop to -.0060624 and -.0255479 respectively are no longer statistically significant. 2.) I find evidence that the series are cointegrated (data not shown). While a VAR model could potentially work, a cointegrating relationship allows for a VEC model which I use instead.

Using `vecrank` I find evidence for two cointegrating vectors and based on `varsoc` I choose to use two lags. A table with the results of the VECM can be found in Appendix B, and Figure A displays the table of results generated from the VECM with the option to include seasonal dummies in the regression. While VECM IRFs in Stata do not have confidence intervals, we see that an increase in gas prices leads, over time, to greater HEV sales. However, it is unclear how statistically significant this is and regardless, an increase over four years of fewer than 300 sales is hardly significant in value.

Figure A. Cumulative Impulse Response Functions, VECM



Source: Author's Calculations

V. Conclusion

[3] See Appendix A for regression equation
[4] See Appendix B for code

My aim was to determine if there is a significant relationship between gas prices and HEV sales. If gas prices were high enough, there is reason to believe that this would persuade more people to purchase hybrid vehicles opposed to their counterparts. In my analysis, I find that while a DOLS model shows evidence of a relationship for certain years, this relationship falters in 2014 on. A VECM does not show evidence of a strong relationship and the resulting CIRF table and graphs show that a unit increase in gas prices would not result in significant increases in HEV sales.

My motivation for this study was to inform how policy could change the incentives for consumers to purchase the more environmentally-friendly HEV over the alternative; in sum, I find that shifts in gas prices are unlikely to incentivize consumers. Perhaps the savings are not enough, or there is something about the hybrid version of a car that is not attractive to consumers. Further research could include a price index for HEVs or, as time goes on and there are more observations, including plug-in HEVs or EVs in the analysis. Perhaps the plateauing of HEV sales growth could be caused by an influx of attractive substitutes into the market.

Of additional interest is that an increase in gas prices also has little to no effect on miles travelled or use of mass transit. This could speak to the transportation system in the US as a whole; where there is little infrastructure for alternative transportation, people have no choice but to drive and have little to no ability to change their behavior.

Works Cited

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Appendix A

```
reg D.lHEV D.lall_gas i.mtnh D.lcar_sales D.lmiles_travelled D.lTRANSIT DL(1/2).lall_gas DL(1/2).lcar_sales
        DL(1/2).TRANSIT DL.lHEV DL(1/2).lmiles_travelled
```

Variable		Estimate
Gas Prices		
	D1	.544763** (.2280651)
	LD	-.194919 (.2392997)
	L2D	-.1444325 (.2166793)
Car Sales		
	D1	.9783209*** (.2401741)
	LD	.1174709 (.2727584)
	L2D	.4283998** (.2325306)
Miles Travelled		
	D1	-10.9502 (13.73912)
	LD	22.36712 (14.26453)
	L2D	-19.2189 (13.80967)
Transit		
	D1	1.369426** (.5611888)
	LD	.9036571 (.6308364)
	L2D	.2767618 (.4978102)
HEV Sales		
	LD	-.071497 (.0926246)
Constant		-.264335** (.0742159)

Source: Author's calculations. Standard errors in parentheses. N = 147, adj. R_2 = 0.6449
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Appendix B

```
. *       cirfs
. irf create vec1, set(vecintro, replace) step(50)
(file vecintro.irf created)
(file vecintro.irf now active)
(file vecintro.irf updated)

. irf table cirf, impulse(lall_gas) response(lHEV lmiles_travelled lTRANSIT lall_gas lcar_sales) noci
```

Results from vec1

step	(1) cirf	(2) cirf	(3) cirf	(4) cirf	(5) cirf
0	0	0	0	1	0
1	.282242	.020246	-.055372	2.07402	.109962
2	1.32981	.008256	-.127938	3.28986	.310271
3	1.35303	-.032306	-.195673	4.83568	.60065
4	.746897	-.033602	-.208193	6.0481	1.02181
5	1.64632	-.007777	-.218357	7.02753	1.5108
6	3.32607	-.036607	-.2831	8.57735	2.02735
7	3.22823	-.096094	-.326442	10.4882	2.64688
8	2.51405	-.085768	-.28428	11.7908	3.40336
9	4.27175	-.04479	-.257041	12.8438	4.19236
10	6.75485	-.09443	-.314561	14.8245	4.97453
11	6.2761	-.173637	-.324452	17.1714	5.87734
12	5.375	-.136568	-.212364	18.467	6.93102
13	8.40944	-.07345	-.151098	19.549	7.96711
14	11.7805	-.15756	-.217058	22.1042	8.95813
15	10.3895	-.259225	-.187339	24.9192	10.1114
16	9.22362	-.174474	.011396	26.0013	11.4355
17	14.1631	-.085063	.093035	27.0561	12.6653
18	18.4011	-.228112	-.006791	30.4037	13.8105
19	15.2474	-.353492	.075044	33.6839	15.1967
20	13.85	-.189254	.383101	34.2233	16.7751
21	21.673	-.0743	.458812	35.2262	18.1394
22	26.557	-.315457	.290469	39.7171	19.3855
23	20.3529	-.45954	.451521	43.3951	21.0076
24	19.0376	-.167268	.900315	42.8956	22.8337
25	31.2346	-.037785	.923925	43.9147	24.2594
26	36.1408	-.436774	.643098	50.0987	25.5545
27	24.9988	-.58022	.936229	53.9734	27.4444
28	24.6439	-.087464	1.56662	51.7063	29.5181
29	43.4049	.025017	1.45938	53.0035	30.9061
30	46.9428	-.619614	1.01415	61.7071	32.2031
31	28.1839	-.714889	1.53451	65.3145	34.4347
32	30.7108	.083033	2.39408	60.2374	36.7555
33	59.1228	.108551	2.02472	62.4409	37.9634
34	58.5212	-.906119	1.36088	74.854	39.2289
35	28.4896	-.854146	2.27046	77.2443	41.9374
36	37.6495	.394318	3.4042	67.9153	44.4896
37	79.8518	.194568	2.55925	72.3056	45.3079
38	69.961	-1.35872	1.63484	90.0612	46.5411
39	23.9267	-.970723	3.19818	89.4333	49.9495
40	46.5563	.920174	4.62682	73.9465	52.6753
41	107.739	.240316	2.96798	82.9198	52.7952
42	79.4618	-2.06691	1.78444	108.128	54.0643
43	11.7743	-1.00395	4.41872	101.248	58.5188
44	59.7397	1.76513	6.09483	77.2461	61.2681
45	145.764	.158497	3.10065	95.039	60.2415
46	83.6618	-3.15411	1.76319	130.202	61.7486
47	-11.5435	-.834019	6.10513	111.502	67.762
48	81.5735	3.07053	7.83109	76.3719	70.2056
49	197.801	-.215446	2.72116	110.164	67.3987
50	76.5603	-4.78202	1.54851	157.822	69.5923

```
(1) irfname = vec1, impulse = lall_gas, and response = lHEV
(2) irfname = vec1, impulse = lall_gas, and response = lmiles_travelled
(3) irfname = vec1, impulse = lall_gas, and response = lTRANSIT
(4) irfname = vec1, impulse = lall_gas, and response = lall_gas
(5) irfname = vec1, impulse = lall_gas, and response = lcar_sales
```