Long-Run Relationship among Transport Demand, Income, and Gasoline Price for the US

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ABSTRACT
Energy used in transport is a particularly important focus for environment-development studies because it is increasing in both developed and developing countries and is largely carbon-intensive. This paper examines whether a systemic, mutually causal, cointegrated relationship exists among mobility demand, gasoline price, income, and vehicle ownership using US data from 1946 to 2006. We find that those variables co-evolve in a transport system; and thus, they cannot be easily disentangled in the short-run. However, estimating a long-run relationship for motor fuel use per capita was difficult because of the efficacy of the CAFE standards to influence fleet fuel economy. The analysis shows that the fuel standards program was effective in improving the fuel economy of the US vehicle fleet and in temporarily lessening the impact on fuel use of increased mobility demand. Among the policy implications are a role for efficiency standards, a limited impact for fuel tax, and the necessity of using a number of levers simultaneously to influence transport systems.

Keywords: Transport demand; Energy consumption and development; Cointegration; Granger-causality; CAFE program.

1. Introduction
Energy used in transport is a particularly important focus for environment-development studies since transport energy use is increasing in both developed and developing countries and is a carbon-intensive activity everywhere. Furthermore, understanding the long-run relationship among transport demand/energy use, income, and fuel price in developed countries is important to project with any accuracy global transport fuel use and carbon emissions. Figure 1 shows that vehicle-miles per capita has increased linearly with GDP per capita in the US since 1946. Income could affect car ownership rates too, which in turn could impact vehicle-miles per capita, as gasoline price could impact miles traveled. In addition, over the long-run economic development is intertwined with spatial development, and spatial development/intensity also influences travel demand. This paper analyzes the relationship among two measures of transport demand and related variables over the long run in the US. It examines whether a systemic, cointegrated relationship exists among vehicle miles, motor fuel use, gasoline price, income, and vehicle ownership.

Figure 1

The historic correlation between energy consumption and economic growth, coupled with concerns over energy consumption's environmental costs (e.g., carbon emissions) and security issues (e.g., foreign supply dependence and nuclear technology proliferation), has drawn considerable attention to the relationship between energy and development. Some of the work dealing with this relationship has used statistical techniques from Granger (1980) to reveal the causal direction (Granger-causality) of the energy consumption-economic growth relationship. Taken as a whole, however, the literature on temporal causality between energy consumption and economic growth has offered neither robust results nor convincing rationale.

For example, in the seminal study on the US, Kraft and Kraft (1978) found causality running from GNP to energy consumption for the US over the period 1947-1974. Subsequently, while Akarca and Long (1980) shortened the Kraft and Kraft period by two years, and Yu and Hwang (1984) lengthened it by four years, neither later study detected evidence of causality. Stern (1993) used a quality-adjusted index of energy, considered capital and labor inputs too, and found energy consumption causes GDP for the US. Up-dating that study, Stern (2000) found cointegration among those variables and again determined that energy causes GDP.

One reason for the lack of conclusive results may be the high level of aggregation of the data analyzed. When considering energy consumption and GDP, it is not at all clear in what direction causality should occur, or how it might evolve temporally. Energy is an input in industrial production; however, in developed countries industry commands a declining share of GDP. Furthermore, a considerable and growing amount of energy consumption in developed countries is for personal transport and use in homes—activities that are "consumptive" in nature, and thus, would be expected to increase with wealth.

Previously, Liddle (2006) evaluated the link between GDP and energy for a number of OECD countries, using levels of disaggregation of GDP and energy consumption where causation between GDP and energy consumption could be predicted a priori. For example, industry energy consumption – production input – was expected to cause industry GDP, while GDP per capita, or income, was expected to cause per capita energy use in transport and residential buildings – normal consumption goods. The surprising result of the work reported in that paper was that GDP and energy are not strongly linked in most of the countries studied.

The current paper expands that earlier work in two important ways. First, focusing on transport in the US allows for the consideration of much longer data sets (60 years) than previous work (typically only 30-40 years). Not having sufficiently long series is a well-known source of spurious results in these types of time series analyses. Second, this paper also considers price and is a multivariate analysis. Considering additional variables improves the stability and accuracy of cointegration and Granger-causality testing.

Although the purpose here is to investigate the possibility of a systemic, i.e., mutually causal, long-run relationship for transport, the cointegration technique and the type of data series used allow for estimates of price and income elasticities; thus, a brief review of this related and extensive literature follows. Dahl and Sterner (1991) contributed a survey of many estimates of transport elasticities. Graham and Glaister (2002) provided an update; but of the studies they cited, only four involved cointegration,[1] and none focused on the US. Likewise, the few studies since that review that employ conintegration have focused on countries other than the US, e.g., Brazil (Alves and Bueno, 2003), Greece (Polemis, 2006), Namibia (De Vita et al., 2006), and South Africa (Akinboade et al., 2008). Furthermore, only one previous cointegration analysis estimated a genuine long-run relationship: Bentzen (1994) considered Denmark using data spanning from 1948 to 1991.

2. Data and methods

Annual data, converted to natural logs,[2] ranging from 1946 to 2006 are used. The analysis begins after the Second World War since many economic series have structural breaks in the period between the two World Wars (Ben-David et al., 2003). The series are: real GDP per capita, from Johnston and Williamson (2008); vehicle-miles per capita, motor fuel use per capita, and number of registered vehicles per capita, all from the US Department of Transportation, Federal Highway Administration's Highway Statistics; and real retail gasoline price, from US Department of Energy, Energy Information Agency. Population data (to convert measures to per capita) is from the US Census Bureau. Table 1 lists the names, definitions, and sources of the data series used.

As noted, spatial intensity influences transport demand; however, since the area of the US has remained constant over the period studied (albeit, US territories Alaska and Hawaii became states in 1959), population density simply increases with increases in population, and thus, is not an appropriate variable for a time series study like this one.[3] A better measure than population density would be population per acre of developed land, a statistic the Natural Resources Conservation Service (NRCS) keeps in its National Resources Inventory;[4] unfortunately they only began recording the statistic in 1982, and then only at four-to-five-year intervals until 2001; thus, it is inappropriate for cointegration.

Table 1

The first step is to test for unit roots in each series since all variables in a Johansen cointegration test should be of the same order. It is expected, that these series (all of which contain noticeable trends) will be nonstationary in levels, but stationary in first differences. The Elliott, Rothenberg, and Stock (1996) Dickey-Fuller test with GLS detrending is used to test for unit roots. This test is appropriate for highly trending data; furthermore, Maddala and Kim (2000) argued that tests with GLS detrending are more powerful than the (often used) Augmented Dickey-Fuller test. Unit root tests allow for either a constant or a constant and a linear time trend in the test regression. The power of unit root tests is sensitive to the number of lagged terms used. To choose the optimal number of lags, Hall's (1994) "general

[1] As Graham and Glaister note, there is debate in the gasoline elasticity research as to the importance of applying methodologies like cointegration to time-series data. Work employing cointegration often states that the lower price elasticities estimated derive from a more appropriate treatment of the non-stationary nature of time-series data.

[2] Among the reasons economic data are often converted to natural logs are that doing so for a log-linear model means the estimated coefficients are elasticities, and for a logged and differenced model all variables are transformed into percentage changes.

[3] As Liddle (2004) showed, population density can be used to represent alternatives to public transport across countries, rather than over time.

[4] Data can be accessed from http://www.nrcs.usda.gov/technical/NRI/.

to specific rule" is employed, where one starts with a maximum number of lags, tests the significance of coefficient on the last lagged term, and reduces the number of lags iteratively until a significant statistic is encountered.

Engle and Granger (1987) point out that a linear combination of two or more nonstationary series may be stationary. If such a stationary linear combination exists, the nonstationary time series are said to be cointegrated. The stationary linear combination is called the cointegrating equation and may be interpreted as a long-run equilibrium relationship among the variables. Evidence of cointegration among variables confirms the presence of Granger-causality as well as rules out the possibility that the estimated relationships are spurious; however, cointegration does not indicate the direction of causality between pairs of variables.

The Johansen (1988) test for multivariate cointegration is used. That test produces two statistics (the trace and maximum eigenvalue statistics), which can conflict –although they do not in the results presented here. To determine the number of cointegrating equations, r, one proceeds sequentially from $r = 0$ to $r = k - 1$, where k is the number of endogenous variables, until one fails to reject. Those two (trace and max-eigenvalue) test statistics are reported for each null hypothesis of r cointegrating equations against the alternative of k cointegrating equations, for r = 0, 1,…, k - 1. Besides determining the number of cointegrating equations, one can impose restrictions on both the estimated cointegration coefficients and the adjustment coefficients. Two of the most common restrictions to impose are, for a particular variable, setting the associated cointegration coefficients to zero (to test if that variable can be excluded from the cointegration space) and setting the associated adjustment coefficients to zero (to test if that variable is weakly exogenous with respect to the cointegration parameters).

If two or more variables are cointegrated, then the relationship between or among the variables can be modeled using vector error correction modeling (VECM), and statistical tests on the individual equations in the VECM can be used to reveal the direction of Granger-causality between pairs of variables. In general a VECM for three[5] cointegrated variables looks like:

$$\Delta x_t = \alpha_1 + \sum_{i=1}^{l} \beta_{1i} \Delta x_{t-i} + \sum_{i=1}^{l} \gamma_{1i} \Delta y_{t-i} + \sum_{i=1}^{l} \delta_{1i} \Delta z_{t-1} + \eta_1 ECT_{t-1} + u_{1t} \tag{1}$$

$$\Delta y_t = \alpha_2 + \sum_{i=1}^{l} \beta_{2i} \Delta x_{t-i} + \sum_{i=1}^{l} \gamma_{2i} \Delta y_{t-i} + \sum_{i=1}^{l} \delta_{2i} \Delta z_{t-1} + \eta_2 ECT_{t-1} + u_{2t} \tag{2}$$

$$\Delta z_t = \alpha_3 + \sum_{i=1}^{l} \beta_{3i} \Delta x_{t-i} + \sum_{i=1}^{l} \gamma_{3i} \Delta y_{t-i} + \sum_{i=1}^{l} \delta_{3i} \Delta z_{t-1} + \eta_3 ECT_{t-1} + u_{3t} \tag{3}$$

where x, y, and z are the variables, Δ is the difference operator, ECT refers to the error-correction terms derived from the long-run cointegrating relationship, and l is the number of lagged difference terms determined in the cointegrating relationship. The ECT terms allow for an additional channel for Granger-causality to emerge, namely a long-run equilibrium relationship that is not treated in the standard Granger test (that is used when cointegration is not found).

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[5] For a system of four cointegrated variables, the VECM would have four equations.

For example, Equation 1 is used to test causation from y and z to x. Short-run causality is tested with an F-test on the sum of the lags of an explanatory variable (e.g., an F-test on the γ s to test y's influence). Long-run causality is tested by a T-test on the ECT term (η_1). This second test is equivalent to restricting the adjustment parameters associated with a variable to zero, and thus, the finding of non-significance of an ECT term is interpreted as the associated variable being weakly exogenous with respect to the long-run parameters. Lastly, a joint test on the significance of the lags of an explanatory variable and the ECT term determines Granger exogeneity or endogeneity of a dependent variable. The finding of nonsignificance implies exogeneity, which prompts a further joint test on all the explanatory variables and on the ECT term simultaneously, i.e., a test for strong Granger exogeneity. Thus, depending on the outcome of these tests, a variable can range from long-run strong Granger-endogeneity to strong exogeneity; and a relationship pair can exhibit short-run Granger- unidirectional or bi-directional causality, or noncausality.

3. Vehicle-miles

Gasoline price could affect vehicle-miles by encouraging switching travel modes or traveling less in general. One would expect as vehicles per capita increased, miles traveled per capita would also increase because, for example, a two-car household is likely to lodge more miles per member than a one-car household. The strong positive relationship between vehicle-miles per capita and income was already displayed in Figure 1. These variables may be inter-related, e.g., vehicle registrations per capita is likely also a function of income, and those possible inter-relationships, besides addressing the time series properties of the data, makes using the cointegration approach particularly appropriate.

The results of the unit root tests appear in Table 2. Assumptions about the presence of a constant or a trend in unit root tests sometimes lead to inconsistent results. However, it is expected all of these series to be of order I (1), i.e., stationary in first differences but not in levels; thus, the results reported in Table 2 are unconvincing evidence to reject the prior belief that all of these series are I (1).

Table 2

Table 3 shows the results of the Johansen cointegration test among vehicle-miles per capita, gasoline price, income, and vehicles per capita. The optimal lag length of four for the cointegration test was selected by the consensus of five information criteria.[6] Yet, both the finding of cointegration and the number of cointegrating equations are not overly sensitive to the selection of lag length.

Because all of the series are trending, a constant is included in the cointegration space. Some of the transport elasticity studies using cointegration (Bentzen, 1994; Polemis, 2006) include a time trend in the cointegration space to account for technical change; this is not done for three reasons: first, GDP per capita is a more accurate measure of technical change than a simple linear trend (indeed, according to the economic growth literature technical change is a primary cause of GDP growth); second, while automakers probably have had the capacity to improve fuel economy as technology has advanced, over the majority of the time-period analyzed, they have chosen to focus technological advances on

[6] Those information criteria are: sequential modified likelihood ratio test statistic, final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion.

enhancing performance characteristics; and third, having a trend in the cointegration equations implies or assumes that some of the series are trend stationary, an assumption I am not prepared to make. However, as with the lag specification, the findings of cointegration and the number of cointegrating equations are not sensitive to the time trend inclusion decision.

Table 3

Both the trace and max eigenvalue test statistics indicate one cointegrating equation at the 1% significance level (only the null hypothesis of zero cointegrating relationships is rejected). This finding of cointegration confirms a long-run, systemic relationship among price, income, mobility demand, and vehicle ownership in the US.

Table 4 presents the coefficients of the cointegrating equation as well as the test statistics for exclusion from the cointegration space and for weak exogeneity for each of the variables. The equation is normalized to vehicle-miles, and the signs of the coefficients are displayed in the table as they would appear on the left-hand side of the equation. Thus, the direction of the relationships between vehicle-miles and the other variables are as expected. Among the most important results are all variables enter the cointegrating vector statistically significantly – none of the four variables can be excluded from the cointegration space; and only price can be considered weakly exogenous. These findings suggest mutual causality among the variables.

Table 4

The top panel of Table 5 shows the causality results for short-run dynamics (the four dependent variables, corresponding to the four equations in the VECM, head the columns). Vehicle-miles per capita are caused by income as expected; however, gasoline price and vehicles per capita do not have a causal impact on vehicle-miles in the short-run. GDP per capita is caused by gasoline price, which is not surprising since gasoline price is highly correlated with oil price and since others (Stern, 1993; 2000) have found that energy has a causal impact on GDP in the US. Finally, the number of vehicles per capita is caused by gasoline price and vehicle-miles, but not by income. The most surprising results are that vehicles per capita do not Granger-cause vehicle-miles, and that income does not Granger-cause vehicles per capita. However, these results only test for short-run causality, and as the other panels in Table 5 show, there is long-run Granger-causality among those variables. The fact that vehicle-miles per capita was found to Granger-cause vehicles per capita, however, reflects that the vehicle-miles variable is a proxy for mobility demand – i.e., as the demand for personal mobility increases, one would expect people to own more cars. One might expect mutual causality between vehicle-miles and income, and expect causality running from vehicles per capita to income; since some of the vehicle-miles include the trucking of goods, and since the US has a domestic car industry, the trucking of goods and purchase of more vehicles would feed GDP. This is indeed the case if the Wald-test for joint significance is used instead of the F-test, as both vehicle-miles per capita and vehicles per capita enter statistically significantly (both at the 5% level) in the GDP per capita equation. Those are the only two coefficients in Table 5 whose statistical significance is materially sensitive to the choice of joint test.

Table 5

The middle panel, long-run causality or weak exogenity test, confirms the earlier result (reported in Table 4) that only price is weakly exogenous. Finally, and most importantly, the last panel in Table 5 shows the joint test or Granger endogeneity test. For all equations, except for price, the results imply the Granger endogeneity of all variables. For price the results imply exogeneity, and indeed, a joint significance test on all the explanatory variables in the price equation (to conserve space result not shown) indicates that price is strongly Granger/econometrically exogenous. This last result is not surprising since gasoline is an internationally traded commodity, and since tax on gasoline is relatively low in the US (running between 10-30% of pump price); thus, gasoline price would not be determined by US demand factors alone.

4. Motor fuel use

Estimating a long-run relationship for motor fuel use per capita in the US is problematic because of the certain, significant impact the Corporate Average Fuel Economy (CAFE) standards have had on overall fleet fuel economy. Fleet fuel economy is a potentially important impact factor on fuel use, but a factor whose impact has been fairly constant in periods when the CAFE standards either did not exist or went unchanged.

In 1975 the US Congress established the CAFE program, which set standards for the sales-weighted average fuel economy of the passenger car and light-duty truck fleets sold in the US. The standard for passenger cars rose from 18 miles per gallon (mpg) in automobile model year (MY) 1978 to 27.5 mpg in MY 1985, where it remains today; the current standard for light trucks is 22.2 mpg.[7] According to the National Highway Traffic Safety Administration, overall fuel economy for cars and light trucks in the US peaked in 1987 at 26.3 mpg; by 2004 that average had fallen slightly to 24.6 mpg. During those intervening years, vehicles increased in size from an average of 3,220 pounds to 4,066 pounds (in part because the share of truck ownership nearly doubled).

Figure 2 shows the real retail gasoline price and the realized fuel economy of passenger cars, i.e., actual miles traveled divided by fuel consumption, along with the CAFE standards for passenger cars over 1946-2006. With the exception of the recent increase in gasoline prices (which are *demand*-driven and very well may be sustained), the primary experience of real gasoline prices in the US is one of decline, with a couple of short-lived, *supply*-driven spikes around the OPEC oil embargo (1973) and the Iranian revolution (1979) and beginning of the Iran-Iraq war (1980-1981). Figure 2 indicates a relatively weak relationship between gasoline price and fuel economy; indeed, the correlation coefficient for the whole period is -0.46, implying that as price increases, fuel economy *decreases*. However, since the recent increase in gasoline prices beginning in 2002, price and fuel economy are positively related with a correlation coefficient of 0.47. On the other hand, the relationship between the CAFE standards and fuel economy appears strong, with fuel economy lagging the standards slightly; indeed, the two curves look more or less parallel.

Figure 2

There are several reasons why actual fuel economy is below the standard: the standard is sales-weighted and based on estimates of fuel economy achieved under idealized conditions; whereas, the realized fuel economy is miles traveled-weighted (e.g., it includes cars made before CAFE or under lower standards and may reflect lower-gas

[7] A law signed in mid-2007 requires that automakers raise fleetwide gas mileage to 35 mpg by 2020.

mileage cars being driven further), and reflects the conditions under which, and the ways in which, people actually drive (e.g., congestion, driving over speed limits).

Table 6 shows the results of subjecting the natural log of realized passenger car fuel economy to a simple linear trend model (i.e., regressed on a constant and a time trend) over three regimes: a period before CAFE standards existed, 1946-1976; the period of influence for CAFE, say 1977-1991 (MY 1978 vehicles first appeared in 1977, and although the standards ceased to increase after 1985,[8] the CAFE program would continue to influence overall fleet fuel economy as the pre-CAFE vehicles are gradually retired[9]); and the current period of constant fuel economy standards, 1992-2006. In the period before CAFE standards (pre-MY 1978), realized fuel economy actually declined at a rate of 0.3% per annum (p.a.), despite obvious technological improvements throughout the economy. Whereas, from 1977-1991, realized fuel economy increased by about 2.6% p.a., and since 1992 has increased at the more modest rate of 0.6% p.a. The R-squared values imply a fairly strong fit for the linear-trend model over those three periods. In addition, this analysis suggests that, at least for the US, using a time trend to account for fuel efficiency improvements leads to a misspecification; although technology may increase nearly linearly, technology improvements are not necessarily channeled into fuel efficiency.

Table 6

A similar pattern—of technology contributing little to fuel economy, then being focused on fuel economy improvement, and again being channelled to areas other than fuel economy—is indeed what a National Research Council (2002) report found. From the period 1978, when CAFE standards were first introduced, through 1985, when they were last increased, the report determined that auto manufacturers channelled technological improvements—in engines, drive trains, and vehicle aerodynamics—toward improved fuel efficiency since fuel economy increased by 62% without any loss in 0-60 mph acceleration times. However, since 1985 technology improvements have been concentrated on performance since fuel economy of new vehicles has stayed essentially the same while vehicles have become 20% heavier and acceleration times 25% faster.

To investigate the existence of a structural break in the motor fuel use per capita series, I adopt the Zivot and Andrews (1992) unit root test that allows for a single unknown break in intercept and trend. The Zivot-Andrews endogenous structural break test is a sequential test that assigns a dummy variable for each possible break date. The break date is selected where the t-statistic from the Augmented Dickey-Fuller test of unit root is at a minimum (most negative), and thus where the evidence is least favorable for the unit root null. To improve the accuracy of the test, all available data are used (Table 7).

Table 7

The Zivot-Andrews test finds evidence that a statistically significant break in the motor fuel use per capita series at the 1% level occurred in 1979 – about the time the CAFE

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[8] The standard was actually revised down to 26.0 mpg for MYs 1986-1988, increased to 26.5 mpg for MY 1989, and then returned to 27.5 mpg for MY 1990.

[9] According to data on the average fuel economy of new cars for 1975 to 1993 from Murrell et al. (1993), the largest percentage improvement in occurred between 1975 and 1980, when new car fuel economy increased by 40% (between 1980 and 1993, new car fuel economy increased by only 17.5%). Furthermore, the expected lifetime of a car manufactured in 1980 was about 12 years (Davis, 1997), so by 1992 nearly all the pre-1980 cars would have been replaced.

standards came into effect. None of the other series used here had statistically significant breaks between 1946 and 2006.[10] Because a statistically significant break was found in the period of analysis, the test is repeated on the motor fuel use per capita series for 1980 to 2006,[11] and again a statistically significant break is calculated: in 1990 – a time when the unchanged CAFE standards' influence would begin to wane (last row of Table 7).

Because of the breaks in the motor fuel use per capita series in 1979 and 1990, and the influence of CAFE standards, the analysis of motor fuel use is separated by periods: 1946-1977, 1978-1990, and 1991-2006. The 1978 start date for the second is a compromise between 1977 used in Table 6, and associated with the initial implementation of CAFE, and the first statistically significant break in 1979 in the motor fuel use per capita series. Because these periods may be too short to accurately estimate cointegration, and because 1991-2006 does not constitute a long-run, standard OLS is used to estimate a relationship (the Newey-West method is used to control for heteroskedasticity and autocorrelation). Since cointegration and VECM are not used to treat the potential nonstationarity in the data, a first difference model is used to ensure all series are stationary. The logged and differenced model means the estimated coefficients are constants of proportionality between percentage changes in the right hand side variables and motor fuel use per capita, rather than elasticities.

During periods when fuel efficiency was unchanged or changing slowly, one would expect fuel consumption per capita to be closely related to miles driven per capita. Indeed, a 1% increase in travel should increase fuel consumption by close to 1%. Even if increases in gasoline price alone are unlikely to encourage the manufacture or purchase of more fuel efficient cars, price may still influence the way people drive, and thus, fuel efficiency and consumption. For example, higher gasoline prices may encourage smoother acceleration and deceleration, lower speeds, and in two-car households, the use of the most fuel efficient vehicle. Per capita GDP is included because income growth should temper the impact on the budget constraint from price growth (or perhaps, exacerbate it in the period around the oil "shocks" when income may fall).

The first three panels of Table 8 show results for the logged-difference model of motor fuel use per capita over the three periods. For the first and third sample periods the coefficient for vehicle-miles is significant, considerably larger than the other coefficients, and near (but, at least for the first period, statistically different from) unity. For the pre-CAFE sample period as well as the third period, the coefficients for price and per capita GDP have the expected signs, but are marginally significant to insignificant at conventional levels. For the first two sample periods, the Durbin-Watson statistic is just outside the accept range (upper bound is 2.35), in the inconclusive zone; for the third sample period that statistic is in the middle of the inconclusive zone; however, the LM test rejects serial correlation for all three sample periods.[12]

Table 8

[10] A statistically significant break in GDP per capita in 1939 for the US is a date similar to that found by Ben-David et al. (2003), who specifically searched for breaks in GDP series for a number of countries.

[11] Running the Zivot-Andrews test on motor fuel use per capita for 1919 to 1978, yields a break (at the 10% level) in 1929.

[12] The Breusch-Godfrey LM test rejected higher order serial correlation as well for all three samples (these results are not shown).

The fourth panel shows the results of a Chow breakpoint test for two breaks in 1978 and 1991. That test provides further evidence that the model is different over the three periods, and that the CAFE program did indeed influence fuel consumption through its impact on fleet fuel economy. Furthermore, the coefficient for price declines in absolute value in each period, suggesting a declining influence of price on fuel consumption. The coefficient for vehicle-miles in the middle period is nearly half its value in the first and third periods, suggesting that CAFE standards helped to decouple somewhat miles traveled and fuel consumption. Table 9 shows the results of difference of means tests on the coefficients of gasoline price and vehicle-miles for the three pairs of the periods.

Table 9

The decline in gasoline price's coefficient is not statistically significant for each period pair (e.g., between the first and second), but is statistically significantly different between the two most recent periods (i.e., between 1978-1990 and 1991-2006). That result is similar to Hughes et al. (2008), who found that the short-run price elasticity of gasoline demand is considerably more inelastic today than in pervious decades, estimating (from monthly data) that it fell from a range of -0.21 to -0.34 over 1975 to 1980 to a range of -0.034 to -0.077 over 2001 to 2006. Lastly, Table 9 shows the coefficient for vehicle-miles was indeed significantly lower during the period of greatest CAFE influence (i.e., 1978-1990).

5. Conclusions and policy implications

The analysis here showed that in the US mobility demand has a long-run systemic, mutually causal relationship with gasoline price, income, and vehicle ownership. Since these variables co-evolve in a transport system, they cannot be easily disentangled in the short-run. However, estimating a long-run relationship for motor fuel use per capita is difficult because of the combination of the efficacy of the CAFE standards to influence fleet fuel economy and the short period for which those standards existed and were increased. The data used shows that before the fuel economy standards were introduced and in the current period when they were kept constant, overall fleet fuel economy was either stable or increasing only slightly despite substantial improvements in technology; furthermore, during those periods of either no or unchanging standards, the growth of motor fuel use per capita was highly dependent on the growth of mobility demand.

These findings have a number of potential implications for policy. First, the fuel standards program was effective both in improving the fuel economy of the US vehicle fleet and in temporarily lessening mobility demand's impact on fuel use. Second, higher gasoline taxes are likely to have a limited impact on mobility and fuel demand. Gasoline price did not have a significant short-run causal impact on vehicle-miles. Also, fuel price had a negative coefficient in the fuel use regressions, but was only marginally significant in two of the three periods, and that coefficient declined in each subsequent period (although that decline was not always statistically different at standard levels). The finding of a declining influence of gasoline price on motor fuel use is supported by Hughes et al. (2008) who found that the short-run price elasticity of gasoline demand is considerably more inelastic now than in the 1970s.

Although gasoline price did have a short-run impact on vehicles per capita, the decision whether to purchase a vehicle is different from the decision of which type of vehicle to purchase. Indeed, gasoline costs' influence on that second kind of decision is small and declining. The American Automobile Association (various years) estimated that the gasoline cost of operating a vehicle for 15,000 miles per year increased 50% in real terms from 1985 to 2006; however, the fixed ownership costs (insurance, license, registration, taxes, depreciation, and finance charges) more than doubled over that time, causing the share of gasoline costs to drop from 24 to 17%.

Finally, lowering or even stabilizing vehicle-miles per capita in the US will require a combination of policies. The empirical evidence that mobility demand, fuel price, and economic growth are part of a mutually causal system reported here is in concert with the latest urban planning research (Ewing et. al., 2007); that research concluded that urban development through its relationship with vehicle travel "… is both a key contributor to climate change and an essential factor in combating it." In other words, creating urban development that lowers the need for personal motorized transport is crucial to lowering fuel use. For example, according to the NRCS, the population per acre of developed land declined by 17% from 1982 to 1997; hence, sprawl increased. Yet, Polzin and Chu (2005) reported that survey data shows the share of people using public transit to get to work fell steadily from 1970 to 1995.

More specifically, in countries with developed, vehicle-intensive transport systems, like the US, a combination of policies would mean higher standards for vehicle efficiency, higher gasoline taxes, and other incentives for more public transit-friendly urban development to take advantage of as many policy levers as possible. Large, economically growing countries still developing their transport systems, like China and India, would be wise to develop a system of prices, technology, and mobility options that help them avoid the difficult choice that the US faces.

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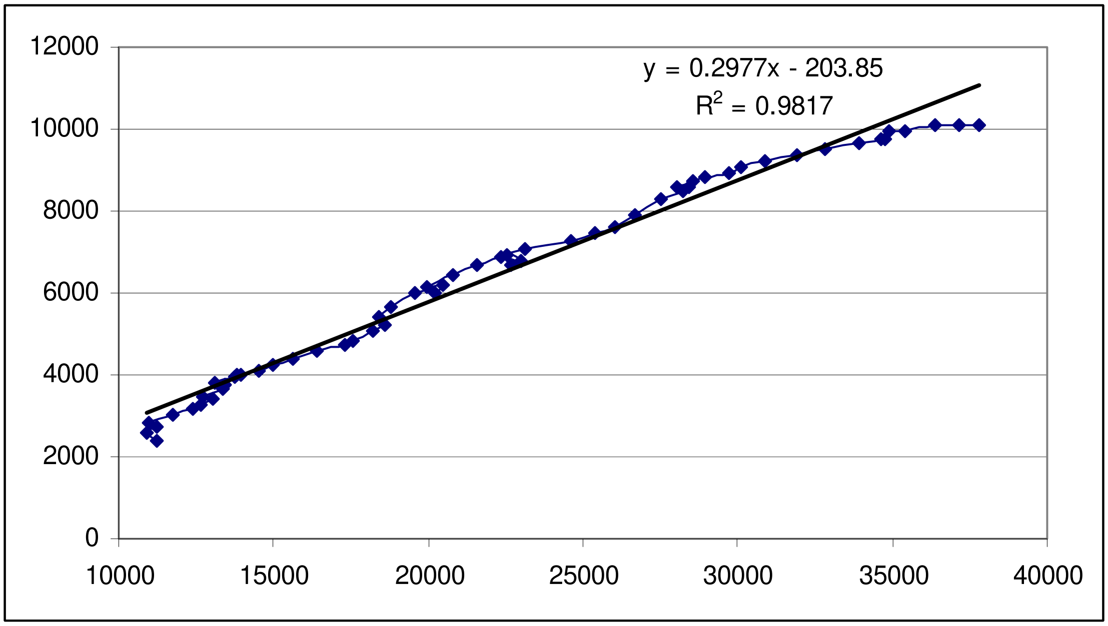
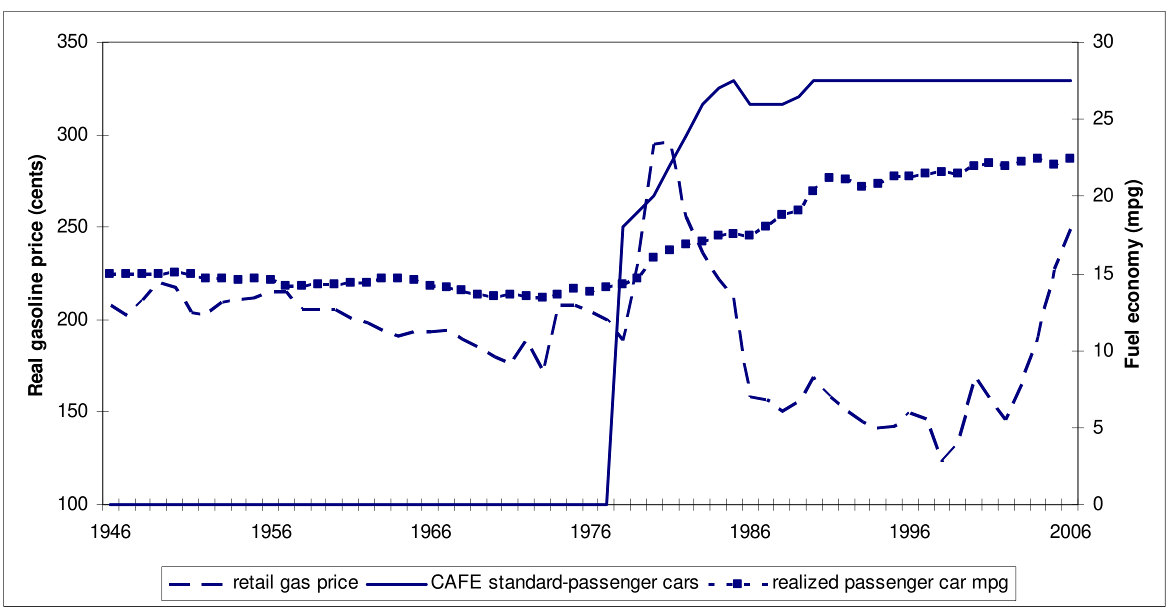


Sources: GDP data are from Johnston and Williamson (2008). Travel data are from the Federal Highway Administration.

Figure 1. Vehicle-miles per capita and real GDP per capita (in 2000 US$), 1946-2006.



Sources: Energy Information Agency, Federal Highway Administration, and National Highway Traffic Safety Administration.

Figure 2. Real gasoline price (per gallon), realized fuel economy for passenger cars, and CAFE standards for passenger cars, 1946-2006.

Table 1. Variable definitions and data sources.

Variable	Definition	Source
LGDP	Natural log real GDP per capita	Johnston and Williamson (2008) http://www.measuringworth.org/usgdp/#
LPRICE	Natural log real retail gasoline price	Energy Information Agency http://www.eia.doe.gov/emeu/steo/pub/fsheets/PetroleumPrices_files/frame.htm
LMFU	Natural log motor fuel use per capita	Federal Highway Administration http://www.fhwa.dot.gov/policy/ohpi/hss/hsspubs.htm
LVMT	Natural log vehicle-miles per capita	Federal Highway Administration http://www.fhwa.dot.gov/policy/ohpi/hss/hsspubs.htm
LREG	Natural log of the number of registered vehicles per capita	Federal Highway Administration http://www.fhwa.dot.gov/policy/ohpi/hss/hsspubs.htm

Table 2. Unit root tests on levels and first differences of GDP per capita, gasoline prices, motor fuel use per capita, vehicle-miles per capita, and registered vehicles per capita using Dickey-Fuller with GLS detrending.

	Levels		First differences	
	Trend & constant	Constant	Trend & constant	Constant
LGDP	-3.20 [4]**	1.68 [1]	-3.58 [0]**	-2.16 [0]**
LPRICE	-2.76 [5]	-2.03 [1]**	-6.25 [0]*	-5.86 [0]*
LMFU	-1.55 [5]	-0.34 [5]	-4.05 [4]*	-2.02 [1]**
LVMT	-3.31 [5]**	-0.24[5]	-4.35[5]*	-3.55[5]*
LREG	-1.46 [5]	-0.32 [5]	-6.76 [3]*	-1.51 [4]

Notes: The Elliott-Rothenberg-Stock DF-GLS test statistic is shown. The numbers in brackets are the optimal lags determined by the general to specific procedure. Levels of significance are indicated by * and **, referring to the 1% and 5% levels.

Table 3. Johansen cointegration test for vehicle-miles per capita, fuel prices, GDP per capita, and vehicles per capita, 1946-2006 (adjustments for four lags).

Null	Alternative	Statistic	5 % Critical value
Trace statistic			
r = 0	r > 0	178.67*	47.86
r <= 1	r > 1	18.09	29.80
r <= 2	r > 2	2.88	15.49
r <= 3	r = 3	0.14	3.84
Maximum eigenvalues			
r = 0	r > 0	160.58*	27.58
r <= 1	r > 1	15.21	21.13
r <= 2	r > 2	2.74	14.26
r <= 3	r = 3	0.14	3.84

Notes: r Indicates the number of cointegrating relationships. * Indicates rejection of the null hypothesis of no cointegration at the 1% level.

Table 4. Cointegrating equation and test statistics for vehicle-miles per capita, fuel prices, GDP per capita, and vehicles per capita, 1946-2006 (adjustments for four lags).

	LVMT	*LPRICE*	*LGDP*	*LREG*	*Constant*
Cointegrating vector	1.00	0.18	-0.46	-0.62	-4.56
(t-stats)		(14.7)	(-24.6)	(-36.7)	
χ^2-test statistic for exclusion from cointegration space	123.6*	65.6*	123.5*	88.6*	
χ^2-test statistic for weak exogeneity	74.8*	0.02	31.7*	11.3*	
Adjustment coefficients	-0.72	-0.04	0.52	-0.18	
(t-stats)	(-10.2)	(-0.1)	(5.4)	(3.0)	

Notes: * Indicates rejection of the null hypothesis at the 1% level. Coefficients of the cointegrating equation are shown as they would appear on the left-hand-side of the equation.

Table 5. Short and long run pair-wise Granger-causality and weak and strong exogeneity tests results based on the vector error correction model.

Dependent variable	$\Delta LVMT$	$\Delta LPRICE$	$\Delta LGDP$	$\Delta LREG$
Short-run causality (F-statistics)				
$\Delta LVMT$	—	0.79	1.76[a]	2.11***
$\Delta LPRICE$	0.98	—	4.38*	2.75**
$\Delta LGDP$	4.86*	0.55	—	0.36
$\Delta LREG$	0.86	0.60	1.93[b]	—
Long-run causality or weak exogeneity (T-statistics)				
ECT	-10.21*	-0.10	5.42*	-2.97*
Granger endogeneity (joint test on short-run causality and ECT, F-statistics)				
$\Delta LVMT$	—	0.76	5.98*	6.73*
$\Delta LPRICE$	25.85*	—	6.89*	4.62*
$\Delta LGDP$	25.78*	0.48	—	2.45**
$\Delta LREG$	30.59*	0.49	6.97*	—

Notes: Levels of significance are indicated by *, **, and ***, referring to the 1%, 5%, and 10% levels, respectively. If the Wald χ^2 test for joint significance is used, then the statistical significance of two coefficients change. The coefficient superscripted *a* becomes 9.26 and is significant at the 5 % level, and that superscripted *b* becomes 10.1 and is significant at the 5 % level.

Table 6. A time-trend model for the natural log of realized passenger car fuel economy over three regimes of CAFE influence.

Time period	Intercept	Trend	Adjusted R^2
1946-1976	2.80*	-0.0034*	0.79
1977-1991	1.15*	0.026*	0.94
1992-2006	2.62*	0.0057*	0.88

Note: * denotes statistical significance at the 1% level.

Table 7. Zivot-Andrews endogenous test for structural break in intercept and trend.

Series	Observations	Break-date	T-statistic
LMFU	1919-2006	1979	-6.44*
LVMT	1936-2006	1954	-3.89
LPRICE	1919-2006	1991	-3.41
LGDP	1919-2006	1939	-7.20*
LREG	1940-2006	1955	-4.46
LMFU	1980-2006	1990	-5.63*

Note: * statistical significance at the 1% level.

Table 8. Logged-difference model of motor fuel use per capita before, during, and after CAFE standards' greatest impact on fuel economy.

	Coefficient	Std. Error	Prob.
	Sample: 1946-1977		
Constant	-0.0032	0.0060	0.60
Δ (LPRICE)	-0.11	0.068	0.11
Δ (LVMT)	0.86	0.051	0.00
Δ (LGDP)	0.19	0.11	0.092
Adj. R-squared 0.81		Durbin-Watson stat. 2.40	
Breusch-Godfrey LM test stat.		1.60 (0.21)	
	Sample: 1978-1990		
Constant	-0.026	0.0023	0.00
Δ (LPRICE)	-0.082	0.016	0.00
Δ (LVMT)	0.46	0.12	0.00
Δ (LGDP)	0.59	0.15	0.00
Adj. R-squared 0.92		Durbin-Watson stat. 2.38	
Breusch-Godfrey LM test stat.		0.94 (0.33)	
	Sample: 1991-2006		
Constant	-0.0010	0.0058	0.11
Δ (LPRICE)	-0.026	0.017	0.16
Δ (LVMT)	0.88	0.20	0.00
Δ (LGDP)	0.46	0.26	0.10
Adj. R-squared 0.66		Durbin-Watson stat. 1.38	
Breusch-Godfrey LM test stat.		0.80 (0.37)	
Chow Breakpoint test with two breaks in 1978 & 1991			
F-statistic	2.54**	LR-statistic	21.19*

Notes: Δ is the difference operator. Dependent variable is Δ (LMFU). The probability associated with the LM test statistic is in parentheses. Levels of significance for the Chow test are indicated by * and **, referring to the 1% and 5%, levels, respectively.

Table 9. Difference of means tests between the three periods for the gasoline price and vehicle-miles coefficients.

Periods compared	Test statistic [a]	Probability
	LPRICE	
1946-1977 & 1978-1990	-0.40	0.69
1978-1990 & 1991-2006	-2.40	0.024
1946-1977 & 1991-2006	-1.20	0.24
	LVMT	
1946-1977 & 1978-1990	3.07	0.00
1978-1990 & 1991-2006	-1.80	0.083
1946-1977 & 1991-2006	-0.10	0.92

a: $t_c = \dfrac{\beta_1 - \beta_2}{\sqrt{(SE_1)^2 + (SE_2)^2}}$, where subscripts refer to two time periods, β to the estimated coefficients, and *SE* to the estimated standard errors.