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Abstract

This paper proposes a dynamic carbon tax (DCT) that stabilises gasoline prices by adjusting inversely to crude oil prices. Compared to a standard fixed-rate carbon tax, the DCT can be expected to cut more CO2 emissions while receiving greater public support. Therefore, it could be a useful instrument for accelerating the ecological transition. The analysis is articulated in three parts. First, we show how, in the context of vehicle choice decisions, any policy that reduces uncertainty about future gasoline prices improves the expected utility of more fuel-efficient vehicles relative to less efficient ones. Second, we show how a DCT could be designed to automatically stabilise gasoline prices and thereby reduce price uncertainty. Third, we conduct an econometric test for whether gasoline price volatility, considered as a proxy for price uncertainty, negatively affects vehicle fuel efficiency. Using microdata from the 2017 National Household Transport Survey, we test for negative correlation between gasoline price volatility and fuel efficiency of new vehicles sold in the US. Evidence of a negative correlation is indeed found despite limited volatility of gasoline prices in the study period. Further tests are warranted using data from different time periods and alternative model specifications.

Keywords

Carbon taxation, Gasoline prices, Vehicle choice, Fuel efficiency, Energy transition

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1. Introduction

To limit global warming and the worst consequences of climate change, global greenhouse gas (GHG) emissions must peak as soon as possible and then hit net zero by around mid-century (IPCC, 2022). Achieving this goal entails drastic and unprecedented reductions in GHG emissions across all major emitting countries and sectors. Some important policy developments have materialised in the last few years, such as the European Green Deal, China's commitment to achieving climate neutrality by 2060, and the US Inflation Reduction Act (its climate measures), only to mention a few. Whether and how governments will be able to establish timely pathways to global climate neutrality, however, is all to be seen.

As most economists have come to recognise, political feasibility is a criterion of priority in the choice of climate mitigation policies (Goulder, 2020, Hepburn et al., 2020). Accordingly, effective policies for climate mitigation would normally represent a compromise between economic efficiency, equity, and social acceptability more generally. This reality of climate policy directly speaks to carbon pricing, which can come in the form of carbon taxation or emissions trading, as a case in point of an economically efficient approach subject to tight political constraints (Jenkins and Karplus, 2016, Jenkins, 2014). Indeed, while carbon pricing has gained traction worldwide, less than 5% of global GHG emissions are currently priced at levels consistent with the 2°C target of the Paris Agreement (WB, 2023). Arguably, for carbon pricing to be used more profitably, both stronger international cooperation and innovative policy designs are needed.

The use of the revenues generated by carbon pricing, for the purpose of improving its various effects and social acceptability, is a question that has received much attention both in the scientific literature and in policy discussions (Edenhofer et al., 2021, Beiser-McGrath and Bernauer, 2019). In fact, specific rules on how carbon revenues should or must be used have become relatively common features of existing carbon pricing schemes. An equally relevant but less explored question is whether and how carbon pricing should be designed in such a way as to take into account volatile and largely unpredictable energy prices. The problem arises as any impact of carbon pricing on final prices of fossil fuels may well be dwarfed by the effects of events or trends occurring in global energy markets. Notably, the swings of the crude oil and natural gas markets can compromise the very environmental effectiveness of carbon pricing when this comes in the form of carbon taxation or the cost effectiveness of carbon pricing when this comes in the form of emissions trading.

In this paper, we propose a mechanism for carbon taxes applied to gasoline with a view to accelerating the decarbonisation of road transport. All over the world, road transport is a major emitting sector with stubbornly high carbon dioxide (CO_2) emissions.[1] In theory, pigouvian carbon taxes, or equivalent fuel taxes, are the most economically efficient instruments for curbing such emissions (Anderson and Sallee, 2016). In practice, major variations in oil prices mean that much of the time a standard fixed-rate carbon tax (hereafter 'standard carbon tax') is either irrelevant – in terms of its influence on consumer choices – when oil prices are low or socially unacceptable when oil prices are high. A dynamic carbon tax (DCT) that stabilises gasoline prices by adjusting inversely to the deviations of oil prices from a given target level could both cut more CO_2 emissions and receive greater public support than a standard carbon tax. Specifically, greater emission reductions may be achieved by inducing demand for more fuel efficient vehicles. The rationale is that the DCT would reduce uncertainty about future gasoline prices and, thus, people deciding which vehicle to buy would discount expected fuel costs less than they otherwise would. This means fuel efficiency as a vehicle attribute would effectively be valued more by buyers. In

[1] In the US, road transport alone makes up almost a quarter of total anthropogenic greenhouse gas emissions (EPA, 2023).

addition, owners of gasoline-fuelled vehicles would likely favour such a carbon tax over a standard one as it would prevent or at least limit gasoline price spikes.

The idea of a tax on gasoline adjusting inversely to oil prices is not new. In fact, it has found applications in real-world policy many times. Energy tax-subsidy schemes aimed at stabilising or smoothing fuel prices have been implemented in many developing and transition economies over the last three decades (Coady et al., 2012, Bacon and Kojima, 2008, Federico et al., 2001). In advanced economies too, energy taxes adjusting inversely to oil prices have been adopted or proposed. In France, a mechanism whereby an excise tax on oil products moved inversely to changes in the Brent price (to be precise: changes greater than 10% in the two-month average) was in force between 2000 and 2002. The *taxe flottante*, as it was called, was abandoned due to its excessive cost for the state.[2] Prompted by the 2008 oil price shock, similar mechanisms were introduced in Italy and in the UK. Yet, neither was ever applied (Di Giacomo et al., 2015, 2012, Bolton, 2022). In Chile, a fuel stabiliser mechanism has been in force since 2014 (Lemus and Luco, 2021). More recently, fuel price stabiliser mechanisms were proposed: a) in France, again, in connection with the *Gilets Jaunes* protests, which were triggered by a preset increase in the national carbon tax at a time when gasoline prices were rising (Bureau et al., 2019); and b) in California, after exceptionally high gasoline prices in the spring of 2022 (Borenstein, 2022).

Compared to past experiences and proposals of dynamic energy taxes on gasoline, the DCT presented in this paper fundamentally differs in the objective. The usual motivation for stabilising or for smoothing fuel prices is to shield consumers from highly volatile global energy markets, as volatile prices at the pump typically reduce consumer welfare (Federico et al., 2001). While providing the same welfare benefits of price stabilisation, our DCT is a carbon tax in the first place.

[2] The impact on the government budget was estimated to be €2.7 billion lower fiscal revenues (Conseil des Impôts, 2005).

As such, its main purpose is to improve on standard carbon taxation, which is therefore the natural term of comparison in evaluating the DCT. A second element of differentiation is that the DCT price stabiliser would operate within the limits of self-financing. It means that the DCT rate could only be reduced insofar as a revenue reserve, or buffer, fed by previous tax rate increases would allow. This feature of the DCT is not secondary as experience clearly shows that the – feared or actual – cost of a price stabiliser mechanism can preclude its adoption or continuation. The finiteness of the revenue reserve would also put a firm limit to the risk that oil exporters take advantage of the DCT by raising oil prices.

The analysis supporting the DCT proposal is developed in three main parts. First, using a standard theoretical model of vehicle choice, we show how any policy that reduces uncertainty about future gasoline prices makes more fuel-efficient vehicles relatively more attractive options in vehicle choice decisions. Second, we show how a DCT could be designed to stabilise gasoline prices and thereby reduce price uncertainty. Third, we run an econometric test for whether gasoline price volatility – a proxy for price uncertainty – negatively affects vehicle fuel efficiency. A negative correlation result would give us an indication (conservative in terms of magnitude) of the environmental benefit that could be achieved by stabilising gasoline prices.

Using a large dataset which combines monthly cross-sectional micro-data from the US National Household Travel Survey and monthly state-level data on gasoline prices, we test for the effect of gasoline price volatility on fuel efficiency of new vehicles sold in the US between May 2015 and February 2017. To our knowledge, we are the first to do this. While many studies have tested for the effect of gasoline price levels on vehicle fuel efficiency, they did not consider the effect of gasoline price volatility or any other proxy for gasoline price uncertainty on the same variable (e.g. Leard et al., 2019, Antweiler and Gulati, 2016, Barla et al., 2016, Klier and Linn, 2013, 2010, Li et al., 2014, 2009). Lin and Prince (2013) and Scott (2015) tested for the effect of gasoline price volatility on gasoline demand, but not on vehicle fuel efficiency specifically. Importantly, their results are consistent with the conjecture that gasoline demand can be more effectively reduced in the long run by making gasoline prices more predictable.

The rest of the paper is organised as follows. Section 2 shows how uncertainty about future gasoline prices can influence consumer choices as to which vehicle to buy. Section 3 shows how a DCT that stabilises gasoline prices could work in practice. Section 4 tests the effect of gasoline price volatility on fuel efficiency of new vehicles sold. Section 5 concludes.

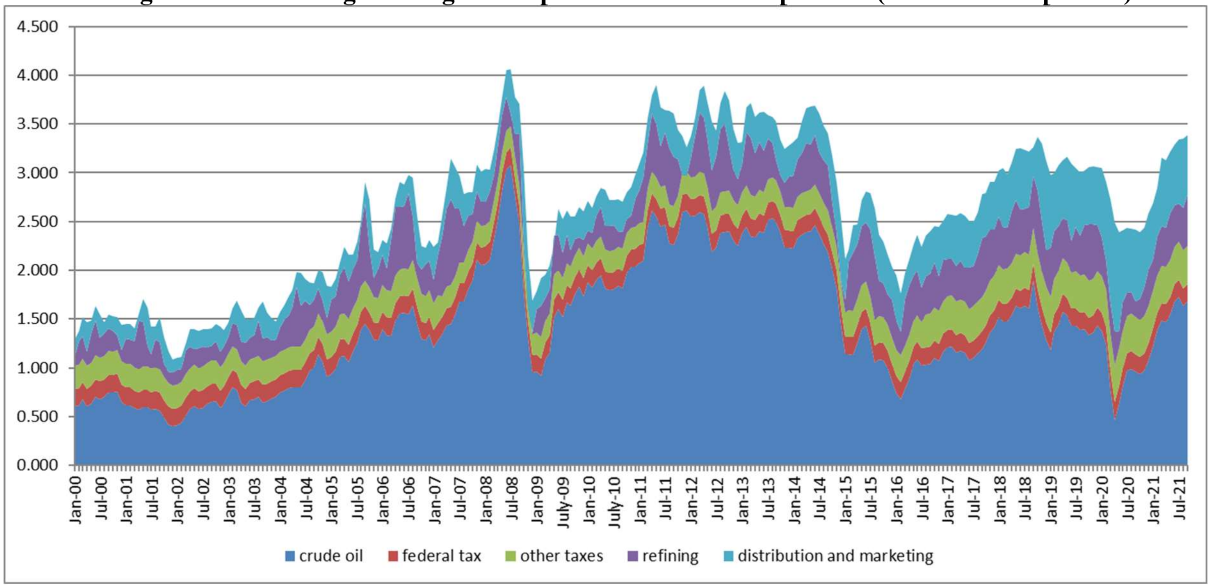
2. Gasoline prices and vehicle choice

2.1 Structure and volatility of gasoline prices

Three facts about the formation of gasoline prices are particularly relevant to our analysis and policy proposal. First, the cost of crude oil is by far the main component of retail gasoline prices. This is especially true in the US, as taxes make up only a small share of retail gasoline prices as compared to other countries, most notably European ones (Sterner, 2007). As Figure 1 shows, over the period 2000-2021 the cost of oil alone represented between a third and three quarters of retail gasoline prices at minimum and maximum price levels, respectively.

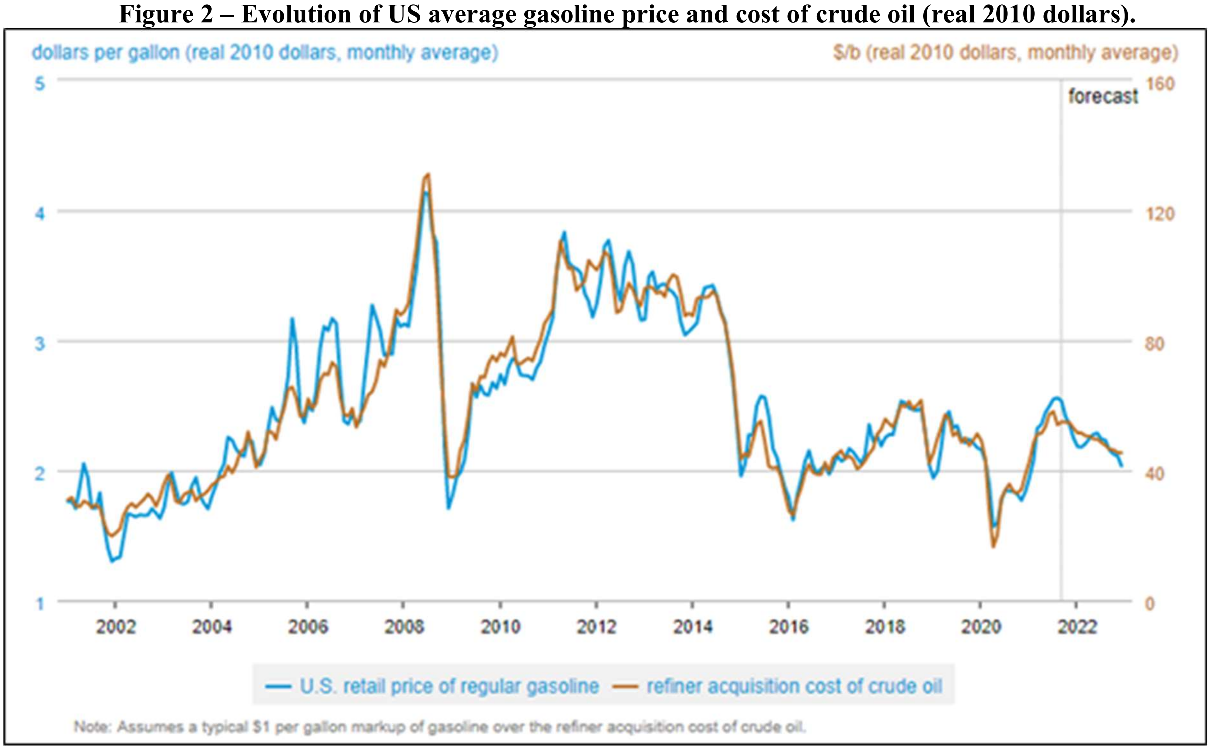
Second, the evolution of retail gasoline prices over time is closely related to that of oil prices, which crucially are largely determined on the global market. Again with reference to the US, Figure 2 shows how the evolution of retail gasoline prices closely follows that of oil prices (here represented by the 'refiner acquisition cost of crude oil'). Whenever gasoline prices temporarily break away from the trend of oil prices, this is typically due to refinery outages or other downstream events.

Figure 1 – US average retail gasoline prices: level and composition (Jan. 2000 - Sep. 2021).



Source: Authors' elaboration on data from the Energy Information Administration.

Figure 2 – Evolution of US average gasoline price and cost of crude oil (real 2010 dollars).



Source: Energy Information Administration.

Third, historically crude oil prices exhibit significant and continued volatility. Due to structural features of the oil industry and of the oil market, including sensitivity of the latter to macroeconomic and geopolitical events (e.g. economic recessions and booms, regional conflicts), oil prices are naturally volatile and subject to somewhat frequent supply-demand shocks (Hamilton, 2009). In turn, the volatility of oil prices translates into highly volatile gasoline prices at the pump.

2.2 Gasoline price uncertainty

Predicting future crude oil prices is a notoriously difficult exercise (Baumeister and Kilian, 2016, Alquist et al., 2013, Hamilton, 2009). The difficulty is due to the complexity of the global oil market and, more important, to the dual nature of crude oil as a commodity and a politically strategic resource: as such, a good that is subject to producer decisions which are hard or just impossible to anticipate. Moreover, as gasoline prices closely depend on crude oil prices, the very low predictability of the latter applies to the former too.

The predictability of (oil and) gasoline prices can only diminish with the time horizon that is considered. In the case of vehicle purchases, the relevant horizon – namely the number of years the buyer expects to use the vehicle – would normally exceed a period of five to seven years, which implies a very long time span for price predictions made with any minimum level of confidence. What is more, most people surely do not have access to sophisticated economic models nor are they sufficiently familiar with the functioning of energy markets to make accurate predictions about future gasoline prices. As shown empirically by Anderson et al. (2013, 2011), people's best guess of future gasoline prices is – barring exceptional economic circumstances – that these will be equal to current prices adjusted by expected general inflation.

Such no-change price forecasts by ordinary people are well justified by the erratic nature of oil prices. Still, the same forecasts come with a lot of uncertainty which can only increase with the time horizon. Concerning this specific type of uncertainty, any direct evidence offered by the literature is very limited. Again the studies by Anderson et al. (2013, 2011), who analyse gasoline price forecasts by US citizens over many years, are probably the most relevant scientific references. Among other interesting results, the authors find that the dispersion of individual gasoline price forecasts correlated positively with two different measures of crude oil price volatility, thus lending support to the argument that such dispersion can be considered a proxy for gasoline price uncertainty. In the next section, we are going to show how gasoline price uncertainty may influence vehicle choice.

2.3 Gasoline price uncertainty and vehicle choice

Consumer expectations about future gasoline prices are a key determinant of vehicle choices. Some aspects of these expectations, however, are less well-established than others. As said, little is known about the uncertainty accompanying point forecasts of gasoline prices. Nonetheless, such uncertainty likely plays a significant role in vehicle purchase decisions. As we are going to show theoretically, greater uncertainty about future gasoline prices favours the purchase of less fuel efficient vehicles. The reason has to do with the fact that vehicles have multiple attributes, of which fuel efficiency is only one, and that people plausibly trade-off between those attributes in response to changes in the expected value of future gasoline prices as well as to changes in the uncertainty around it.

But how exactly can uncertainty about the level of future gasoline prices affect vehicle choice? Let us consider the problem of a consumer who has decided to buy a vehicle. Using the framework underlying most of the literature on vehicle choice, the buyer will choose the vehicle that maximises her expected utility subject to a budget constraint. Specifically, the utility that consumer i expects to derive from purchasing vehicle j at time t, u_{ijt}, depends on: a) the price of the vehicle, p_{jt}, b) the present value of expected fuel costs over the vehicle's T-year lifetime, and c) a number of vehicle characteristics other than fuel efficiency, such as volume, horsepower, acceleration, colour, etc., each of which – unlike fuel efficiency – has an intrinsic utility to the buyer. By contrast, expected fuel costs depend on the buyer's expectation about future gasoline prices, the number of miles that she expects to drive, and of course on the vehicle's fuel efficiency. Using Anderson et al.'s (2013) notation,

$$u_{ijt} = -\alpha p_{jt} - \gamma \left[\sum_{k=0}^{T} (1 + r_i)^{-k} \mu_{it,t+k} m_{ij,t+k} MPG_j^{-1} \right] + \beta X_j \tag{1}$$

where: T is the vehicle's lifetime; r_i is i's discount rate; $\mu_{it,t+k}$ is i's expected gasoline price, g, in year $t+k$ given her own information set (I), i.e., $\mu_{it,t+k} = E_{it}\{g_{t+k}|I_{it}\}$; $m_{ij,t+k}$ is the number of miles that i plans to drive with the vehicle in year $t+k$; MPG_j is the vehicle's fuel efficiency, as measured by miles per gallon (MPG); and X_j is a vector of vehicle characteristics other than fuel efficiency.

Taking the model in [1] as the reference model, we augment it to introduce uncertainty about future gasoline prices. The change is implemented by making the buyer's discount rate dependent on the expected variability of the gasoline price between t (the year the vehicle is purchased) and $t+T$ (the last year the vehicle will be used), with greater variability reflecting greater uncertainty.

A risk-adjusted discount rate is then considered, $r^*_{it,t+k}$, which increases with gasoline price uncertainty.[3,4] In formal terms,

$$u_{ijt} = -\alpha p_{jt} - \gamma \left[\sum_{k=0}^{T} \left(1 + r^*_{it,t+k}\right)^{-k} \mu_{it,t+k} m_{ij,t+k} MPG_j^{-1}\right] + \beta X_j \qquad [2]$$

$$r^*_{it,t+k} = r_i + f\left(\sigma_{it,t+k}\right) \qquad [3]$$

$$f'_\sigma > 0 \qquad [4]$$

where $\sigma_{it,t+k}$ is i's expected standard deviation of the gasoline price, g, in year $t+k$, i.e. $\sigma_{it,t+k} = E_{it}\{(|g_{t+k} - \mu_{it,t+k}|)|I_{it}\}$.

The augmented model (equations [2] to [4]) implies that, all else equal, an increase in uncertainty about the level of future gasoline prices ($\sigma_{it,t+k} \uparrow$) has a positive effect on the utility of each and every vehicle considered by the buyer merely because it raises her discount rate ($r^*_{it,t+k}$). Crucially, however, the effect is larger for less fuel efficient vehicles than for more fuel efficient ones. In other words, higher uncertainty about future gasoline prices has a positive effect on the utility of any vehicle simply because it results in more heavily discounted fuel costs. The effect is larger for less fuel efficient vehicles, however, because their expected fuel costs are larger in the

[3] To learn more about subjective implicit discount rates in energy-related investment decisions, see e.g. Haq and Weiss (2018), Schleich et al. (2016), Newell and Siikamaki (2015), and Greene (2011). This literature analyses the different factors, including uncertainty about future energy prices, that may explain the 'energy efficiency gap', i.e. the difference between cost-minimizing levels of energy efficiency and the levels actually observed.

[4] Heterogeneity in subjective discount rates across individuals is well documented by empirical studies. By contrast, empirical validation of context-dependent, time-varying subjective discount rates hardly exists, most likely due to limited availability of suitable longitudinal data. Stephens and Krupka (2006), who show subjective discount rates increased dramatically during an inflationary period, is one relevant study that we were able to find.

first place. This result is shown by the derivative of u_{ijt} with respect to $\sigma_{it,t+k}$ as MPG_j appears in the denominator:

$$\frac{du_{ijt}}{d\sigma_{it,t+k}} = \gamma k \frac{\mu_{it,t+k} m_{ij,t+k}}{\left(1 + r_i + f\left(\sigma_{it,t+k}\right)\right)^{k+1}} \frac{1}{MPG_j} f'_\sigma$$

[5]

Equation [5] tells us that higher uncertainty about future gasoline prices plays in favour of less fuel efficient vehicles by increasing their relative utility. In turn, since the positive effect of higher gasoline price uncertainty on new vehicles' utility is bigger for less fuel efficient vehicles, it is plausible that more of these would be sold as a result. The same logic applies to the case of lower uncertainty about future gasoline prices, leading to the opposite outcome. Here, smaller negative effects on the utility of more fuel efficient vehicles may result in more of these being chosen by consumers. A clear policy implication is thus derived: the average fuel efficiency of vehicles sold may be improved by reducing uncertainty about future gasoline prices.

3. Dynamic carbon taxation

3.1 Rationale

Economists often indicate pigouvian carbon prices or equivalently fuel taxes as the most economically efficient policy instruments for decarbonising road transport, at least in theory (Anderson and Sallee, 2016). Economists also justify the use of fuel efficiency standards or CO_2-related vehicle purchase taxes on the grounds of people's supposed undervaluation of future fuel costs in vehicle purchase decisions or as a second-best alternative to pigouvian pricing (Allcott and Greenstone, 2012). These instruments can be critical for limiting CO_2 emissions of road transport, all the more in contexts where carbon prices or fuel taxes are inefficiently low, as in the

US case (Parry and Small, 2005). We know little, however, about the relative importance of the different factors explaining undervaluation of fuel costs. Along with behavioural factors, such as myopia or inattention, uncertainty about future gasoline prices may also increase discount rates in vehicle choices. To the extent that this is true, any intervention that reduces such uncertainty – we have shown it formally – will also improve the relative utility of fuel efficient vehicles.

A dynamic carbon tax (DCT) can be designed so as to automatically stabilise gasoline prices and thereby reduce uncertainty about their future levels. The mechanism we propose involves inverse and proportional adjustments of the DCT rate to the deviations of a reference crude oil price, e.g. the West Texas Intermediate (WTI) price or the Brent price, from a target level, e.g. $60/barrel or $80/barrel. While our analysis is focused on the effect of more stable gasoline prices on vehicle choice, the role of the oil target price is no less important. As the oil target price determines the level around which gasoline prices are stabilised, its level would reflect a preferred gasoline price trajectory for decarbonising road transport. The effect of reduced price uncertainty on vehicle fuel efficiency would determine the greater effectiveness of the DCT in reducing emissions as compared to an equivalent standard (fixed-rate) carbon tax. A second advantage of the DCT over standard carbon taxation would be its likely greater appeal to current drivers of gasoline-fuelled vehicles, meaning higher social acceptability and higher political feasibility of the policy. The DCT would likely appeal more to the public than a standard carbon tax because the price stabiliser mechanism would prevent or limit gasoline price spikes. The stabilisation of gasoline prices alone indeed can be expected to have a positive impact on consumer welfare.[5]

[5] Based on a survey of the relevant literature, Federico et al. (2001) draw the following conclusion: "The high impact of consumption of petroleum products on households' and firms' budgets, the relatively low price elasticity of demand for these products, and the likely presence of both risk-aversion and adjustment costs all seem to suggest that consumers would prefer to have stable petroleum prices."

3.2 Illustration

We now show how the proposed DCT would work in practice. First of all, the DCT rate ($/gallon) is given by the sum of two components: a) a time-invariant element, which is related one-to-one to the chosen carbon tax rate ($/t$CO_2$), and b) a monthly or, if feasible, a weekly adjustment that varies in size depending on the distance of the observed oil price from the target price. The criterion for choosing the carbon tax rate could be economic efficiency, in which case the rate could equal the marginal social cost of carbon, or it could be any other criterion that for whatever reason is preferred by the legislator. As regards the periodical adjustment of the DCT rate, in any given period it can be positive or negative. The adjustment at time *t* is proportional to the difference between the oil target price and the actual oil price observed at time *t-1*. To minimise the volatility of gasoline prices, the adjustment would fully offset the impact of any deviation of the oil price from the target level on the wholesale gasoline price.[6] Therefore, an estimate of such impact is needed to operate the mechanism.

To ensure that the DCT does not require additional fiscal revenues for its own functioning, the size of the tax rate adjustment is bound by the value of a reserve, which is a revenue buffer accumulated by the DCT over time since its inception. As a rule, the value of the DCT reserve increases (/decreases) whenever the observed oil price is lower (/higher) than the target price. This is indeed the condition for applying a positive (/negative) rate adjustment, which results in a replenishment (/depletion) of the reserve. Of course the reserve could be exhausted at some point, meaning that all revenues have been used for limiting gasoline prices. If and when this happens, the DCT rate would be constant in the subsequent periods – just as with a standard carbon tax – so long as oil prices exceed the target price. Persistently high oil prices and, therefore, persistently

[6] As Borenstein (2008) points out with reference to a similar tax design, it would be impossible to target a retail gasoline price exactly.

high gasoline prices might eventually require some additional policy intervention. By contrast, low oil prices persistently below the target level would simply result in a growing DCT reserve. Regardless, regular – but not too frequent – revisions of the DCT parameters would be needed for fine-tuning the mechanism to an ever-changing environment or to new policy targets.

In formal terms, the level of the proposed DCT at time t, C_t, is determined as follows:

$$C_t = \bar{C} + A_t \tag{6}$$

$$A_t = \begin{cases} \beta(\bar{P} - P_{t-1}) & if \;\; P_{t-1} < \bar{P} \\ 0 & if \;\; P_{t-1} = \bar{P} \\ -MIN\{-1[\beta(\bar{P} - P_{t-1})];\; R_{t-1}\} & if \;\; P_{t-1} > \bar{P} \end{cases} \tag{7}$$

$$R_t = \sum_{i=1}^{t} A_i \tag{8}$$

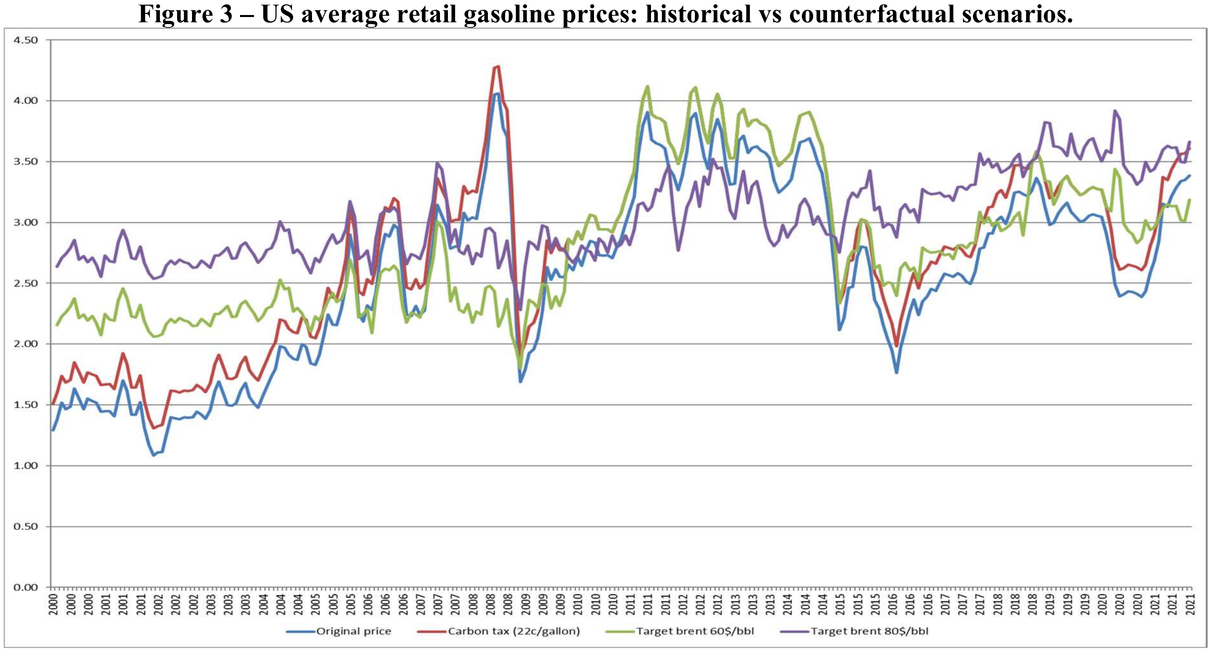
where:

- C_t is the DCT rate ($/gallon) at time t, $\bar{C}$ is its time-invariant component, and A_t is the rate adjustment;
- $\bar{P}$ is the oil target price, and P_{t-1} is the observed oil price at time $t-1$;
- β is an estimated parameter measuring the change in the wholesale gasoline price ($/gallon) for a $1 change in the oil price ($/barrel); and
- R_t is the sum of all (positive and negative) adjustments in all previous periods since the start of the DCT up to time t included.[7]

[7] Assuming no change in gasoline demand over time, equations [7] and [8] together ensure that the DCT reserve never falls below zero.

Had the DCT been applied in the past, how would have retail gasoline prices looked like? To answer this question, let us consider a \$25/tCO_2 carbon tax, which translates into a tax on gasoline of \$0.22/gallon ($\bar{C}$), and two different oil target prices ($\bar{P}$): \$60/barrel and \$80/barrel. Borenstein (2008) conveniently provides us with an estimate for β that specifically applies to the US market. The author calculated that, in the medium run, every \$1 change in the crude oil price (\$/barrel) translated into a \$0.024 change in the wholesale gasoline price (\$/gallon). We use this estimate to derive counterfactual monthly series of the US average retail gasoline price under different carbon tax regimes. Full pass-through of carbon taxation is assumed throughout – a harmless simplification in our analysis.

Figure 3 – US average retail gasoline prices: historical vs counterfactual scenarios.



With reference to the period 2000-2021, Figure 3 compares the historical observed US average retail gasoline price (blue line) with three hypothetical counterfactuals. Each counterfactual represents the US average retail gasoline price under a given carbon tax regime, specifically: a) a standard carbon tax of \$25/tCO_2, translating into a fixed gasoline tax of \$0.22/gallon ('FCT' – red line); b) a DCT of \$25/tCO_2 (hence, $\bar{C}$ = \$0.22/gallon) with a \$60/barrel oil target price ('DCT60' – green line); and c) a DCT of \$25/tCO_2 (hence, again, $\bar{C}$ = \$0.22/gallon) with a \$80/barrel oil target price ('DCT80' – purple line).

Two main remarks are in order. First, compared to historical prices as well as to prices inclusive of the standard carbon tax (FCT), gasoline prices turn out to be much less volatile under both DCT60 and DCT80. Notably, the dramatic variations of the years 2008-2009 would have been absorbed by both DCT mechanisms. Second, over the whole period 2000-2021, DCT80 clearly does a better job than DCT60 at reducing price volatility. Up until 2007, oil prices stayed well below \$60/barrel, which implies the reserve of DCT60 and even more so that of DCT80 would have increased substantially. Only the reserve of DCT80, however, would have grown sufficiently to finance subsidies in all subsequent periods, when crude oil prices often far exceeded the \$60 target price.

4. Testing the effect of gasoline price volatility on vehicle fuel efficiency

The added value of the proposed DCT depends on its ability to reduce gasoline price uncertainty by stabilising prices and on the ensuing positive effect on vehicle fuel efficiency. We have explained the theoretical reasons why both of these conditions should hold if a DCT is adopted. We now turn to consider whether the same conjecture is supported by empirical evidence. Not having suitable data to assess how gasoline price volatility affects gasoline price uncertainty, nor how this in turn affects vehicle fuel efficiency, we test econometrically the effect of price volatility directly on fuel efficiency. A negative effect would corroborate the greater effectiveness of the DCT in reducing gasoline consumption, and hence CO_2 emissions, compared to standard carbon taxation. To conduct such test, we use household survey data including data on individual vehicles purchased by US households, between May 2015 and February 2017, and on the corresponding state-level retail gasoline prices. The empirical model and the estimation method, the data used, and the estimation results are illustrated below.

4.1 Model and estimation method

Our empirical model for vehicle fuel efficiency, measured in miles per gallon (MPG), is a modified version of that used by Li et al. (2014) in a highly cited study. In our model, the MPG of a purchased light-duty vehicle, be it a car, a van, an SUV or a pickup truck, is a function of: a) the gasoline price level at the time (month) of vehicle purchase; b) the monthly volatility of gasoline prices prior to vehicle purchase; and c) a series of control variables related to the household that bought the vehicle and to its local context. The model differs from Li et al.'s (2014) in two main ways. First, it includes gasoline price volatility, our main variable of interest, among the regressors.[8] Second, the statistical unit is different, reflecting a more convenient organisation of the survey data in pooled cross sections. In our model, MPG_{it} refers to vehicle *i* purchased in month *t*, which can correspond to any time between 0 and 12 months before the household was interviewed. In Li et al.'s model, MPG_{it} is the average efficiency of all vehicles purchased during the past 12 months by household *i* interviewed in month *t*. Since T (t = 1, 2, …, T) representing the total number of vehicle purchase months is greater than T representing the total number of household interview months, our approach results in a sample with a longer time dimension. That is, we obtain a larger number of pooled cross sections.[9]

[8] Li et al. (2014) did not consider gasoline price uncertainty at all nor, therefore, did their empirical model include a proxy for it.

[9] With household survey data, *N* is always large. The same is not necessarily true for T, especially if only one survey wave is considered. Extending T in some way would normally be desirable. In our application, the greater the T

Using Ordinary Least Squares, we estimate the following model:

$$MPG_{it} = \alpha + \beta g_{st} + \gamma \sigma_{st} + X_j \Delta + \eta_s + \theta_\tau + u_{it}$$

[9]

where: *i* denotes the vehicle, *t* the vehicle purchase month, *j* the household, *s* the state where the household lives; *g* is the average real tax-inclusive gasoline price; σ is a proxy for uncertainty about future gasoline prices; *X* is a vector of variables controlling for (a) household income, size, and composition, (b) age, sex, and education level of the survey respondent, and (c) local transport- and other context-related conditions; η and θ are state fixed effects and year fixed effects, respectively; and finally u is the error term.

Focusing on $\hat{\sigma}$, our proxy for gasoline price uncertainty is the rolling standard deviation of the gasoline price (Scott, 2015)[10]:

$$\sigma_{st,K} = st.dev.(g)_{st,K} = \sqrt{\frac{1}{K}\sum_{j=1}^{K}\left(g_{s,t-j+1} - \bar{g}_{st,K}\right)^2}$$

[10]

where $\bar{g}_{st,K} = \frac{1}{K}\sum_{j=1}^{K} g_{s,t-j+1}$ and *K* is the number of months in the rolling window.

But what number should *K* be? In other words, how long is the time window of past gasoline prices that tends to most strongly correlate with uncertainty about future gasoline prices? As this is ultimately an empirical question, our approach is to consider different plausible values for *K*.

dimension of the estimation sample, the greater the time variation of gasoline prices that can be and, therefore, the greater the chances of identifying statistically significant effects.

[10] Scott (2015): "Price volatility may be taken as a rough proxy for future price uncertainty because it implies that future prices are harder to predict; volatility may also lead consumers to believe that current price changes will be short-lived."

Accordingly, the same model [9] is estimated five times, with K = 3, 6, 9, 12, and 18 (months), respectively.

4.2 Data

Our dataset was constructed by combining two types of data: a) cross-sectional household survey data, containing information on US households' transport habits and means, as well as on their socio-demographic characteristics; and b) monthly state-level data on gasoline prices. The survey data were sourced from the 2017 wave of the National Household Travel Survey (NHTS), which is published by the Federal Highway Administration every six or seven years (FHWA, 2017). The price data were derived by adding together pre-tax monthly gasoline prices – publicly available for nine states[11] and purchased from HIS Markit for all other states – and corresponding annual gasoline taxes, which are also published by the FHWA[12]. Furthermore, monthly state-level data on the Consumer Price Index, which were needed to derive real gasoline prices, were taken from the Bureau of Labor Statistics.

In the 2017 NHTS, data from a total of 126,969 households interviewed between May 2016 and May 2017 were included in the initial dataset. However, as our interest is in the determinants of fuel efficiency of vehicles sold, we focused on the subset of households that bought a light-duty vehicle within 12 months prior to the interview.

Table 1 - Summary statistics, estimation sample.

Variable	N	Mean	Std. Dev.	CV	Min	Max
Miles per gallon	30,221	22.41	5.15	0.23	6.00	50.00
Gasoline price ($/gallon)	30,221	2.21	0.34	0.15	1.46	3.76
Gasoline tax ($/gallon)	30,221	0.44	0.06	0.14	0.26	0.77

[11] The Energy Information Administration publishes pre-tax gasoline prices for the following nine states: California, Colorado, New York, Washington, Texas, Florida, Massachusetts, Minnesota, and Ohio.
[12] https://www.fhwa.dot.gov/policyinformation/statistics.cfm

3-month gasoline price volatility	30,221	0.09	0.05	0.56	0.00	0.33
6-month gasoline price volatility	30,221	0.14	0.07	0.50	0.02	0.41
9-month gasoline price volatility	30,221	0.18	0.08	0.44	0.03	0.42
12-month gasoline price volatility	30,221	0.22	0.08	0.36	0.06	0.51
Age of respondent	30,221	52.16	15.36	0.29	18	92
Sex of respondent[(a)]	30,221	1.52	0.54	0.36	1	2
Educational attainment of respondent[(b)]	30,221	2.49	0.75	0.30	1	3
Race of respondent[(c)]	30,221	1.17	0.37	0.32	1	2
Household size	30,221	2.59	1.32	0.51	1	13
Number of adults	30,221	2.05	0.80	0.39	1	10
Number of workers	30,221	0.98	0.89	0.91	0	7
Household income category[(d)]	30,221	5.97	2.61	0.44	1	11
Census block population density[(e)]	30,221	4,065.97	5,587.18	1.37	50	30,000
MSA population size category[(f)]	30,221	3.75	1.70	0.45	1	6
Urban/rural indicator[(g)]	30,221	2.83	1.31	0.46	1	5
Rail indicator[(h)]	30,221	1.15	0.36	0.31	1	2

Notes: **(a)** 1 = "Male", 2 = "Female"; **(b)** 1 = "Less than high school", 2 = "High school (or GED)", 3 = "More than high school"; **(c)** 1 = "White", 2 = "Other"; **(d)** 1 = "<$10,000", 2 = "$10,000-$14,999", 3 = "$15,000-$24,999", 4 = "$25,000-$34,999", 5 = "$35,000-$49,999", 6 = "$50,000-$74,999", 7 = "$75,000-$99,999", 8 = "$100,000-$124,999", 9 = "$125,000-$149,999", 10 = "$150,000-$199,999", 11 = "$200,000 or more"; **(e)** Persons per square mile, 50 = "0-99", 300 = "100-499", 750 = "500-999", 1500 = "1,000-1,999", 3000 = "2,000-3,999", 7000 = "4,000-9,999", 17000 = "10,000-24,999", 30000 = "25,000-999,999"; **(f)** Population of metropolitan statistical area (MSA), 1 = "<250,000", 2 = "250,000-499,999", 3 = "500,000-999,999", 4 = "1,000,0000-2,999,999"; 5 = "3,000,000 or more"; 6 = "Not in MSA"; **(g)** 1 = "Second city", 2 = "Rural", 3 = "Suburban", 4 = "Small town", 5 = "Urban"; **(h)** 1 = "MSA does not have rail, or household not in an MSA", 2 = "MSA has rail".

While the choice of a 12-month period is arbitrary, we deemed it represented an acceptable compromise for our purposes. On the one hand, a wider interval would have given us a larger sample, notably a longer series of pooled cross sections. On the other hand, this precise advantage would have come to the cost of increasing measurement error in the explanatory variables recorded at the time of the interview and not at the time of vehicle purchase (e.g., household income, household size, the household's place of residence). It thus seemed to us a tenable assumption that household characteristics key to our analysis would not substantially change within a few months or a year at most. These considerations and the fact that gasoline price data were only available up to February 2017, resulted in an estimation sample comprising over 30,000 light-duty vehicles bought between May 2015 and February 2017. The dataset was completed with monthly state-level data on gasoline prices which were matched on the vehicle purchase month. Table 1 above shows summary statistics for the variables used in the estimation.

Focusing on gasoline prices, cross-state variation is substantial and – as one might expect – this is mainly due to differences in taxation levels (see Figure 4). Gasoline tax rates themselves were constant or virtually constant for almost all states in the study period. Noteworthy is the exception of California, where the tax rate increased by 20% between 2015 and 2017.

Figure 4 - Nominal gasoline prices and taxes, selected states (2015-2017).

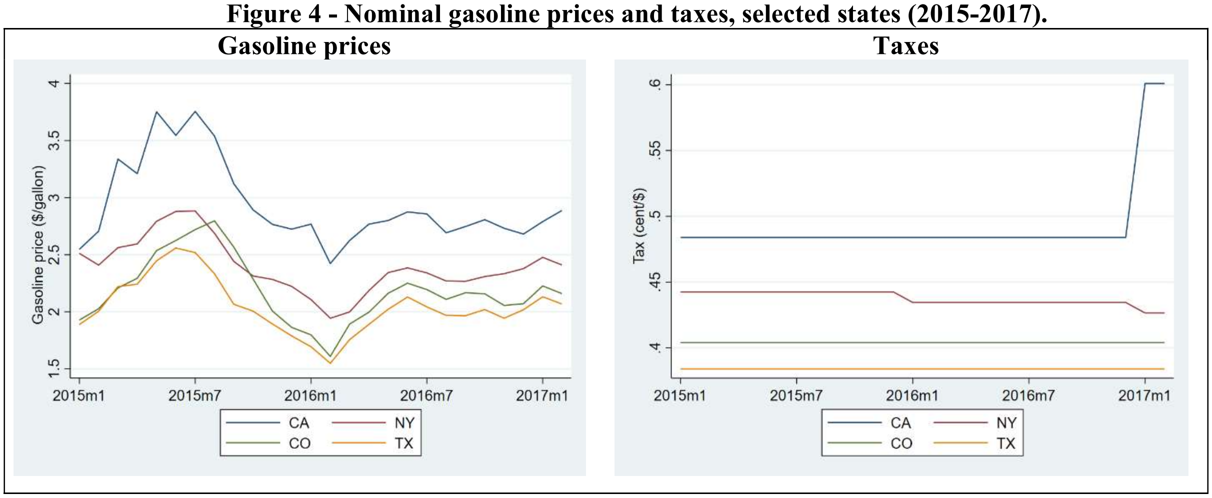
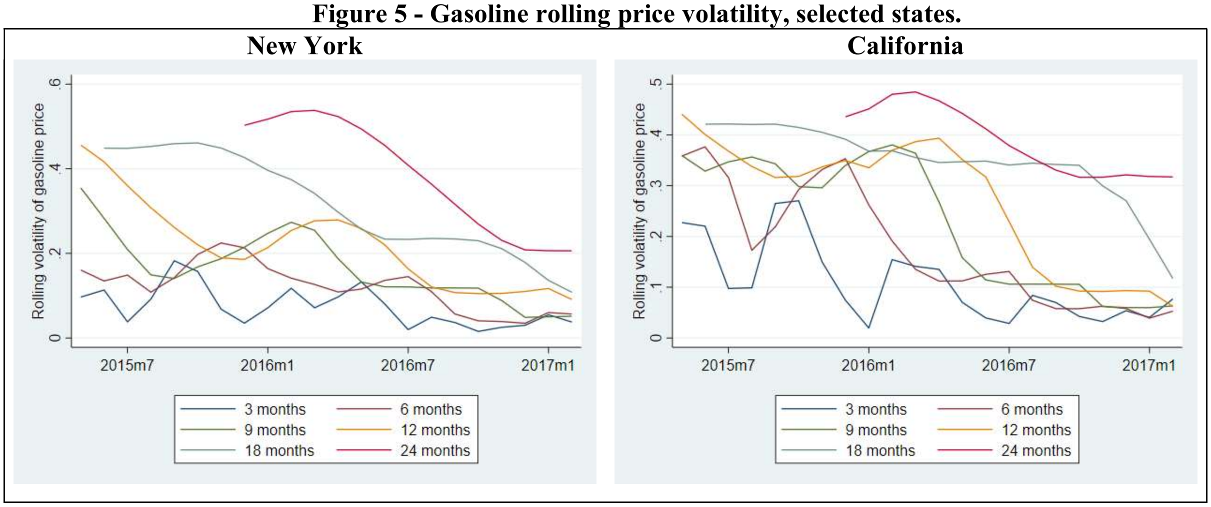


Figure 5 - Gasoline rolling price volatility, selected states.



Furthermore, as far as the rolling volatility of the gasoline price ($\hat{\sigma}$) is concerned, this exhibits similar trends across states, given highly correlated gasoline prices. Also, the same volatility necessarily varies more smoothly over time as the relevant time window (i.e., the number of months considered, K = 3, 6, 9, 12, or 18) increases (see Figure 5).

4.3 Results

Table 2 reports the estimation results for the preferred specification of our model. The four sets of results correspond to model variants that differ from one other by the time window over which the gasoline price volatility is calculated, namely K = 3, 6, 9, and 12 months. In the following, before presenting the results – first focusing on the effects of gasoline prices and then on those of socio-demographic and other factors – we discuss the issue of state fixed effects in our empirical setting.

State fixed effects

Ideally our empirical model would include state fixed effects. By controlling for any relevant time-invariant factor within a state, state fixed effects would allow us to more comfortably interpret estimation results on gasoline price volatility as a test of our main hypothesis, i.e., that greater uncertainty about gasoline prices negatively affects the fuel efficiency of new vehicles sold. In practice, however, estimation with state fixed effects runs into a severe multicollinearity problem due to high correlation between state dummies and monthly average gasoline prices at the state level. The problem arises with our sample as differences in gasoline taxes between states tend to result in persistent differences in gasoline prices at the pump. In other words, gasoline prices in different states tend to move parallel or almost parallel to one another (see Figure 4 showing 'typical' patterns of gasoline taxes and prices). Consequently, estimates of the coefficients on the gasoline price and its volatility are not robust. In addition, the multicollinearity issue associated with state fixed effects is compounded by the presence of year fixed effects in the model. Here, the combination of state dummies and year dummies makes identification of any effect of gasoline prices hardly possible given limited within-year variation of state-level monthly prices. For these reasons the preferred specification of our model is ultimately without state fixed effects.

Gasoline price effects

With reference to Table 2, the estimated coefficients of the gasoline price ($\hat{\beta}$) indicate that, depending on the model variant, fuel efficiency of new vehicles sold increases between 0.45 MPG and 0.51 MPG for a $1 increase in gasoline price. In elasticity terms (elasticity of fuel efficiency relative to gasoline price), the corresponding effects at sample mean values are 0.04 and 0.05. These numbers, which probably seem small, are comparable to those found in the closest empirical literature. In Li et al. (2014), for example, the same estimated elasticity ranges between 0.06 and 0.08.

The estimated coefficient of gasoline price volatility ($\hat{\gamma}$) turns out to be -1.52 and -1.33 for K = 3 months and K = 6 months, respectively. This means that a $1 average deviation of the gasoline price from its mean over three and six months prior to vehicle purchase is associated with a worsening of fuel efficiency of new vehicles sold by 1.52 and 1.33 MPG, respectively. For longer time intervals (K > 6) the estimated coefficients, while with a negative sign as expected, are not statistically different from zero. On the one hand, this could be interpreted as evidence that consumers tend to have limited memory of gasoline price volatility (not exceeding six months) at the time of vehicle purchase. On the other hand, the same result may simply reflect the fact that the variability of gasoline price volatility decreases as the time window (K) increases (see the curves in Figure 5 and the coefficients of variation in Table 1). In fact, both explanations may be correct as one does not exclude the other.

Table 2 - Estimation results.

	(1)		(2)		(3)		(4)	
	Coeff.	St. Err.	Coeff.	St. Err.	Coeff.	St. Err.	Coeff.	St. Err.
Gasoline price level	0.460***	(0.115)	0.457***	(0.117)	0.451***	(0.118)	0.518***	(0.133)
Gasoline price volatility:								
3-month (K = 3)	-1.524*	(0.903)						
6-month (K = 6)			-1.330*	(0.741)				
9-month (K = 9)					-0.662	(0.720)		
12-month (K = 12)							-0.804	(0.652)
Household size	-0.483***	(0.026)	-0.483***	(0.026)	-0.482***	(0.026)	-0.483***	(0.026)
Number of adults	0.311***	(0.082)	0.310***	(0.082)	0.311***	(0.082)	0.311***	(0.081)
Number of workers	0.094*	(0.055)	0.095*	(0.055)	0.094*	(0.055)	0.093*	(0.055)
Household income (0/1):								
<$10,000	Ref. cat.		Ref. cat.		Ref. cat.		Ref. cat.	
$10,000-$14,999	0.126	(0.246)	0.123	(0.245)	0.124	(0.246)	0.126	(0.246)
$15,000-$24,999	0.394*	(0.196)	0.388*	(0.197)	0.389*	(0.197)	0.392*	(0.196)
$25,000-$34,999	0.421*	(0.230)	0.418*	(0.228)	0.418*	(0.229)	0.420*	(0.229)
$35,000-$49,999	0.438**	(0.204)	0.436**	(0.203)	0.435**	(0.204)	0.438**	(0.204)
$50,000-$74,999	0.246	(0.190)	0.243	(0.190)	0.242	(0.190)	0.246	(0.190)
$75,000-$99,999	0.115	(0.222)	0.112	(0.221)	0.113	(0.222)	0.115	(0.222)
$100,000-$124,999	0.155	(0.205)	0.151	(0.204)	0.151	(0.204)	0.153	(0.204)
$125,000-$149,999	-0.043	(0.206)	-0.047	(0.205)	-0.045	(0.205)	-0.045	(0.204)
$150,000-$199,999	-0.248	(0.264)	-0.250	(0.263)	-0.248	(0.264)	-0.246	(0.264)
$200,000 or more	-0.537*	(0.269)	-0.538*	(0.268)	-0.537*	(0.268)	-0.534*	(0.268)
Age of respondent	0.014***	(0.003)	0.014***	(0.003)	0.014***	(0.003)	0.014***	(0.003)
Sex of respondent (0/1): female	0.315***	(0.041)	0.316***	(0.042)	0.316***	(0.042)	0.316***	(0.042)
Education of respondent (0/1):								
< High school	0.218	(0.173)	0.213	(0.173)	0.217	(0.172)	0.217	(0.173)
High school	Ref. cat.		Ref. cat.		Ref. cat.		Ref. cat.	
> High school	1.055***	(0.099)	1.055***	(0.100)	1.056***	(0.100)	1.055***	(0.100)
Race of resp. (0/1): non-white	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
MSA population size cat. (1-6)	-0.087***	(0.023)	-0.087***	(0.023)	-0.087***	(0.023)	-0.086***	(0.023)
Population density cat. (1-8)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Rail (0/1)	0.929***	(0.165)	0.930***	(0.165)	0.931***	(0.167)	0.925***	(0.162)
Urban/rural (0/1):								
Second city	0.657***	(0.098)	0.657***	(0.099)	0.659***	(0.980)	0.660***	(0.097)
Urban	0.854***	(0.139)	0.858***	(0.136)	0.860***	(0.135)	0.858***	(0.137)
Suburban	0.808***	(0.077)	0.810***	(0.076)	0.810***	(0.076)	0.812***	(0.077)
Town/rural	Ref. cat.		Ref. cat.		Ref. cat.		Ref. cat.	
Year of purchase (0/1):								
2015	Ref. cat.		Ref. cat.		Ref. cat.		Ref. cat.	
2016	-0.144**	(0.055)	-0.201**	(0.078)	-0.118**	(0.057)	-0.107**	(0.048)
2017	-0.244**	(0.119)	-0.350**	(0.135)	-0.251*	(0.146)	-0.260**	(0.128)
Constant	19.607***	(0.345)	19.695***	(0.375)	19.580***	(0.389)	19.511***	(0.361)
Observations	30,221		30,221		30,221		30,221	
R^2	0.040		0.040		0.039		0.040	

Notes: Robust standard errors (in parentheses) clustered at the state level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

In any case, the two coefficients statistically different from zero, $\hat{\gamma}$ = -1.52 (K = 3) and $\hat{\gamma}$ = -1.33 (K = 6), indicate that gasoline price volatility is a relevant variable both in a statistical and economic sense. By computing the elasticity of fuel efficiency to gasoline price volatility, we can compare the (negative) effects of the latter on the former with the (positive) effects of the gasoline price level on the same variable. Let us then consider the elasticities $\varepsilon_{MPG,\sigma}$ = -0.006 (K = 3) and $\varepsilon_{MPG,\sigma}$ = -0.008 (K = 6), calculated at sample mean values. If we interpret them in relation to the proposed DCT, we realise that their magnitude is not negligible. For example, $\varepsilon_{MPG,\sigma}$ = -0.008 implies that a 100% reduction in price volatility – as would occur with a DCT that perfectly stabilises the gasoline price – would result in a 0.8% increase in MPG. If applied to the sample mean value of MPG, 0.8% makes an increase in absolute terms of 0.18. It follows that price stabilisation alone, i.e., gasoline price stabilisation independent of the gasoline price level, would have an impact on fuel efficiency exceeding a third of the effect of a $1 price increase. This ratio between the two effects, which exceeds 1:3, is the most relevant quantitative result as it points to a potential substantial improvement of carbon pricing in terms of environmental effectiveness. What is more, the effect of a hypothetical gasoline price stabilisation scheme on fuel efficiency may well be even larger in real life. These econometric results come from data generated in a context where nothing resembling a policy for gasoline price stabilisation was in place. Therefore, by virtue of more effectively reducing uncertainty about future gasoline prices, the proposed DCT would likely have a greater impact on fuel efficiency than these estimated parameters indicate.

Socio-demographics and other factors

The richness of the NHTS data also offers us some interesting results on correlations between fuel efficiency of new vehicles sold and both buyers' socio-demographics and local contextual factors. We comment on these results by distinguishing three groups of variables which refer, respectively, to characteristics of the family, of the survey respondent, and of the place where the family lives. As regards household income, we note a pattern whereby the effect on fuel efficiency grows across the first income categories, it then decreases and stabilizes, with coefficients statistically not different from that of the lowest-and-reference income category, and finally it becomes negative, with a rather large coefficient (-0.54) when compared to that of the gasoline price (representing the effect of an extra $1 at the pump). Among the other household-level variables, we note that fuel efficiency is negatively correlated with the number of household members (-0.48), but positively correlated with the number of adults (0.31). These relationships make sense if one imagines that it is usually larger households and especially households with children who need bigger cars. Coming to the characteristics of the survey respondent, the results are interesting – also probably expected – whereby fuel efficiency is positively correlated to the level of educational attainment (1.06 for the highest category compared to the lowest reference category) and to female gender (0.32 compared to male). By contrast, a positive correlation between fuel efficiency and the age of the survey respondent appears to be way more modest (0.1). Furthermore, urban and infrastructural factors characterising the place where the household lives turn out to be very important. We find here clear differences between urban and suburban contexts (0.85 and 0.81) relative rural contexts, as well as quite a large coefficient on a variable capturing proximity to a rail (0.93).

5. Concluding remarks

This study shows the potential environmental added value of policies that stabilise gasoline prices and related agents' expectations. The estimated negative effect of gasoline price volatility on fuel efficiency of new vehicles sold supports the research hypothesis that uncertainty about future gasoline prices makes fuel efficient vehicles less likely to be purchased. Given the important policy implications of this result, we firstly stress the desirability of further empirical tests using different data, models, and approaches.

In the context of the ecological transition, the environmental benefits achievable through policies that reduce uncertainty about future energy prices seem to us a topic as important as it is understudied. It is indeed legitimate to expect that over the next two to three decades the progressive abandonment of fossil energy sources at the global level will be accompanied by erratic fluctuations in energy markets, no less than those of the past. Strong volatility of fossil fuel prices and high uncertainty about their future levels, potentially combined with low fossil fuel prices as predicted by the Green Paradox (Sinn, 2012), would penalise investments for climate change mitigation. Under mandatory carbon markets, the question of energy price uncertainty could be addressed through fluctuation bands ('collars') for carbon prices (see, e.g., Doda et al., 2022, and Philibert, 2009). By contrast, how carbon taxes could be designed and implemented in such a way as to address energy price uncertainty in relation to climate change mitigation has not yet been identified or even debated in depth.

Furthermore, it is important to recognise that the proposed DCT or any other similar mechanism would not operate in a policy vacuum nor would it likely be the main instrument for decarbonising road transport. Absent a cap-and-trade system that already covers emissions from road transport, the proposed DCT would operate in a complementary manner alongside a series of other policy instruments including, e.g., emissions-related vehicle registration taxes, purchase subsidies for electric vehicles, and fuel efficiency standards for internal combustion engine vehicles. Finally, a key question is clearly at what level gasoline prices should be stabilised. Under the proposed DCT mechanism, this question translates into what the target price of crude oil should be (e.g., $80/barrel, $100/barrel, $120/barrel …?). Answering this question requires identification of an optimal trajectory of the crude oil price for a politically feasible, effective, timely, and economically efficient decarbonisation of road transport.

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