A Hedge Fund in Your Garage:
Automobile purchases under gasoline price uncertainty*

James Archsmith†
University of Maryland, College Park

Simon Levin‡
University of Maryland, College Park

Draft Date: March 4, 2025

Preliminary and incomplete

Please do not circulate or cite without permission of the Author.

Please review and cite the most recent version of this paper available at
https://econjim.com/WP2401

*We would like to thank Soren Anderson, Spencer Banzhaf, Susanna Berkhouwer, Severin Borenstein, Finoa Burlig, Kenneth Gillingham, Michael Greenstone, Rodger van Haefen, Mark Jacobsen, Ryan Kellogg, Joshua Linn, Erin Mansur, Louis Preonas, Blake Schafer, Paige Weber, Andy Yates, and seminar participants at the ASSA Annual Meeting, Carnage Mellon University, the RTI TREE Seminar, and the UC Berkeley Energy Camp for helpful feedback on this paper. We thank Joshua Linn and Resources for the Future for access to data. Any errors are our own. This paper was previously circulated and presented under the title "You Don't Know? Pump it Up: Consumer Beliefs and Gasoline Price Uncertainty".

†Assistant Professor, Department of Agricultural and Resource Economics, University of Maryland, College Park, MD 20742 Email: archsmit@umd.edu, URL: https://econjim.com, ORCHID: 0000-0002-6052-0302

‡PhD Candidate, Department of Agricultural and Resource Economics, University of Maryland, College Park, MD 20742 Email: snlevin3@umd.edu

Abstract

College education, home ownership, and automobiles are all examples of purchases where consumers sink a large up-front investment expecting to enjoy a stream of future net benefits. Often those benefits are uncertain at the time of purchase. We consider how uncertainty in future operating costs impacts the choice of vehicle fuel economy. Using measures of forward gasoline price uncertainty from Real Options Theory and comprehensive data on sales of automobiles in the US, we find future gasoline price uncertainty has economically meaningful impacts on vehicle demand, with a one standard deviation increase in the variance of the future price distribution increasing willingness-to-pay for fuel economy by 10%, slightly improving mean fuel economy, but substantially reducing total vehicle sales. This new finding has implications for policy surrounding energy use in transportation. As an example, we find the uncertainty in compliance costs under cap-and-trade climate regulation reduces vehicle sales more than twice as much as an equivalent carbon tax with no uncertainty.

JEL: Q41, D84, L62

Keywords: Uncertainty, Consumer beliefs, Gasoline prices, Automobile demand, Energy Efficiency

1 Introduction

People regularly make large up-front investments with expectations that they will deliver a future stream of benefits. College education, home and automobile purchases are but a few examples. In many cases, however, the future stream of benefits is uncertain—unanticipated future conditions may alter the benefits a consumer derives from utilizing the investment. For example, changing labor market conditions may increase or decrease the value of a college degree. Alternatively, the ongoing costs associated with using the investment may change, *e.g.*, changing fuel prices may make an SUV more expensive to drive.

A long literature shows consumers rationally incorporate their expected future benefits into their willingness to pay for sunk investments which are enjoyed over time. For example, for many US residents, primary residences are their most valuable assets. Amenities delivering a stream of benefits to the homeowner, such as air quality (*e.g.*, Harrison and Rubinfeld (1978)), recreation benefits from improved water quality (Kuwayama, Olmstead, and Zheng (2022)) or access to high-quality public schools (*e.g.*, Fack and Grenet (2010)) are capitalized into the up-front cost of buying a home. There is less understanding, however, of how the level of uncertainty over those future benefits impacts the decision to make such investments.[1]

In this paper we examine how consumers of automobiles respond to uncertainty in future operating costs when making the vehicle purchase decision. Improved fuel economy not only reduces the expectation of future operating costs, it reduces exposure to uncertainty in future operating costs as a given fuel cost shock will have a smaller impact on the total operating cost of a more fuel efficient vehicle. Consistent with consumers having risk-averse preferences over future operating costs, we find that conditional on the central expectation of future operating costs, automobile purchasers value reducing their exposure to future *uncertainty* in those costs. Namely, as uncertainty in future gasoline prices increases, consumers' willingness-to-pay for fuel economy increases as well.

Measuring individual responses to uncertainty is empirically challenging because it can be difficult to measure their perceived level of uncertainty. In both field and laboratory experiments, participants frequently state prior probabilities over future outcomes which are inconsistent with their revealed behavior (Danz, Vesterlund, and Wilson (2022)) or express differing assessments of their own uncertainty depending on the elicitation mechanism (Pedroni et al. (2017)). Rather than rely on stated beliefs of future uncertainty, we derive market measures of future price uncertainty by applying Real Options theory to data from US oil and gasoline markets. These implied volatility measures of future uncertainty are the outcome of revealed behavior of traders with substantial financial stakes in these markets. We further show these market measures of uncertainty are correlated with the dispersion of consumers' stated beliefs over future gasoline prices.

We estimate the impact of future price uncertainty on consumer automobile purchases using a comprehensive state-level panel of new automobile purchases in the United States (US) and a nested logit model of demand following Berry (1994). We find future price uncertainty has statistically and economically significant impacts on consumer's willingness-to-pay (WTP) for fuel economy. A one-standard deviation increase in implied volatility increases the mean consumer's marginal WTP for an additional miles per gallon (MPG) of fuel economy by \$89 from a baseline of \$889/mpg. This can have large effects on the vehicle stock, which is slow to turn over. Similar

[1] The primary exceptions center on responses of real estate prices to the risk of catastrophic losses, *e.g.*, MacDonald, Murdoch, and White (1987) or Bakkensen and Barrage (2022). There is also a substantial finance literature analyzing optimal portfolio choice under dynamic uncertainty, *e.g.*, Chacko and Viceira (2005). The investments they consider are generally transacted in thickly-traded markets, have relatively low transaction costs and the truly "sunk" component of the investment is quite small.

to other work modeling vehicle choice in response to the level of future operating costs, such as Leard, McConnell, and Zhou (2019), we find future price uncertainty can have large extensive margin effects on the decision to purchase any vehicle, with a 1-standard deviation increase in future price uncertainty reducing overall vehicle sales by 6.8%. The intensive margin effect on the fuel efficiency is more muted, with that same 1-standard deviation increase leading to a 0.5% increase in the mean MPG rating of vehicle purchased, primarily driven by a shift in the composition sales from pickups and SUVs to more efficient sedans and crossovers.

These results also have important implications for the design of climate policy in automobiles. Many proposed policies to address greenhouse gas emissions utilize either price based (*e.g.*, carbon taxes or fees) or quantity-based (*e.g.*, cap-and-trade) compliance mechanisms. Weitzman (1974) finds uncertainty in marginal abatement costs can cause these policies to differ from the first-best in expectation. This paper identifies a new channel. While compliance costs under a price instrument are *ex ante* known with certainty, compliance costs under an equivalent quantity instrument are uncertain. This uncertainty passes through to uncertainty in fuel costs and leads consumers to make different vehicle purchase decisions than under an equivalent (in expectation) price instrument. Again the effects are economically meaningful. We simulate the impact of price and quantity instruments for climate regulation using the European Union Emissions Trading System (EU-ETS) as a model for the level and future uncertainty in compliance costs. Compared to an equivalent price instrument, a quantity instrument induces consumers to purchase moderately more fuel-efficient vehicles, but reduces overall vehicle sales by more than double the effect of a comparable price instrument. New vehicles tend to be more efficient than the vehicle they replace, which insulates drivers from higher fuel prices, which induces additional driving that can outweigh the benefits of improved fuel efficiency of new vehicles sold. This reinforces it is important to account for consumer responses to uncertainty in the design climate regulation.

1.1 Measuring Valuation of Durable Goods

Standard economic theory and a long history of empirical analysis show consumers consider their future stream of net benefits when making irreversible investments. This trade-off between a sunk investment and future benefits can occur in a diversity of settings. For example, Attanasio and Kaufmann (2017) find private expectations of the financial return to college education and/or marriage (both sunk investments) impact the likelihood an individual undertakes either. Chay and Greenstone (2005) show US homeowners capitalize policy-induced improvements in air quality into the purchase price of homes. Further, they find heterogeneity in preferences for air quality induce taste-based sorting of homeowners. Gowrisankaran and Rysman (2012) examine how changes the up-front cost of a durable good (video camcorders) impacts the timing of purchase behavior. They find price increases have a large short-run effect, but a much more muted long-run impact on sales.

Much of the work examining how WTP for up-front investments varies with expected future net benefits focuses on energy-consuming durable goods. These purchases are ideal settings to examine forward-looking consumer behavior; first because the bulk of operating costs are directly attributable to energy consumption, which is often well-measured both by the consumer and the econometrician. Further, conditional on other attributes there is frequently a clear cost-efficiency trade-off. Finally, energy prices are observable and exhibit sufficient time-series variation to enable estimation of the impacts of expected future operating costs on WTP. Automobiles are the the most-considered example, likely due to their large capital cost and salient fuel costs. They are not the only such energy-consuming durable, *e.g.*, Hausman (1979) and Rapson (2014) both consider how WTP for home air conditioners varies with anticipated future operating costs from energy inputs. Considering energy production, Gillingham and Watten (2024) find incomplete capitalization of the future benefits of residential solar panels (which depend on future electricity prices) into home values.

The bulk of this literature considers how only the central expectation of future operating costs impacts WTP, often assuming future benefits are well-approximated by current conditions. In this paper we consider how both the central expectation and the *uncertainty around that expectation* of future operating costs impact the willingness-to-pay for fuel efficiency in automobiles.

1.2 Valuation of Energy Efficiency

Much of this literature finds consumers value the benefits of energy efficiency in durable goods less than the present discounted value of the implied cost savings. This observation, outlined by Jaffe and Stavins (1994) who coined it the "energy efficiency paradox" is most often noted in automobiles, *e.g.*, Allcott and Wozny (2014) or Greene, Evans, and Hiestand (2013). However, research finds similar undervaluation in other durable goods such as air conditioners (Hausman (1979)) or energy-efficient light bulbs (Allcott and Taubinsky (2015)). Particularly with automobiles, there is substantial debate on the sources of this paradox,[2] or whether it exists at all.[3] Greene (2011) argues it may arise because consumers are uncertain about the true energy savings at the time of purchase, causing them to undervalue marginal efficiency improvements relative to their present value energy savings.

Considering automobiles, field experiments in Allcott and Knittel (2019) find little evidence that prospective automobile buyers are poorly-informed of fuel economy. In a quite different context, Berkouwer and Dean (2022) find inattention to energy consumption is not a major contributor to the underadoption of energy-efficient cook-stoves. Also consistent with Greene (2011), they find households classified as risk averse exhibit lower WTP for the unfamiliar technology. In contrast, Oliva et al. (2020) find uncertainty over future costs increases adoption of a new technology when those costs are incurred after the uncertainty is resolved. Here, in contrast, we examine the role of future *fuel price* uncertainty on valuation of energy efficiency. We find consumers value fuel economy in automobiles less than the full NPV cost savings, however, we also show that ignoring uncertainty substantially understates the true WTP for fuel economy.

1.3 Expectations of Future Energy Prices

Finally, much of the work examining valuation of fuel economy embeds an assumption that automobile purchasers believe future gasoline prices will be identical to their current level. This assumption is justified through analysis in Anderson, Kellogg, and Sallee (2013) and Anderson, Kellogg, Sallee, and Curtin (2011) who find consumers have beliefs over future fuel prices consistent with a no-change forecast.[4] In contrast, Archsmith and Levin (2025), using similar but more recent survey data, shows evidence that consumers' beliefs over future gasoline prices started to deviate from a no-change forecast beginning with the large increase in the level and uncertainty in gasoline prices during the leadup to the financial crisis of 2008. We reinforce this later finding using the revealed behavior of automobile purchases. We find consumers act in a manner consistent with risk-aversion with respect to uncertainty in future fuel prices with implications for automobile demand, energy and climate policy.

Our analysis will proceed as follows: As motivation for our empirical analysis, in Section 2 we outline a simple

[2] Bento, Li, and Roth (2012) argue unobserved consumer heterogeneity may bias estimates toward undervaluation of fuel economy.

[3] Some estimates of WTP for fuel economy find full valuation or little evidence of undervaluation., *e.g.*, Busse, Knittel, and Zettelmeyer (2013) or Sallee, West, and Fan (2016).

[4] Using aggregate data, Binder (2018) finds US consumers anticipate some mean reversion in future gasoline prices.

theoretical model of vehicle choice under fuel price uncertainty and derive predictions of consumer behavior under various assumptions of the nature of uncertainty and consumer risk preferences. Section 3 will describe data used in our empirical analysis. Section 4 will describe methods used in our analysis including our calculation of market-based measures of future uncertainty and our structural model of automobile demand. Section 5 describes estimates and tests of robustness from the demand model. Section 6 applies these estimates to derive predictions of the impact of policy-induced uncertainty in climate regulation and Section 7 concludes.

2 Motivation

2.1 A Model of Consumer Vehicle Choice Under Future Gasoline Price Uncertainty

As motivation, we develop a model of consumer vehicle choice when future gasoline price are uncertain and consumers may not be risk-neutral. We start with the vehicle purchase decision, then describe the flow of utility from using the vehicle and finally introduce uncertainty. Proofs of results presented here are available in the Appendix A.

2.1.1 Vehicle Purchase Decision

Consider a consumer that makes an irreversible decision to purchase some new vehicle i from the set of all available vehicles I at time $t = 0$. Each vehicle has some set of attributes x_i, a fuel-intensity of operation[5] g_i, and up-front cost p_i.

Consumers own the vehicle over the subsequent T periods, deriving utility U_t in each period from use of the vehicle. At $t = 0$ the consumer believes future states of utility in period t have density Ω_t^U. The consumer is forward-looking with discount factor β, has risk preferences $R(U_t)$, receives income ω_t with constant marginal utility of money normalized to one. Thus, when purchasing a vehicle at $t = 0$, the consumer will choose the vehicle i that maximizes current period expected utility

$$EU(i = i) = R\left(\omega_0 - P_i^V\right) + \sum_{t=1}^{T}\left[\beta^t \int R(U_t)\Omega_t^U(U_t)dU_t\right] \tag{1}$$

2.1.2 Vehicle Operation Decision

A vehicle has a life of T periods. In each period $t \in [1, T]$, the consumer observes gasoline prices in that period f_t and decides how much they will drive the vehicle V_t. Consumers derive additively-separable utility from the vehicle's attributes $A(x_i)$ and driving $h(V_t)$ with positive, diminishing marginal utility for positive V_t, thus $h > 0$, $h' > 0$ and $h'' < 0 \; \forall V_t > 0$. They must also pay for fuel with a cost that is the product of the fuel price, vehicle fuel intensity and the amount driven. Thus in each period, the consumer derives utility from use of vehicle i

$$U_t\left(V_t | i = i\right) = \omega_t + A(x_i) + h(V_t) - f_t g_i V_t \tag{2}$$

[5] In the US fuel consumption of vehicles is generally expressed in MPG, which is the inverse of the fuel-intensity. In both the theory here and empirical models later, we will use the fuel intensity expressed in gallons per mile (GPM) so it enters the cost expression multiplicatively. Importantly, while fuel-economy is a good, fuel-intensity (conditional on other attributes) is a bad.

and chooses V_t to maximize utility

$$V_t(f_t|i=i) = \underset{V}{\operatorname{argmax}} \{\omega_t + A(x_i) + h(V) - f_t g_i V\} \tag{3}$$

Because h is concave, conditional on a vehicle fuel intensity, there is a unique $V(f_t|g_i) : f_t \rightarrow V_t$ that maximizes current period utility with $\frac{\partial V_t}{\partial f_t} < 0$.

2.1.3 Operating Cost Uncertainty

When purchasing the vehicle, consumers are making a decision to maximize expected utility in the future. However, gasoline prices are uncertain. Gasoline prices impact operating costs and the operation decision, and directly impact a consumer's valuation of a vehicle at the time of purchase. Suppose only future gasoline prices are uncertain. At time $t = 0$ the consumer believes the distribution of potential future gasoline prices at time t has pdf Ω_t^f. Then at time $t = 0$ the consumer's expected utility of purchasing vehicle i is

$$EU(i=i) = R(\omega_0 - p_i) + \sum_{t=1}^{T} \left[\beta^t \int R(\omega_t + A(x_i) + h(V(f_t \cdot g_i)) - V(f_t \cdot g_i) \cdot f_t g_i) \, \Omega_t^f(f_t) df_t \right] \tag{4}$$

2.1.4 Consumer Valuation of Fuel Intensity

We are interested in how future uncertainty may impact a consumer's willingness to pay for a specific new vehicle. In particular, how future gasoline price uncertainty may impact the consumer's valuation of the fuel intensity of a vehicle.[6] For a specific vehicle we derive the marginal willingness to pay for fuel intensity (MWTPg) as the ratio of the marginal change in expected utility from a marginal increase in fuel intensity to the marginal utility of money at time zero. Thus

$$\begin{aligned} MWTPg =& \frac{\frac{\partial EU}{\partial g}}{R_0'} \\ =& \frac{1}{R_0'} \sum_{t=1}^{T} \left[\beta^t \int \underbrace{-f_t V(f_t \cdot g_i)}_{\partial \text{op. costs}} \underbrace{R'(\omega_t + A(x_i) + h(V(f_t \cdot g_i)) - V(f_t \cdot g_i) \cdot f_t g_i)}_{\partial U_t} \Omega_t^f(f_t) df_t \right] \end{aligned} \tag{5}$$

This expression shows consumers MWTPg is the present-value discounted expected change in operating costs across time, weighted by the corresponding marginal utility in each possible gasoline price state. This leads us to consider MWTPg under different assumptions of consumer risk preferences and future gasoline price uncertainty.

Risk Neutrality: Suppose the consumer is risk neutral. Then $R'(u) = R \; \forall U_t$ In this case MWTPg is

$$MWTPg = -\sum_{t=1}^{T} \beta^t \int [f_t V(f_t g_i)] \, \Omega_t^f(f_t) df_t \tag{6}$$

or the present value expected additional fuel costs from a unit increase in g_i.

[6] Recall that operating costs increase with increases in fuel intensity, so conditional on other attributes consumers should have a negative valuation of marginal changes in fuel intensity.

Risk Preferences and No Uncertainty: Suppose the consumer has some preference over future states of the world, thus $R(u)$ is not constant. Second, assume there is no uncertainty over future gasoline prices and the consumer believes $f_t = \hat{f}_t$ with certainty. Risk preferences weight utility in each state. For notational simplicity we define $\mathbf{R}'_t(\Delta f_t)$ as the marginal utility of consumption in period t under a gasoline price change of Δf_t from period 0.[7] In this case Ω_t^f is the Dirac delta function centered on f_t and, after integrating over this distribution, the MWTPg is

$$MWTPg = -\sum_{t=1}^{T} \beta^t \left[f_t V(f_t g_i)\right] \tfrac{\mathbf{R}'_t(\Delta f_t)}{R'_0} \tag{7}$$

or the present value of the future stream of fuel cost changes weighted by marginal utility in each period. If we further assume that consumers believe the gasoline price in all future periods will be identical to the price today and income in each period is constant then up to a scalar factor, this expression reduces to the current gasoline price times the present discounted sum of future miles traveled.

Risk Preferences and Uncertainty: Suppose the consumer has preferences over future states of the world and future gasoline prices are uncertain. For simplicity assume the consumer believes the gasoline price at time t is drawn from a distribution $f_t \sim \Omega_t^f$ parameterized by its mean μ_t and a measure of it's spread σ_t where if $\sigma_t = 0$ then $f_t = \mu_t$ with certainty but $E\left[|f_t - \mu_t|\right]$ is strictly increasing in σ. Consistent with evidence in Anderson, Kellogg, and Sallee (2013) assume $\mu_t = f_0 \ \forall t$. Now, consider the first-order Taylor expansion of the MWTPg around $\sigma = 0$:

$$\begin{aligned} MWTPg &= \left.\frac{\partial EU}{\partial g}\right|_{\sigma=0} + \sigma \left.\frac{\partial^2 EU}{\partial g \partial \sigma}\right|_{\sigma=0} + \dots \\ &\approx \underbrace{- f_0 \sum_{t=1}^{T} \beta^t V(E[f_t] g_i) \tfrac{\mathbf{R}'_t(\Delta f_t)}{R'_0}}_{\partial MWTPg \text{ with certainty}} \underbrace{+ \sigma \sum_{t=1}^{T} \beta^t \int \left[f_t V(f_t g_i) \tfrac{\mathbf{R}'_t(\Delta f_t)}{R'_0} \left.\frac{\partial \Omega_t^f}{\partial \sigma}\right|_{\sigma=0} \right] df_t}_{\partial MWTPg \text{ from } \partial\sigma} \end{aligned} \tag{8}$$

This expression highlights how a consumer's valuation of fuel intensity will be impacted when they have risk preferences and future fuel prices are uncertain. The first term is the consumer's valuation absent uncertainty over future prices, or the marginal present discounted change in operating costs from a marginal increase in fuel intensity, weighted by marginal utility of money in each period. The second term is the present discounted value of the change in marginal operating costs, weighted by marginal utility of money in that period, integrated over changes in the probability distribution of gasoline prices as the spread increases. In general the sign of this term is ambiguous. However, assuming Ω_t is symmetric around the expectation f_t, then for risk-averse consumers this terms must be less than zero and than zero and increasing σ must decrease MWTPg. In other words, valuation of *fuel economy* is increasing in uncertainty over future prices.

[7] Total utility must be decreasing in gasoline prices. Therefore, for risk-averse agents $\mathbf{R}'_t(\Delta f_t)$ is increasing in Δf_t.

3 Data

3.1 Commodity Price Data

Our measures of current gasoline prices and future uncertainty are built using futures and options contract prices. Derivative contracts for both refined gasoline (specifically Reformulated Blendstock for Oxygenated Blending (RBOB)) and crude oil (specifically West Texas Intermediate crude oil (WTI)) are traded on the New York Mercantile Exchange.[8] For these commodities we have collected the daily closing price and volume for each futures contract listed for sale on that day and the volumes and closing prices of all options contracts for each of those futures contracts. We collect these data from Refinitiv. Using their API it is not possible to reconstruct a list of all options that ever traded for a particular futures contract. We are, however, able to reconstruct the full series of futures contracts. For each futures contract, we determine the highest and lowest daily closing prices for those contracts and attempt to collect options contract data for all possible contracts with strike prices within the range of observed futures prices $\pm 10\%$.[9]

[Table 1 about here.]

We additionally obtain refiner spot prices for WTI and RBOB and retail gasoline prices by PADD from the Energy Information Administration (EIA).

3.2 Vehicle Registration Data

Our analysis of consumer automobile purchase behavior primarily relies on data from IHS Markit vehicle registration data for the United States. The data cover new vehicle registrations, by state and quarter, between 2010 and 2019. Observations are differentied by registration type, vehicle make, model,series, fuel types[10], body style, drive type, and engine displacement. In addition, the data contains vehicle MSRP and new registration counts. For additional vehicle characteristics, we merge our registration data with more detailed specification data from Wards Intelligence, matching vehicles based on characterstics available in the IHS data. From the Wards data, we obtain vehicle fuel efficiency, horsepower, curb weight, and wheelbase length. To manage dimensionality of our dataset, we aggregate vehicles in each quarter by make, model, body style, and power type, taking sales-weighted averages of other vehicle characteristics. To calculate market shares, we use the count of licensed drivers in each state.

Before estimation, we perform a few additional data processing steps. First, we remove fleet registrations from our observations; our analysis focuses on consumer behavior and fleet vehicle purchases are likely based on different factors than individual vehicle purchases (*e.g.*, Leard, McConnell, and Zhou (2019) find different responses to gasoline price increases in fuel economy of vehicle purchased across different types of fleet buyers). In addition, we omit registrations of battery electric vehicles (BEVs), implicitly including them (along with used vehicles) in our outside good. We do this because our estimation is focused on fuel price uncertainty, as measured through implied volatility of oil prices. Because BEVs do not use gasoline, we believe including them would be inappropriate. Given

[8] We also obtain futures and options contracts for emissions allowances under the European Union Emissions Trading System, traded on Eurex.

[9] Generally our calculation of implied volatility will only consider options contracts that are close to "in-the-money". These contracts will always have strike prices falling within the range of observed futures contract prices.

[10] Fuel type classifications include electricity for hybrid and non-hybrid vehicles.

that BEVs make up a very small percentage of the overall market in this time period (less than 1%), we believe this is reasonable step.

3.3 Additional Data

We rely on the following additional data for some analyses:

Interest Rates: As we will describe in Section 4.1.2, we compute a forward-looking measure of implied volatility in future fuel prices using methods from Real Options Theory. These models require a measure of the risk-free interest rate. As an approximation we use 1- and 3-year zero-coupon US Federal Treasury bond interest rates obtained from the St. Louis Federal Reserve.

VIX: Our analysis in this paper focuses on uncertainty in future gasoline prices, which may contribute to general macroeconomic uncertainty. To control for time-varying macroeconomic uncertainty, we include the CBOE VIX index as a control in some of our analyses. VIX is a forward-looking measure of future uncertainty in equities composing the S&P 500 stock index, computed using methods similar to the our calculation of forward-looking fuel price uncertainties. We obtain daily values of the VIX index from the St. Louis Federal Reserve. When the time unit of analysis is larger we aggregate the series, taking averages over the length of the time unit.

EU-ETS Market Data: In a policy analysis presented in Section 6 we simulate consumer behavior under counterfactual prices and future uncertainty from a climate regulation similar to the EU-ETS. We compute GHG emissions prices and their future uncertainty using futures and options contracts for EU-ETS emissions allowances traded on the Eurex exchange from April 2010 to the present. These contracts are traded under two ticker symbols: CFI2 and EFOM. As with other commodity market data, we collect these data from Refinitiv.

4 Methods

4.1 Modeling Uncertainty

The model in Section 2.1 posits that the agent has some belief about the distribution of possible prices in the future. One can characterize the agent's uncertainty as the variance or spread of this distribution. During periods of low uncertainty this variance is low and the agent can say with high confidence they believe the future price will fall within some narrow range. If the variance of this distribution increases, then the agent will have lower confidence in any given prediction. We will refer generally to the level of uncertainty over future prices as *volatility*.

It is important to distinguish the concept of forward-looking uncertainty from variability in prices. While high volatility may be associated with a period of highly variable prices, it can also signal other forms of uncertainty, *e.g.*, whether prices will remain near their current level or trend upward for an extended period. Conversely, the agent may believe there will be high variability of prices within a narrow band, in which case they can still say with high confidence that prices will fall within that band. In this case, while variability may be high, volatility will be low due to the narrow distribution of their beliefs over future prices.

4.1.1 Models of Asset Price Uncertainty

In this paper, we empirically investigate how individuals purchasing automobiles respond to volatility of future fuel prices, which requires we have an objective measure of forward-looking uncertainty. There are two broad approaches to measuring volatility of asset prices. Both assume that at least some portion of the evolution of future prices is stochastic, they place structure on the process of price evolution, and then empirically estimate or analytically derive parameters of that structural model. The distribution of that stochastic component will identify the volatility of the asset price.

The first set of methods for estimating volatility are retrospective measures. These operate under the assumption that changes of asset prices in the recent past inform how they may change in the future. There is a large taxonomy of these time series models (*e.g.*, ARCH, GARCH) with differing underlying assumptions on the evolution of prices. The principal advantage of these models is that one can estimate volatility using only historical price data. Conversely, since estimates are based only on how prices changed in the past, the volatility estimates from these models are inherently backward-looking. If some change in market conditions changes volatility, one must observe the evolution of prices for some period of time before the volatility estimate will update to reflect true future uncertainty.

The second approach for estimating volatility is derived from the asset pricing literature, originating with Black and Scholes (1973) and Merton (1974) as the basis of real options theory (RTO). These approaches rely on the fact that under a no-arbitrage condition, the price of certain derivative financial instruments, often options contracts, are a function of the asset price[11] and future uncertainty over the asset price. Thus, given information on asset and options prices, one can compute the *implied volatility* of future prices of a particular asset pricing model. The principal advantage to these approaches is that the computed volatility is a market-based expectation of *future* price uncertainty and it should incorporate new information as it becomes available. RTO approaches are used less frequently due to the data requirements. One must have data on both asset prices and the required derivatives. Further, the derivatives markets must be sufficiently thick that one would expect prices to converge to their no-arbitrage values.

Our central question is how consumers respond to uncertainty about future operating costs when purchasing a long-lived durable good and we will principally rely on RTO-based forward-looking measures of volatility. One may be concerned that these measures are complicated to compute and rely on data not readily available to typical automobile purchasers and, therefore, may be a poor measure of consumers' beliefs over future fuel price uncertainty. However, while RTO tools are quite far removed from the everyday experience of most car buyers, financial analysts do compute and report gasoline implied volatility.[12] This information feeds financial news reporting, which will inform the general public's beliefs on future uncertainty. We expect very few individuals can precisely define their beliefs over the future distribution of prices, but we expect that the majority form heuristics of future uncertainty which are correlated with implied volatility from financial markets. In related work, Archsmith and Levin (2025) uses a long-term, nationally representative survey to show evidence suggesting US households' expectations of future gasoline price changes are correlated with similar implied volatility measures.

[11] In commodity markets, this is often the futures price of the commodity.

[12] *e.g.*, Bloomberg Financial provides an oil volatility index derived from the implied volatility of 1-month oil options contracts and the Chicago Board of Trade computes a similar 30-day volatility index with ticker symbol OVX.

4.1.2 Measuring Implied Volatility Using Real Options Theory

Our preferred approach for modeling implied volatility uses the asset pricing model of Black (1976), Black and Scholes (1973) and Merton (1974) or Black-Scholes-Merton (BSM).[13] This model assumes that the log price of an asset follows a Brownian motion with some constant variance (σ), which characterizes future price uncertainty in this model. Given some value of σ, the forward contract price of a commodity, the risk-free interest rate, and the strike price and time to maturity of an options contract, this model provides a unique price for that contract. In our setting, we observe prices and interest rates, then use that information to compute the value of σ they imply. This value of σ is the implied volatility at any given point in time.

At any given time commodity markets offer a range of options contracts that vary in attributes such as their strike date, strike price, and type (call or put). The trading volume, or thickness, of each contract can vary substantially across these details. We want to use as much market data as possible to inform our estimate of implied volatility while at the same time avoid relying on prices for thinly-traded contracts that may be traded at prices far away from their no arbitrage price.

With these goals in mind, we estimate σ from NYMEX commodity price data on each trading day as follows. We first choose a time horizon of either 60 days or 1 year for computing the implied volatility. We identify the set of contracts with the first strike date on or after the horizon date. We further limit this set of contracts to American-style call options[14] with at least 10 contracts traded on that day. There may be several contracts meeting these criteria. We compute the value of σ that minimizes the trading volume-weighted root mean squared error of the actual contract price and the price computed by BSM. This provides a daily market measure of forward-looking volatility. Much of our empirical analysis uses month or quarterly time units. When we aggregate to coarser time units, we compute the trading volume-weighted mean across all days in that time unit.[15]

We have computed implied volatility for both RBOB and WTI. Assuming full pass-through of crude oil input costs into gasoline prices, implied volatility from each series should be very similar. As we show Appendix B, for periods in which we are able to compute both implied volatility series, they are strongly correlated. Further WTI options contracts cover a longer time series and are more thickly traded. Our implied volatility measure is unitless and is invariant to the underlying asset price. Consequently, our preferred measure of future gasoline price uncertainty is derived from WTI contracts, however our results are robust to using RBOB volatility instead.

4.2 Estimating Vehicle Demand

To determine the impact of fuel price uncertainty on vehicle choice, we utilize a linear model of vehicle demand, derived from a nested logit framework (Berry (1994)). The nesting structure relaxes the independence of irrelevant alternatives property of the standard logit model, allowing for more realistic substitution patterns. To determine nests, we follow the literature and use vehicle class designations (Goldberg (1995); Verboven (1996)); specifically,

[13] There are many other asset pricing models. We have selected BSM due to the model's simplicity, widespread use, and the fact that uncertainty is characterized by a single parameter which simplifies including uncertainty in our later structural demand model.

[14] It is well-documented that put options generally transact at a discount relative to prices predicted by BSM, so we limit our primary analysis to volatility computed using only call options.

[15] The heaviest trading day for commodity options are typically the final day to trade options on the current front-month as traders close out existing positions and open new contracts. This day usually dominates each monthly calculation. Because we consider contracts expiring at least 60 days in the future, none of the prices we use to compute implied volatility are based on contracts that are about to expire.

we rely on categorizations of body style from our vehicle sales data.[16] The linear specification we employ is

$$\ln s_{jt} - \ln s_{0t} = \boldsymbol{\beta}'\boldsymbol{X}_{jt} - \alpha_1 \ln p_{jt} - \alpha_2 GPM_{jt} \times f_t - \alpha_3 GPM_{jt} \times \sigma_t + \rho \ln s_{j/g(j)t} + \boldsymbol{\gamma} + \epsilon_{jt}, \tag{9}$$

where j indexes vehicle models and t indexes markets; markets are defined as a combination of state and quarter-of-sample. On the left-hand side of the equation, s_{jt} is the vehicle market share and s_{0t} is outside good market share. The dependent variable, $\ln s_{jt} - \ln s_{0t}$, is derived from inverting the nested logit market share equation (Berry (1994)). On the right-hand side, $\boldsymbol{X}_{jt}$ is a vector of vehicle characteristics, p_{jt} is vehicle price, GPM_{jt} is fuel-intensity,[17] f_t is fuel prices, σ_t is implied volatility (our measurement of fuel price uncertainty), $s_{j/g(j)t}$ is the within-nest share of vehicle j, and $\boldsymbol{\gamma}$ is a vector of market, power type-year, and make-year fixed-effects.

4.2.1 Identification

In Equation 9, we include typical elements of vehicle demand equations, such as vehicle characteristics, prices, and operating costs as measured through an interaction of fuel intensity and fuel prices (Berry, Levinsohn, and Pakes (1995)). In addition to market fixed effects, we include power type-year and make-year fixed effects.[18] The former help control for broad changes in vehicle tastes over time, such as the increase in penetration of hybrids and plug-in hybrids over time. The latter control for changes in brand-specific trends such as deviations in quality of vehicle brands across time or the entry and exit of makes, such as the spinoff of the Genesis brand from Hyundai.

Conditional on these fixed effects we still note two identification concerns:

Simultaneity of Price: Prices are an equilibrium outcome of supply and demand and present a simultaneity concern. To identify our price parameter, we employ instrumental variables in the spirit of Berry, Levinsohn, and Pakes (1995). Here we assume vehicle characteristics, except for price, are exogenous and rely on BLP-style instruments following their approach. For each vehicle in market t, we calculate the average of characteristics $\boldsymbol{X}_{jt}$ and fuel economy across vehicles produced under the same brand and produced under other brands. This implementation of BLP-style instruments follows Verboven (1996) and avoids instrument collinearity issues created by using sums of characteristics in conjunction with market fixed effects.

The relationship of these instruments to prices stems from their effect on supply-side markups. Vehicles with characteristics more similar to others' will be more substitutable than vehicles with less similar characteristics, and will command lower markups (Berry, Levinsohn, and Pakes (1995)).

Unobserved Macroeconomic Confounders: A second concern is that fuel price levels (f_t) and future uncertainty (σ_t) may be correlated with unobserved macroeconomic factors influencing automobile purchase behavior. We address this using two approaches. First, we note that fuel price uncertainty does not have a uniform impact across all vehicles on operating cost uncertainty. As fuel price uncertainty increases, uncertainty in the operating costs of more fuel intensive vehicles (*i.e.*, less fuel efficient) will increase more than the uncertainty in operating costs for less fuel intensive (*i.e.*, more fuel efficient). To account for this, we interact fuel intensity with σ_t. This interaction measures the exposure of each vehicle's operating costs to fuel price volatility and allows us to capture both the

[16]The IHS data categorizes vehicles into 9 body-styles: convertible, coupe, hatchback, passenger vans, pickups, sedan, sport utility, station wagon, and van.

[17]Fuel-intensity is measured as the inverse of fuel-efficiency, as measured in miles-per-gallon.

[18]Power types categorize vehicles by engine technology; categories include gasoline, diesel, hybrid, and plug-in hybrid.

impact changes in fuel price uncertainty have on demand, as well as its heterogeneous impact across vehicles. Likewise, we capture a particular vehicle j's operating cost exposure to the level of fuel prices by interacting fuel prices with fuel intensity. This is is a common approach to capture the impacts of gasoline prices on vehicle sales (*e.g.*, Klier and Linn (2010)).

An additional identification concern of fuel price uncertainty stems from the potential for omitted variable bias. For example, oil market shocks that drive variation in σ_t may reflect broader economic shocks, which if uncontrolled for would lead to biased parameter estimates. This issue is addressed through market fixed-effects, which capture idiosyncratic economic shocks occurring at the state-quarter of sample level. Analysis presented in the Appendix B shows fuel prices, future fuel price uncertainty, and general macroeconomic uncertainty measured by CBOE VIX Index (VIX) all exhibit substantial independent time-series variation.

4.3 Interpreting the Demand Model

The model in Section 2.1 provides a theoretical basis for how uncertainty in future gasoline prices may impact consumers' vehicle purchase decisions, while in Section 4.2 we propose a method of estimating these impacts on automobile demand. Here, we connect the theoretical model to our empirical specification by deriving MWTPg from parameters in our demand model.

To do so, we use three parameters from our estimating equation (Equation 9). The parameters from our nested logit specification can be interpreted as parameters for the mean utility that consumers derive from vehicles. Here, the parameter on log price (α_1) is the own-price elasticity of demand. Next, taking the derivative of this equation with respect the vehicle fuel intensity (GPM_{jt}) then dividing by α_1 yields:

$$MWTPg = \frac{\partial p_{it}}{\partial GPM_{jt}} = \frac{\alpha_2}{\alpha_1} f_t \cdot p_{it} + \frac{\alpha_3}{\alpha_1} \sigma_t \cdot p_{it} \tag{10}$$

Recall from Equation 8 the MWTPg can be decomposed into two components. Comparing to this equation, you can see $\frac{\alpha_2}{\alpha_1}$ will capture the fuel intensity (GPM)-vehicle price semielasticity assuming fuel prices remain constant at their current level with certainty. $\frac{\alpha_3}{\alpha_1}$ is future fuel price variance (σ)-vehicle price semielasticity. This variance in the distribution of potential future fuel prices is precisely our measure of uncertainty.

In this model, consumers have a distaste for future operating costs and we expect the sign on α_2 to be negative. Following from results in Section 2, if consumers are risk neutral, we would expect α_3 to be zero but negative for risk averse consumers.

5 Results

Now we turn to estimating the impacts of future price uncertainty on consumers' preferences for purchasing new automobiles, following the demand model presented in Section 4.2. We first estimate the demand model, demonstrate its robustness to our modeling choices, and then discuss implications for vehicle choice and WTP for fuel economy when future fuel prices are uncertain.

5.1 Results from Primary Specification

Results from our primary regression are presented in Table 2. Column (1) presents our baseline regression, which does not include parameters related fuel price volatility. Column (2) presents our preferred specification, which includes an interaction between fuel intensity and the implied volatility 2-month WTI futures. Column (3) replaces this implied volatility with that of 12-month WTI futures, and Column (4) utilizes the implied volatility of 2-month RBOB futures.[19]

Across all specifications, all coefficient estimates are highly significant and of similar magnitudes. Estimates of distaste for log price, α, range between -4.1 and -4.2 and imply an own-price elasticity of roughly -4.1. This range is consistent with other estimates from the literature,[20] and implies that consumer are price sensitive, as expected. The coefficient on the interaction between fuel intensity and fuel prices ranges between -14.9 and -16.3, implying consumers prefer vehicles with lower operating costs. Importantly, parameter estimates for this variable are robust to the inclusion of our volatility terms.

The parameter estimates on the volatility interaction term, GPM$\times$ Vol, are our primary parameters of interest. By interacting fuel intensity with volatility, we can measure the exposure of each vehicle's operating costs to fuel price volatility. Given a value of volatility, the interaction term increases as fuel intensity increases; in other words, less fuel efficient vehicles will have a larger exposure to operating costs than more fuel efficient vehicles.

Estimates of this parameter are all negative and significant. First, this indicates that increases in fuel price volatility have a negative impact on vehicle demand, overall. Using the parameter estimate from column (2), a standard deviation increase in volatility would translate to a roughly 6.8% decrease in vehicle sales. Second, these estimates imply differential effects across the distribution of vehicle fuel intensities. For example, if we partial the sample by within-market fuel efficiency quartile, sales would decline by 9.4% for the least fuel efficient vehicles, while declining 6.1% for the most efficient vehicles. These effects on vehicle sales are large, but represent the concurrent response to changes in future uncertainty in automobiles. Just as in Gowrisankaran and Rysman (2012), we anticipate over longer horizons the impact on sales would be more muted.

While the estimates for the parameter in columns (2) and (4) are quite similar, the estimate in column (3) is notably lower in magnitude. This is likely due to the time-horizon of the implied volatility measurements; columns (2) and (4) utilize measures of 2-month implied volatility, while column (3) utilizes 1-year implied volatility. The difference in magnitudes between the two time-horizons suggests that consumers are either more aware of or more concerned with short-term uncertainty in fuel prices than with long-term uncertainty fuel prices.

[Table 2 about here.]

These results are broadly consistent with predictions from the model in Section 2. Here, consumers clearly respond to both the current level and future uncertainty in gasoline prices. Increased uncertainty in future gasoline prices leads consumers to purchase, on average, more fuel efficient vehicles. Uncertainty also impacts the extensive margin, reducing the total volume of vehicles sold. These results are inconsistent with consumer beliefs that either future gasoline prices will be identical to the current price or that they follow a random walk with constant variance. If that were the case, we would expect to see virtually no impact from future uncertainty in gasoline prices on vehicle sales.

[19] Across the specifications including interactions of GPM and implied volatility there is little difference in the parameter estimates. The underlying WTI options data are most thickly-traded for options contracts in the 2-month horizon, leading to the most precise estimates of implied volatility using the 2-month measure. Consequently, we prefer this specification (Column (2)) and employ these estimates as the basis of the simulations and counteractuals that follow.

[20] Berry, Levinsohn, and Pakes (1995) presents price elasticities between -4 and -7, while Goldberg (1998) estimates an average price elasticities of -3.1.

5.2 Robustness Checks

To test the impact of modeling choices on our parameter estimates, we perform robustness checks examining the impact of nest designations and fixed effect choices. Results from these robustness checks are presented in Table (3).

Columns (1) to (3) examine alternative nesting structures. Column (1) removes nests, column (2) separates nests by luxury designations, and column (3) combines convertibles, coupes, hatchbacks, and station wagons. Adjusting the nest specifications in columns (1) to (3) affects the magnitude of coefficient estimates, but results are still qualitatively the same. Coefficients on log price are similar to our primary estimates, falling between -3.3 and -5.1. Coefficients for the fuel price uncertainty interaction term are less consistent, ranging from -5.0 to -32.0. These imply a range of 1.7% to 10.7% decrease in vehicle demand from a standard deviation increase in volatility.

In column (4), we use the same nesting structure as in our primary specification and relax the market level fixed effects to a state-year levels and observe a GPM $\times$ Vol coefficient of -34.6, which implies that a standard deviation increase in volatility would result in a 11.5% decrease in vehicle sales. Because we have relaxed the market fixed effects, we can also include contemporaneous economic indicators as additional controls. To that end, in column (5), we add an uninteracted volatility term, as well as the VIX, which measures stock market volatility. While the coefficient on our volatility term is positive, the combined effects of the volatility term and its interaction term imply that a standard deviation increase results in 10.9% reduction in vehicle sales, which is consistent with the results of the specification in column (4).

[Table 3 about here.]

[Table 4 about here.]

5.3 Implications for the Willingness to Pay for Fuel Economy

Our results show that automobile purchasers place a substantial premium on fuel economy when future price uncertainty is high, independent of the central expectation of future prices. There is a schism in literature estimating consumers' WTP for fuel economy, with some finding marginal valuation of fuel economy in line with expected present value discounted costs savings ("full valuation") versus other research showing marginal valuation less than those same cost savings ("myopia"). One may naturally ask whether omitting the future fuel price uncertainty effect explains some or all of the observed myopia.

In our demand model excluding the uncertainty effect (Column 1 of Table 2), which mirrors many demand models estimating WTP for fuel economy, one can compute the operating cost to price elasticity as

$$\epsilon^{DPM} = \frac{\alpha_2}{\alpha_1} \times GPM_{it} \times f_t \tag{11}$$

This is the percent change in vehicle price a consumer would be willing to exchange for a one percent reduction in operating costs. Assuming a vehicle price, fuel consumption, and current gasoline price, one could translate this to the level effect – the marginal WTP for a one MPG increase in fuel efficiency. If this value is less than the present value of reduced operating expenses from a 1 MPG improvement in fuel economy, the vehicle purchaser would be considered myopic.[21]

[21]For example, Allcott and Wozny (2014) find vehicle prices are consistent with car buyers valuing a $1.00 reduction in operating costs at $0.76.

In Table 5 we perform this calculation for the three most commonly purchased vehicle classes during our sample period: sedans, pickups, and sport utility vehicles. For each vehicle class we compute the national sales-weighted median vehicle price and fuel economy rating in each quarter and match this to mean gasoline price and implied volatility. We first compute the marginal change in present value of fuel cost savings for a marginal improvement in fuel economy assuming: future gasoline prices remain constant at the price at the time of vehicle purchase, vehicles are driven 15,000 miles per year, vehicles have a lifetime of 16.5 years[22], and consumers discount future cost savings at a rate identical to the return on 10-year US Treasury Bonds at the time of purchase. We then compute the implied marginal willingness to pay for a MPG on the same median vehicles using estimates from our demand model. Specifically, we assume vehicle j has a price and fuel-intensity identical to the median values of all vehicles of a particular class sold in quarter t. We then compute the total WTP for fuel economy implied by the demand model[23]

$$\exp\left[\ln p_{jt} + \left(\alpha_2 \times GPM_{jt} \times f_t + \alpha_3 \times GPM_{jt} \times \sigma_t\right)/\alpha_1\right] \tag{12}$$

And finally compute the marginal WTP for a unit change in MPG using the centered finite difference.[24] We compute this WTP under two scenarios: First, assuming consumers have no response to uncertainty following Column 1 of Table 2 ("WTP no Vol") and second using our preferred estimates including a volatility response from Column 2 of the same table ("WTP /w Vol"). We compare the present value fuel cost savings with these WTPs in Table 5.

The simulation summarized in Table 5 computes values for each quarter from 2010Q1 through 2019Q4 and shows the mean value followed by the interquartile range in brackets. The first three row sets show the present discounted cost savings of a marginal 1 MPG improvement in fuel economy, the marginal WTP for a 1 MPG improvement in fuel economy from our demand model without uncertainty effects, and finally our preferred model with uncertainty effects. It is important to note here that there is substantial variation in both WTP for and the NPV of marginal improvements in fuel economy, both across time and across vehicle classes. Second, empirical estimates that do not account for future price uncertainty understate WTP for fuel economy relative to models that do.

The next two row sets show the over- or under-valuation of marginal fuel economy improvements relative to the present value cost savings from models excluding or including future fuel price uncertainty effects. Consistent with some literature showing consumer myopia, sedan and sport utility buyers undervalue fuel economy, however pickup buyers overvalue fuel economy relative to the cost savings. The final row shows the ratio of WTP from our demand model including uncertainty effects to the model excluding them. Across the board, we see failing to account for the uncertainty effect understates WTP for fuel economy by approximately 9%.

[Table 5 about here.]

Present value fuel cost savings and WTP for fuel economy improvement vary over time as vehicle prices, vehicle fuel efficiency, gasoline prices, implied volatility, and interest rates change. Figure 1 shows the time series

[22] Annual VMT and vehicle lifetime are drawn from assumptions used by the Environmental Protection Agency (EPA) in modeling benefits and costs of policies such as CAFE. The purchaser may not own the vehicle for its full lifetime, but should be able to capitalize fuel efficiency benefits into any future resale price.

[23] Recall α_1 is the parameter on log price, α_2 the parameter on the fuel intensity-gasoline price interaction, and α_3 the parameter on the fuel intensity-implied volatility interaction. p_{jt} is the vehicle price, f_t is the price of gasoline, and σ_t is the implied volatility. In the demand model excluding uncertainty effects α_3 is zero.

[24] To denominate the marginal WTP in MPG terms, we perturb GPM as $1/(1/GPM \pm \delta)$.

of present value cost savings (black), WTP ignoring volatility (orange), or including volatility (blue) from 2010 through 2019 for sedans, pickups, and SUVs. Across the time series, sedan purchasers exhibit undervaluation whereas pickup purchasers exhibit overvaluation, but the overvaluation effect is largest from 2011 to 2013 – a period of relatively high price and volatility levels.

[Figure 1 about here.]

6 Applications

From the empirical estimates presented in Section 5 it is clear future uncertainty is an economically-significant impact on the valuation of fuel economy in new car purchases. This begs the question: What implications does this have for policy? Clearly, uncertainty results in a disutility for consumers and they could be made explicitly better off by reducing the level of uncertainty in future gasoline prices. Reducing uncertainty, however, would induce consumers to purchase less efficient vehicles, which runs counter to the goals of both energy and climate policy in transportation. In this section we explore the impacts consumer distaste for operating cost uncertainty may have for typical climate policy.

6.1 Prices vs. Quantities in Climate Regulation

Economists often consider price-based (emissions taxes) or quantity-based instruments (*e.g.*, cap-and-trade) for the regulation of externalities such as GHG emissions. Absent uncertainty, one achieves identical first-best outcomes either when the regulator uses an optimal price instrument (*e.g.*, an emissions fee with the price set to marginal damages at the social optimum) or an optimal quantity instrument (*e.g.*, an emissions cap-and-trade with the cap set at the socially optimal quantity). Weitzman (1974), however, notes that when the marginal cost of compliance is uncertain from the perspective of the regulator, both approaches will have deadweight loss in expectation and the *ex ante* preferred instrument depends on the elasticity of the marginal damages function.

Consumer responses to uncertainty introduce an additional complication to this prices-versus-quantities comparison. Under a price-based instrument future compliance costs are fixed and known. With a quantity mechanism, future compliance costs are uncertain as they depend on the marginal cost of abatement for the final unit required to meet the cap. There is strong evidence that taxes and regulatory fees are fully passed through into gasoline prices. For example, EU-ETS emissions allowance are completely passed through to gasoline prices (Alexeeva-Talebi (2011)). In the US, gasoline tax increases Doyle and Samphantharak (2008) and RIN credit costs – an ethanol production mandate with tradable compliance – (Knittel, Meiselman, and Stock (2017)) are fully passed through into gasoline prices. As such, the uncertainty in future compliance costs under a quantity instrument should also pass through into future gasoline price uncertainty. Given our results, this implies automobile consumers will respond differently to price and quantity instruments due to the latter's uncertain impact on future prices, even when both have identical future compliance costs in expectation.

To investigate the magnitude of these effects we conduct a simulation using parameters from our preferred demand model, comparing the preference for fuel economy and the set of vehicles purchased under a price-based instrument (which raises gasoline prices but not future uncertainty) and a quantity-based instrument (which increases both gasoline prices and uncertainty over future prices). This simulation will project counterfactual GHG pricing policies on US automobile purchases during our sample period. There are myriad possible policy designs and here we will focus on two specific hypothetical policies that highlight the welfare impacts of a price instrument versus an cost-equivalent quantity instrument.

6.1.1 Uncertainty in Emissions Compliance Costs

Constructing this counterfactual requires we take a stand on how a quantity-based carbon regulation would impact future gasoline price uncertainty. Carbon cap-and-trade programs exist in the US but markets for allowances clear infrequently and do not make a setting amenable to computing future uncertainty in allowance prices.

As an alternative, we assume regulation identical to the EU-ETS, a comprehensive carbon cap-and-trade implemented in the European Union starting in 2005, in both prices and uncertainty over future prices. In the EU-ETS, allowances are sold at national auctions, but futures and options contracts on emissions allowances are traded on the Eurex commodities exchange. Using data on these contract transactions we compute the implied volatility of EU-ETS emissions futures during our sample period of 2010 to 2019.[25]

Consistent with the empirical evidence outlined above, we assume full pass-through of EU-ETS compliance costs into gasoline prices. Consumption of one gallon of gasoline requires remitting 8.887 kg of CO_2 allowances.[26] Thus, under a quantity-based regulation with allowance price of p^{CO_2} in $\frac{\$}{\text{ton}}$ and baseline gasoline price f^G, one would expect the counterfactual price of gasoline inclusive of compliance costs (f^{GQ}) to be

$$f^{GQ} = f^G + \frac{8.887}{1000} \cdot p^{CO_2}$$

Computing the implied volatility inclusive of compliance costs is more complicated. Shocks to future oil and emissions allowance prices may be correlated. Thus the volatility of oil prices inclusive of compliance costs will also depend on the correlation in those shocks. Recall, consistent with the BSM asset pricing model, our measure of volatility is the variance of the Brownian motion in log asset returns. Let ret^O and ret^{CO_2} be the ratio of a future price to the current price of oil and emissions allowances, respectively. Then the implied volatility of oil prices inclusive of compliance costs is[27]

$$\sigma^{OG} = \sigma^O + (0.43)^2 \cdot \sigma^{CO_2} + 2 \cdot 0.43 \cdot Cov\left(\ln(ret^O), \ln(ret^{CO_2})\right)$$

Using historical data on WTI and EU-ETS emissions allowance prices, we compute the covariance their log returns in rolling 3-year windows. In practice, the covariance small, ranging from approximately zero to 0.03 during our sample period.

Next, using realized EU-ETS emissions allowance prices and our estimates of the implied volatility in those prices, we compute counterfactual gasoline prices and crude oil implied volatility under two scenarios:

Quantity Instrument: We assume during our sample period the US implemented a CO_2 cap-and-trade program with emissions allowance prices and uncertainty identical to what was observed in the EU-ETS over the same period. This requires we adjust gasoline prices for the level of the emissions allowance price and crude oil implied

[25] We were able to obtain options contract data beginning in April 2010, so we are unable to include the the 2010Q1 in the following analysis.

[26] This is the US EPA's current gasoline to CO_2 conversion factor. See https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle Accessed on 04 November 2024.

[27] The US EPA conversion factor for oil is 0.43 ton CO_2/bbl. See https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references.

volatility for the future uncertainty in allowance prices.

Price Instrument: We assume during our sample period the US implemented a CO_2 emissions fee with a predetermined schedule of identical to realized EU-ETS allowance price from 2010 to 2019. Applying the counterfactual price instrument requires we adjust gasoline prices for the level of the emissions fee, but since the fee schedule increases deterministically, there is no impact on the implied volatility of crude oil.

Time series of the baseline and counterfactual prices and volatility are shown in Figure 2. For much of the sample gasoline prices are virtually identical to their baseline values under either instrument. There is, however, a persistent increase in the implied volatility of oil prices throughout our sample period.

[Figure 2 about here.]

6.1.2 Counterfactual Scenarios

Using our preferred demand specification, we calculate sales in each quarter[28] under a baseline scenario and two counterfactual scenarios. The baseline scenario uses observed gasoline prices and implied volatility, while the counterfactual scenarios use prices and implied volatility calculated under the quantity and price instruments.

In Table 6, we provide results from our counterfactual scenarios across all years, focusing on the impact of policy instruments on total sales and sales-weighted average fuel economy. Columns (1) and (2) provide sales and fuel economy in the baseline scenario, while columns (3) and (4), and columns (5) and (6) provide percentage changes to sales and fuel economy under the price and quantity instruments, respectively.

[Table 6 about here.]

Across all years, under our price instrument, we find a 6.4% reduction in total vehicle sales and a 0.5% increase in average fuel economy. Under our quantity instrument, we find a 14.6% reduction in total vehicle sales and a 1.2% increase in average fuel economy. These results are consistent with our model's predictions, as the quantity instrument increases fuel price uncertainty, in addition to fuel prices, while the price instrument only affects prices.

In our counterfactual, compliance costs and future price uncertainty vary over time, and aggregating over our sample period masks some important variation. We plot the time series of vehicle sales (Figure 3) and mean MPG (Figure 4) across all vehicles and the three most commonly-sold vehicle classes: sedans, pickups, and SUVs. Sales are consistently lower across vehicle classes, with the largest effects over time in pickups and SUVs, particularly in the latter half of the 2010s when future price uncertainty was high. Looking at all vehicles, changes in fuel economy are most pronounced under the quantity instrument during periods of high future price uncertainty, where the quantity instrument may induce mean fuel economy improvements in excess of 0.5 MPG. In contrast, neither policy instrument induces significant changes in fuel economy *within* vehicle classes. This highlights that the channel for the predicted improvement in average fuel economy is mostly driven by a shift from fuel-inefficient vehicle classes, such as pickups and SUVs, to more efficient body styles.

[Figure 3 about here.]

[Figure 4 about here.]

[28] Our counterfactual scenarios cover the period from Q2 2010 through Q4 2019.

To further examine the heterogeneous effects of the policy instruments across vehicle classes (which form the nests in our demand model), we look at counterfactual results in 2015 and 2019, presented in Table 7. The single-year decomposition allows us to see the impact of the policy instruments, without concern about changes to the composition of nests. In line with expectations, nests with more fuel efficient vehicles experience smaller declines in sales than nests with less fuel efficient vehicles.

[Table 7 about here.]

6.2 Policy Implications

Our counterfactual results suggests that the choice of price-based or quantity-based instruments has a significant impact on consumer purchase behavior. Because quantity-based instruments increase fuel price uncertainty, in addition to fuel prices, they depress vehicle sales more than price-based instruments. However, the increased uncertainty also drives consumers toward more fuel efficient vehicles.

The welfare impacts of these results are largely dependent on the pricing of carbon emissions relative to the social optimum. If carbon emissions are priced at their marginal damages, then consumers will be unequivocally worse off under quantity-based policies than under price-based policy. The increased uncertainty will reduce their ability to optimize their vehicle holdings, leading them to forgo purchases and over-invest in fuel efficiency. Because emissions are properly priced at their marginal damages, this reduction in consumer welfare will not be offset by overall social welfare gains.

Might we prefer a quantity-based instrument if carbon emissions are under-priced? While the increased uncertainty will still depress sales, it will simultaneously improve average fuel economy. In this case, losses to consumer welfare may be offset by gains in social welfare from reduced emissions. However, more fuel efficient vehicles are less expensive to drive – which may induce more driving under the quantity instrument, offsetting the emissions benefits of increased efficiency. In Appendix C.3, we simulate lifetime vehicle gasoline consumption under these policy scenarios. If the VMT is not responsive to operating costs, gasoline consumption is always lower under the quantity instrument. If driving increases in response to lower operating costs,[29] however, gasoline consumption is similar to or lower under the price instrument. This highlights that the additional uncertainty in future gasoline prices introduced by the quantity instrument is quite likely welfare-reducing, even when the externality is underpriced.

7 Conclusions

This paper considers how consumers' expectations of future gasoline prices impact their automobile purchase decisions. We find consumers vehicle purchases are inconsistent with the assumption that they believe future gasoline prices will be identical to the current price. In particular, as market measures of the uncertainty over future prices increase, consumers' WTP for fuel economy increases. This effect is economically significant in magnitude, a 1-standard deviation increase in uncertainty increases the WTP for 1 MPG by approximately $89 or 10.0%. This effect shifts vehicle choice amongst new car buyers when future uncertainty is large. That same increase in future price uncertainty increases the fuel efficiency of new vehicle purchases 0.5%, mostly through buyers choosing cars and crossovers over pickups and SUVs. Vehicle operating costs are a disamenity, however, and increased fuel price uncertainty has a net effect of reducing overall vehicle demand.

[29] Again, following Archsmith, Gillingham, et al. (2020) we assume a operating cost-VMT elasticity of -0.45.

These results demonstrate that consumers take a much more complicated view of future gasoline costs when purchasing an automobile than has been previously assumed in the literature. Examining stated beliefs in a nationally representative survey, consumers anticipate price changes implied by futures markets, expect mean reversion in spot prices, and incorporate future uncertainty in the realizations of prices, all contrary with beliefs that prices follow a random walk. This aligns with evidence from Archsmith and Levin (2025) who show consumer's stated beliefs over future gasoline prices begin to deviate from a no-change expectation in the leadup to the financial crisis of 2008, when changes to the time series of oil prices caused returns to paying attention to future prices and uncertainty substantially increased.

These results have implications for applying carbon pricing, or any other tradable compliance regulation, to transportation fuels. Quantity-based instruments, such as a carbon cap-and-trade, have uncertain future costs of compliance which necessarily introduces additional uncertainty in future gasoline costs, shifting consumer preferences for vehicles relative to a price instrument. These effects are non-trivial. Uncertainty in future compliance costs under a quantity-based GHG regulation similar to the EU-ETS substantially reduces overall vehicle demand relative to a policy with identical emissions prices that are known in advance with certainty. Effects on fuel efficiency of vehicle purchased are more muted, with much of the effect driven by sales shifting from pickups and SUVs to more efficient sedans and crossovers. It is important to note that, assuming an *ex ante* optimal policy, these improvements in fuel economy under a quantity instrument are not welfare-improving. Additional uncertainty alters vehicle choice and the decision to replace a vehicle, reducing welfare over an alternative policy that does not introduce additional uncertainty. Further, consumers are induced to purchase more fuel-efficient vehicles than they would otherwise, increasing the amount they choose to drive after purchasing the vehicle.

In contrast to previous literature examining durables and energy efficiency (*e.g.*, Greene (2011)) who find uncertainty over the *level of energy efficiency* reduces the WTP for improved efficiency, we find uncertainty over the *cost of energy* increases WTP for improved efficiency. This may have implications beyond gasoline-powered automobiles. As an example, the lack of reliable electric vehicle charging infrastructure has been identified as an impediment to more widespread EV adoption (Zhou and Li (2018)). Lack of accessible charging may increase the utility or time cost of charging an EV. The future stock of EV chargers is uncertain due to the dynamic interdependence between EV adoption and charging station buildout, uncertainty around future policy promoting new charging station construction, and many other reasons. Uncertainty in the hassle costs of charging may have similar impacts on EV demand as uncertainty in fuel costs have on fuel-inefficient vehicle demand, and may explain the strong preference for range in new EVs and further present an additional barrier to EV adoption.

References

Alexeeva-Talebi, Victoria (Dec. 2011). "Cost pass-through of the EU emissions allowances: Examining the European petroleum markets." *Energy Economics* 33 (SUPPL. 1). DOI: 10.1016/j.eneco.2011.07.029.

Allcott, Hunt and Christopher R. Knittel (Feb. 2019). "Are consumers poorly informed about fuel economy? Evidence from two experiments." *American Economic Journal: Economic Policy* 11 (1), pp. 1–37. DOI: 10.1257/pol.20170019.

Allcott, Hunt and Dmitry Taubinsky (Aug. 2015). "Evaluating behaviorally motivated policy: Experimental evidence from the lightbulb market." *American Economic Review* 105 (8), pp. 2501–2538. DOI: 10.1257/aer.20131564.

Allcott, Hunt and Nathan Wozny (Dec. 2014). "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics* 96 (5), pp. 779–795. DOI: 10.1162/REST_a_00419.

Anderson, Soren T, Ryan Kellogg, and James M. Sallee (2013). "What Do Consumers Believe About Future Gasoline Prices?" *Journal of Environmental Economics and Management* 66 (3), pp. 383–403. DOI: 10.1016/j.jeem.2013.07.002.

Anderson, Soren T, Ryan Kellogg, James M. Sallee, and Richard T Curtin (2011). "Forecasting Gasoline Prices Using Consumer Surveys." *American Econmic Review: Papers& Proceedings* 101 (3), pp. 110–114. DOI: 10.1257/aer.101.3.110.

Archsmith, James, Kenneth Gillingham, Christopher R. Knittel, and David S Rapson (2020). "Attribute Substitution in Household Vehicle Portfolios." *RAND Journal of Economics* 51 (4), pp. 1162–1196. DOI: 10.1111/1756-2171.12353.

Archsmith, James and Simon Levin (2025). "Changing consumer expectations of future gasoline prices." *Working paper.*

Attanasio, Orazio P. and Katja M. Kaufmann (Aug. 2017). "Education choices and returns on the labor and marriage markets: Evidence from data on subjective expectations." *Journal of Economic Behavior and Organization* 140, pp. 35–55. DOI: 10.1016/j.jebo.2017.05.002.

Bakkensen, Laura A and Lint Barrage (July 2022). "Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics." *The Review of Financial Studies* 35 (8), pp. 3666–3709. DOI: 10.1093/rfs/hhab122.

Bento, Antonio M, Shanjun Li, and Kevin Roth (Apr. 2012). "Is There an Energy Paradox in Fuel Economy? {A} Note on the Role of Consumer Heterogeneity and Sorting Bias." *Economics Letters* 115 (1), pp. 44–48. DOI: 10.1016/j.econlet.2011.09.034.

Berkouwer, Susanna B. and Joshua T. Dean (Oct. 2022). "Credit, Attention, and Externalities in the Adoption of Energy Efficient Technologies by Low-Income Households." *American Economic Review* 112 (10), pp. 3291–3330. DOI: 10.1257/aer.20210766.

Berry, Steven (1994). "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2), p. 242. DOI: 10.2307/2555829.

Berry, Steven, James Levinsohn, and Ariel Pakes (July 1995). "Automobile Prices in Market Equilibrium." *Econometrica* 64 (4), pp. 841–890. DOI: 10.2307/2171802.

Binder, Carola Conces (2018). "Inflation expectations and the price at the pump." *Journal of Macroeconomics* 58 (May), pp. 1–18. DOI: 10.1016/j.jmacro.2018.08.006.

Black, Fischer (Jan. 1976). "The pricing of commodity contracts." *Journal of Financial Economics* 3 (1-2), pp. 167–179. DOI: 10.1016/0304-405X(76)90024-6.

Black, Fischer and Myron Scholes (1973). “The Pricing of Options and Corporate Liabilities.” *Journal of Political Economy* 81 (3), pp. 637–654. DOI: 10.1086/260062.

Busse, Meghan R., Christopher R. Knittel, and Florian Zettelmeyer (Feb. 2013). “Are consumers myopic? Evidence from new and used car purchases.” *American Economic Review* 103 (1), pp. 220–256. DOI: 10.1257/aer.103.1.220.

Chacko, George and Luis M. Viceira (Dec. 2005). *Dynamic consumption and portfolio choice with stochastic volatility in incomplete markets*. DOI: 10.1093/rfs/hhi035.

Chay, Kenneth Y and Michael Greenstone (2005). “Does Air Quality Matter? Evidence from the Housing Market.” *Journal of Political Economy* 113 (2). DOI: 10.1086.427462.

Danz, David, Lise Vesterlund, and Alistair J. Wilson (Sept. 2022). “Belief Elicitation and Behavioral Incentive Compatibility.” *American Economic Review* 112 (9), pp. 2851–2883. DOI: 10.1257/aer.20201248.

Doyle, Joseph J. and Krislert Samphantharak (Apr. 2008). “$2.00 Gas! Studying the effects of a gas tax moratorium.” *Journal of Public Economics* 92 (3-4), pp. 869–884. DOI: 10.1016/j.jpubeco.2007.05.011.

Fack, Gabrielle and Julien Grenet (Feb. 2010). “When do better schools raise housing prices? Evidence from Paris public and private schools.” *Journal of Public Economics* 94 (1-2), pp. 59–77. DOI: 10.1016/j.jpubeco.2009.10.009.

Gillingham, Kenneth T. and Asa Watten (July 2024). “How is rooftop solar capitalized in home prices?” *Regional Science and Urban Economics* 107. DOI: 10.1016/j.regsciurbeco.2024.104006.

Goldberg, Pinelopi Koujianou (July 1995). “Product Differentiation and Oligopoly in International Markets: The Case of the U.S. Automobile Industry.” *Econometrica* 63(4), p. 891. JSTOR: 2171803. DOI: 10.2307/2171803.

Goldberg, Pinelopi Koujianou (Mar. 1998). “The Effects of the Corporate Average Fuel Efficiency Standards in the {U.S.}” *The Journal of Industrial Economics* 46 (1), pp. 1–33.

Gowrisankaran, Gautam and Marc Rysman (2012). “Dynamics of Consumer Demand for New Durable Goods.” *Journal of Political Economy* 120 (6). DOI: 10.1086/669540.

Greene, David L. (July 2011). “Uncertainty, loss aversion, and markets for energy efficiency.” *Energy Economics* 33 (4), pp. 608–616. DOI: 10.1016/j.eneco.2010.08.009.

Greene, David L., David H. Evans, and John Hiestand (Oct. 2013). “Survey evidence on the willingness of U.S. consumers to pay for automotive fuel economy.” *Energy Policy* 61, pp. 1539–1550. DOI: 10.1016/j.enpol.2013.05.050.

Harrison, David and Daniel L Rubinfeld (Mar. 1978). “Hedonic housing prices and the demand for clean air.” *Journal of Environmental Economics and Management* 5 (1), pp. 81–102. DOI: 10.1016/0095-0696(78)90006-2.

Hausman, Jerry A (1979). “Individual Discount Rates and the Purchase and Utilization of Energy-Using Durables.” *The Bell Journal of Economics* 10 (1), pp. 33–54. DOI: 10.2307/3003318.

Jaffe, Adam B. and Robert N. Stavins (May 1994). “The energy paradox and the diffusion of conservation technology.” *Resource and Energy Economics* 16 (2), pp. 91–122. DOI: 10.1016/0928-7655(94)90001-9.

Klier, Thomas and Joshua Linn (Aug. 2010). “The Price of Gasoline and New Vehicle Fuel Economy: Evidence from Monthly Sales Data.” *American Economic Journal: Economic Policy* 2(3), pp. 134–153. DOI: 10.1257/pol.2.3.134.

Knittel, Christopher R., Ben S. Meiselman, and James H. Stock (Dec. 2017). “The pass-through of RIN prices to wholesale and retail fuels under the renewable fuel standard.” *Journal of the Association of Environmental and Resource Economists* 4 (4), pp. 1081–1119. DOI: 10.1086/692071.

Kuwayama, Yusuke, Sheila Olmstead, and Jiameng Zheng (Mar. 2022). "A more comprehensive estimate of the value of water quality." *Journal of Public Economics* 207. DOI: 10.1016/j.jpubeco.2022.104600.

Leard, Benjamin, Virginia McConnell, and Yichen Christy Zhou (2019). "The Effect of Fuel Price Changes on Fleet Demand for New Vehicle Fuel Economy." *Journal of Industrial Economics* 67 (1), pp. 127–159. DOI: 10.1111/joie.12198.

MacDonald, Don N, James C Murdoch, and Harry L White (1987). "Uncertain Hazards, Insurance, and Consumer Choice: Evidence from Housing Markets Evidence from Housing Markets." *Land Economics* 63 (4), pp. 361–371. DOI: 10.2307/3146293.

Merton, Robert C. (1974). "On the Pricing of Corporate Debt : The Risk Structure of Interest Rates." *The Journal of Finance* 29 (2), pp. 449–470. DOI: 10.2307/2978814.

Oliva, Paulina, B. Kelsey Jack, Samuel Bell, Elizabeth Mettetal, and Christopher Severen (July 2020). "Technology adoption under uncertainty: Take-up and subsequent investment in zambia." *Review of Economics and Statistics* 102 (3), pp. 617–632. DOI: 10.1162/rest_a_00823.

Pedroni, Andreas et al. (Oct. 2017). "The risk elicitation puzzle." *Nature Human Behaviour* 1 (11), pp. 803–809. DOI: 10.1038/s41562-017-0219-x.

Rapson, David (2014). "Durable goods and long-run electricity demand: Evidence from air conditioner purchase behavior." *Journal of Environmental Economics and Management* 68 (1), pp. 141–160. DOI: 10.1016/j.jeem.2014.04.003.

Sallee, James M., Sarah E. West, and Wei Fan (Mar. 2016). "Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations." *Journal of Public Economics* 135, pp. 61–73. DOI: 10.1016/j.jpubeco.2016.01.003.

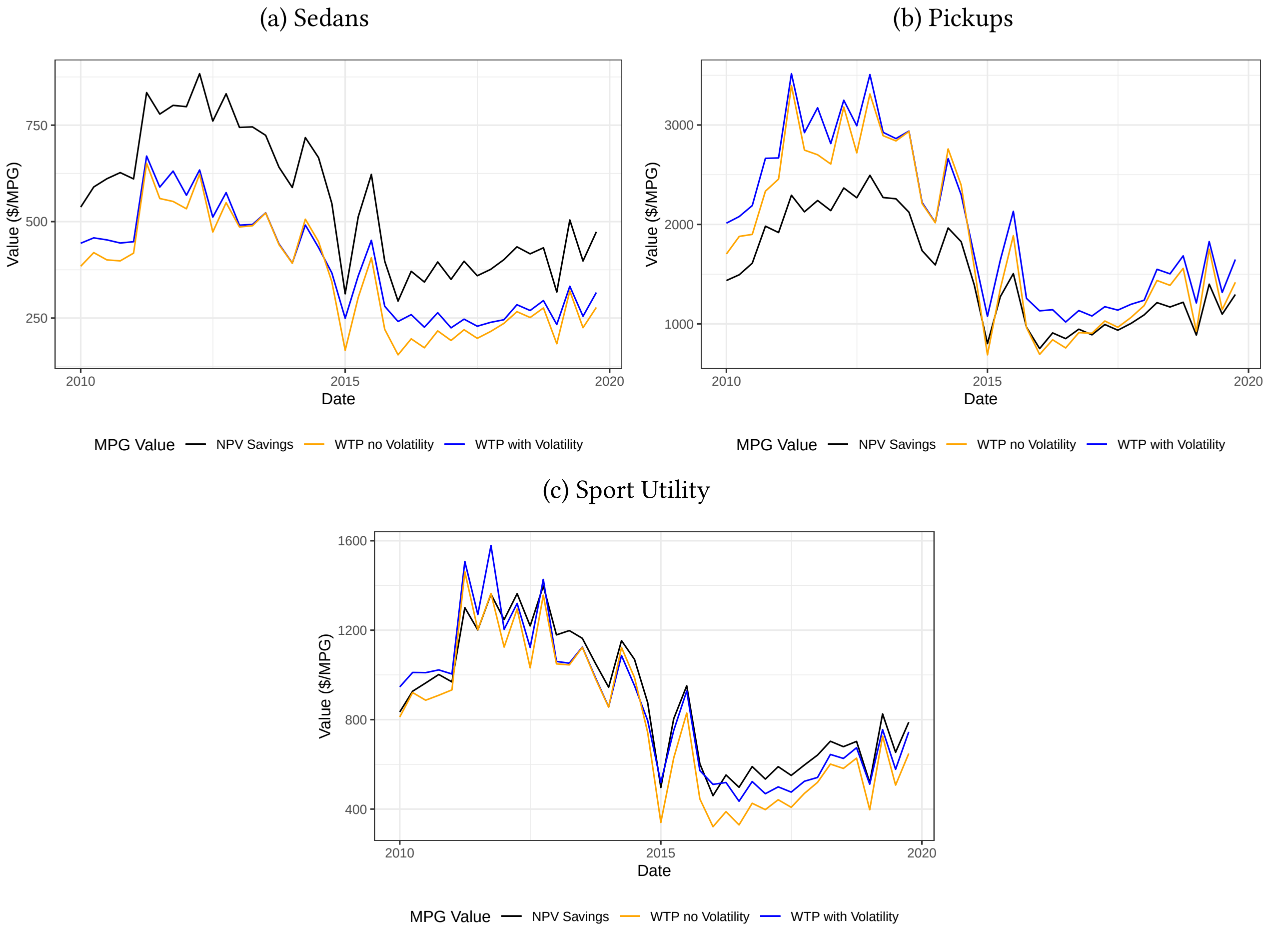
Verboven, Frank (1996). "International Price Discrimination in the European Car Market." *The RAND Journal of Economics* 27(2), p. 240. DOI: 10.2307/2555925.

Weitzman, Martin L (Oct. 1974). "Prices vs. Quantities." *The Review of Economic Studies* 41 (4), pp. 477–491. DOI: 10.2307/2296698.

Zhou, Yiyi and Shanjun Li (June 2018). "Technology Adoption and Critical Mass: The Case of the U.S. Electric Vehicle Market." *Journal of Industrial Economics* 66 (2), pp. 423–480. DOI: 10.1111/joie.12176.

Figures

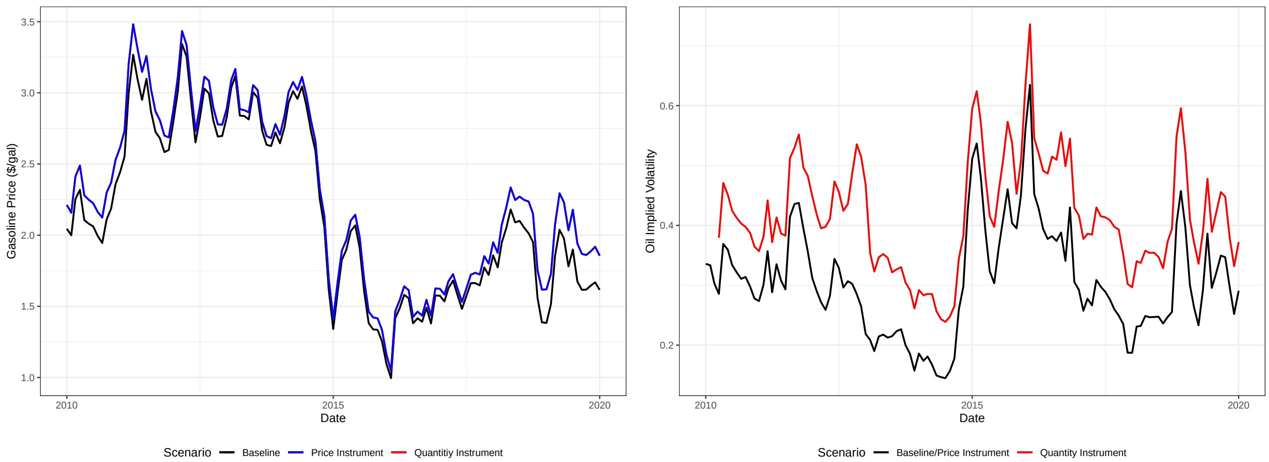
Figure 1: Simulated WTP for a 1 MPG Improvement in Fuel Efficiency



Simulation of the WTP for a one dollar reduction in present discounted lifetime operating costs for the sales-weighted median price and fuel efficiency vehicle, using historical gasoline prices and implied volatility. Panels (a), (b), and (c) show sedans, pickups, and SUVs, respectively. Vehicles are assumed to be driven 15,000 miles per year and last 16.5 years. The black line shows the present discounted cost savings of a 1 MPG improvement in fuel economy. The blue line performs the calculation using a model excluding the uncertainty effect (Column 1 of Table 2). The orange line uses our preferred model, including the volatility effect (Column 2 of Table 2).

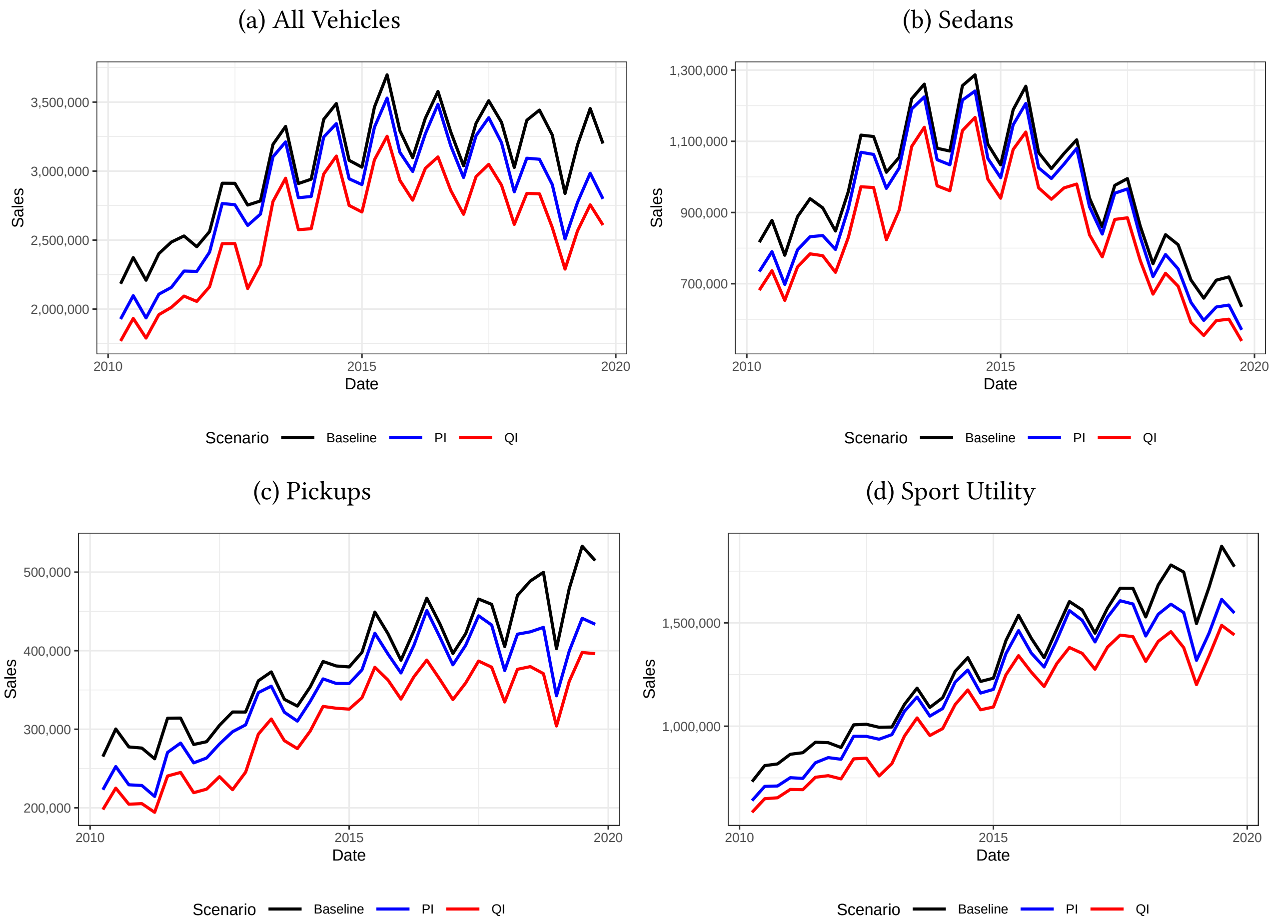
Figure 2: Counterfactual Price and Implied Volatility under Price or Quantity Instruments

(a) Gasoline Price | (b) Oil Price Implied Volatility



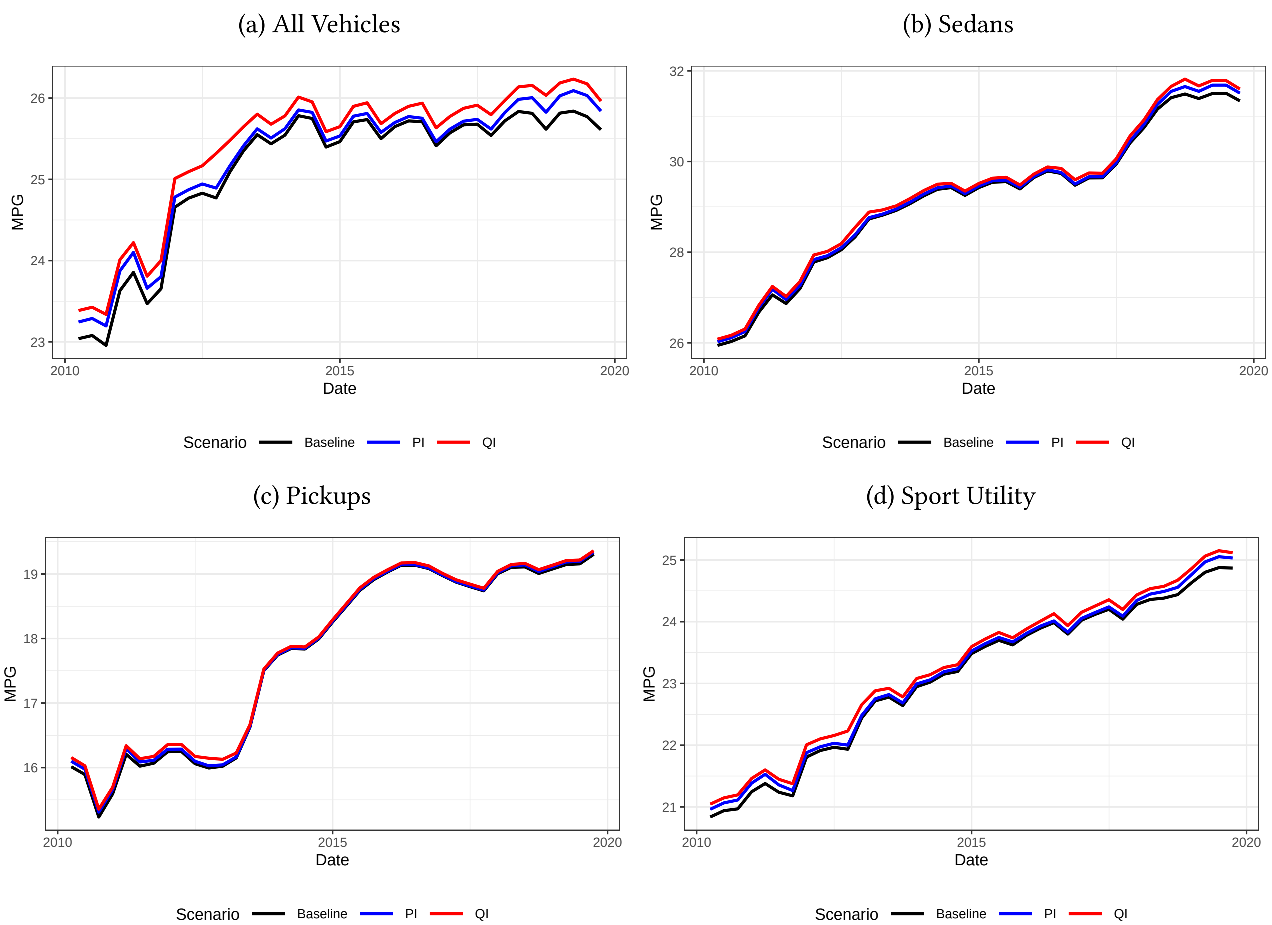
Time series plots of the counterfactual price of gasoline (Panel (a)) and implied volatility of crude oil (Panel (b)) assuming a quantity instrument with allowance prices and future uncertainty identical to the EU-ETS during the same period or a price instrument with prices set identically to the realized EU-ETS allowance prices with certainty. Calculation of counterfactual prices and volatility described in Section 6.1.1. Realized compliance costs are assumed identical under the Price and Quantity instruments, thus gasoline prices are identical under these instruments in Panel (a). Allowance prices under the price instrument are known with certainty and do not impact implied volatility, hence the Baseline and Price Instrument implied volatility in Panel (b) are identical.

Figure 3: Sales Under Baseline and Counterfactual Scenarios



Sales of vehicles under baseline and counterfactual scenarios. Baseline (black) uses observed gasoline prices and future volatility. PI (blue) imposes a price instrument for GHG regulation with prices identical to the EU-ETS. QI (red) imposes a quantity instrument for GHG regulation with prices and additional future uncertainty identical to the EU-ETS. Panels (a), (b), (c), and (d) show sales for vehicles, sedans, pickups, and SUVs, respectively.

Figure 4: Average Fuel Economy Under Baseline and Counterfactual Scenarios



Average fuel economy of vehicles under baseline and counterfactual scenarios. Baseline (black) uses observed gasoline prices and future volatility. PI (blue) imposes a price instrument for GHG regulation with prices identical to the EU-ETS. QI (red) imposes a quantity instrument for GHG regulation with prices and additional future uncertainty identical to the EU-ETS. Panels (a), (b), (c), and (d) show sales for vehicles, sedans, pickups, and SUVs, respectively. Values presented are sales-weighted averages.

Tables

Table 1: Summary Statistics for Commodities Futures and Options Data

	WTI $/bbl (1)	RBOB $/gal (2)
Futures		
1m Forward Price	63.66	2.15
	(25.61)	(0.623)
Daily Volume	277,823	40,753
	(216,495)	(23,205)
First Date	1999-12-23	2005-12-01
Last Date	2024-09-23	2024-09-23
Options		
1m Forward Price	5.76	0.109
	(9.96)	(0.178)
Daily Volume	230.9	6.45
	(832.8)	(49.04)
First Date	2003-11-18	2006-08-29
Last Date	2024-09-23	2024-09-13

Summary statistics for commodity options and futures data. Data limited to front-month contracts.

Table 2: Nested Logit Model of Vehicle Demand: Primary Results

Dependent Variable:	$\ln s_{jt} - \ln s_{0t}$			
	Base	2-Month Vol (WTI)	1-Year Vol (WTI)	2-Month Vol (RBOB)
Model:	(1)	(2)	(3)	(4)
ln Price	-4.107***	-4.111***	-4.187***	-4.097***
	(0.1794)	(0.1792)	(0.1795)	(0.1791)
GPM x PriceFuel	-16.32***	-14.93***	-15.75***	-14.85***
	(0.2706)	(0.3350)	(0.3761)	(0.3483)
GPM $\times$ Vol		-19.98***	-8.686**	-21.15***
		(2.686)	(3.531)	(2.956)
ln Nest Share	0.4154***	0.4155***	0.4169***	0.4153***
	(0.0111)	(0.0111)	(0.0110)	(0.0111)
HP/Weight	9.932***	10.03***	10.36***	9.936***
	(1.540)	(1.546)	(1.541)	(1.544)
HP	0.0061***	0.0062***	0.0063***	0.0062***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Tons	3.212***	3.239***	3.260***	3.232***
	(0.1022)	(0.1022)	(0.1021)	(0.1022)
Wheelbase	-0.0006	-0.0006	-0.0011	-0.0006
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
Fixed-effects				
State-QoS	Yes	Yes	Yes	Yes
Power Type-Year	Yes	Yes	Yes	Yes
Make-Year	Yes	Yes	Yes	Yes
std. dev. SIGMA	N/A	0.08568	0.05675	0.06982
Observations	720,885	720,885	720,885	720,885
R^2	0.58898	0.58895	0.58623	0.58944
Within R^2	0.31533	0.31528	0.31075	0.31610
F-test (1st stage), ln Price	185.72	185.70	185.94	185.68
F-test (1st stage), ln Nest Share	501.21	492.84	496.08	492.68

Clustered (State-QoS) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Nests are defined by body types defined in IHS vehicle specifications. Regressions cover sales from Q1 2010 through Q4 2019. Mean characteristics of other vehicles produced by firm and mean characteristics of vehicles produced by rival firms are used to instrument for log(Price) and log(Nest Share).

Table 3: Nested Logit Model of Vehicle Demand: Primary Results: Robustness

Dependent Variables:	$\ln s_{jt} - \ln s_{0t}$				
	No Nests	Alternative Nests 1	Alternative Nests 2	Alternative FEs 1	Alternative FEs 2
Model:	(1)	(2)	(3)	(4)	(5)
ln Price	-4.130***	-3.276***	-5.112***	-3.623***	-3.608***
	(0.2429)	(0.2247)	(0.1534)	(0.3024)	(0.3034)
GPM x PriceFuel	-18.76***	-15.90***	-9.818***	-9.804***	-8.660***
	(0.3911)	(0.3985)	(0.2969)	(0.3367)	(0.4326)
GPM $\times$ Vol	-31.99***	-23.46***	-4.993**	-34.60***	-52.70***
	(3.563)	(3.018)	(2.247)	(1.328)	(3.150)
ln Nest Share		0.2387***	0.9246***	0.5124***	0.5043***
		(0.0154)	(0.0129)	(0.0218)	(0.0222)
HP/Weight	38.14***	18.67***	15.00***	-1.053	-0.5266
	(1.616)	(1.999)	(1.080)	(2.668)	(2.719)
HP	-0.0015***	0.0011***	0.0137***	0.0075***	0.0073***
	(0.0004)	(0.0004)	(0.0003)	(0.0006)	(0.0006)
Tons	3.781***	3.088***	2.797***	2.710***	2.737***
	(0.1300)	(0.1284)	(0.0861)	(0.1675)	(0.1695)
Wheelbase	0.0133***	0.0086***	-0.0639***	-0.0014	-0.0011
	(0.0013)	(0.0012)	(0.0013)	(0.0016)	(0.0016)
Vol					0.8367***
					(0.1652)
VIX					0.0060***
					(0.0012)
Fixed-effects					
State-QoS	Yes	Yes	Yes		
Power Type-Year	Yes	Yes	Yes	Yes	Yes
Make-Year	Yes	Yes	Yes	Yes	Yes
State-Year				Yes	Yes
std. dev. SIGMA	0.08568	0.08568	0.08568	0.08568	0.08568
Observations	720,885	720,885	720,885	720,885	720,885
R^2	0.43186	0.57433	0.72518	0.60562	0.60630
Within R^2	0.05360	0.29092	0.54222	0.34473	0.34587
F-test (1st stage), ln Price	185.70	185.70	185.70	138.01	136.36
F-test (1st stage), ln Nest Share		374.53	204.76	223.41	219.09

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Nests in column (2) include additional nest designations for luxury convertibles, coupes, hatchbacks, sedans, and wagons. Nests in column (3) combine convertibles, coupes, hatchbacks, sedans, and wagons into a single nest. Nests in columns(4) and (5) are defined by body types defined in IHS vehicle specifications. Regressions cover sales from Q1 2010 through Q4 2019. Mean characteristics of other vehicles produced by firm and mean characteristics of vehicles produced by rival firms are used to instrument for log(Price) and log(Nest Share).

Table 4: Effects from a 1 standard deviation in implied volatility

(a) Impacts Using Preferred Specification and Alternative Specifications

	Actual		Preferred		No Nests		Alternative Nests 1	
Nest	Sales	MPG	% Δ Sales	% Δ MPG	% Δ Sales	% Δ MPG	% Δ Sales	% Δ MPG
All Vehicles	120.4	25.2%	-6.8%	0.5%	-10.7%	0.6%	-8.0%	0.5%
Sport Utility	51.3	23.4%	-7.2%	0.3%	-11.2%	0.3%	-8.3%	0.3%
Van	0.3	23.2%	-7.1%	0.2%	-11.2%	0.2%	-8.3%	0.2%
Convertible	1.0	24.1%	-6.9%	0.2%	-10.8%	0.2%	-8.1%	0.2%
Sedan	38.4	29.0%	-5.8%	0.2%	-9.1%	0.2%	-6.7%	0.2%
Coupe	3.6	24.0%	-7.0%	0.3%	-10.9%	0.3%	-8.1%	0.3%
Pickups	15.1	18.0%	-9.1%	0.2%	-14.2%	0.2%	-10.6%	0.2%
Hatchback	5.8	36.7%	-4.8%	0.6%	-7.6%	0.6%	-5.6%	0.5%
Station Wagon	1.6	29.4%	-5.7%	0.3%	-9.0%	0.3%	-6.7%	0.2%
Passenger Vans	3.3	21.6%	-7.6%	0.1%	-11.9%	0.1%	-8.9%	0.1%

(b) Impacts Using Additional Alternative Specifications

	Actual		Alternative Nests 2		Alternative FEs 1		Alternative FEs 2	
Nest	Sales	MPG	% Δ Sales	% Δ MPG	% Δ Sales	% Δ MPG	% Δ Sales	% Δ MPG
All Vehicles	120.4	25.2%	-1.7%	0.7%	-11.5%	1.0%	-10.9%	1.5%
Sport Utility	51.3	23.4%	-1.8%	0.6%	-12.0%	0.7%	-11.7%	1.0%
Van	0.3	23.2%	-1.8%	0.3%	-12.0%	0.4%	-11.7%	0.6%
Convertible	1.0	24.1%	-5.3%	0.5%	-11.6%	0.5%	-11.1%	0.8%
Sedan	38.4	29.0%	-1.5%	0.4%	-9.7 %	0.5%	-8.2 %	0.7%
Coupe	3.6	24.0%	-5.5%	0.6%	-11.7%	0.6%	-11.2%	1.0%
Pickups	15.1	18.0%	-2.4%	0.3%	-15.3%	0.4%	-16.6%	0.6%
Hatchback	5.8	36.7%	1.8 %	1.1%	-8.1 %	1.2%	-5.6 %	1.8%
Station Wagon	1.6	29.4%	-1.6%	0.6%	-9.7 %	0.6%	-8.1 %	0.9%
Passenger Vans	3.3	21.6%	-2.0%	0.2%	-12.8%	0.2%	-12.8%	0.4%

The first two columns of this table present total sales and sales-weighted average fuel economy. The remaining columns present the percentage change in sales and sales-weighted average fuel economy from a 1 standard deviation increase in implied volatility, using parameters from our estimates in Table 2 and Table 3. The Preferred columns use parameter estimates from column (2) in Table 2, while the remaining Alternative columns use estimates from the corresponding columns in Table 3.

Table 5: Impact of Volatility on WTP for and Undervaluation of Fuel Economy

	MWTP ($/MPG)			
	Sedan	Pickups	Sport Utility	All Vehicles
NPV	$553.70	$1,518.33	$879.08	$848.48
	[$397.44 – $719.28]	[$1,001.83 – $2,017.61]	[$601.24 – $1,155.94]	[$558.30 – $1,072.83]
WTP no Vol	$357.27	$1,835.43	$781.08	$811.84
	[$220.58 – $476.26]	[$1,055.53 – $2,630.89]	[$463.83 – $1,034.97]	[$384.06 – $1,055.78]
WTP /w Vol	$389.03	$2,012.60	$853.62	$888.71
	[$257.86 – $490.90]	[$1,230.71 – $2,704.80]	[$537.19 – $1,054.37]	[$432.09 – $1,150.27]
WTP no Vol to NPV	-35.48%	20.88%	-11.15%	-4.32%
	[-44.50% – -33.79%]	[5.36% – 30.40%]	[-22.85% – -10.46%]	[-31.21% – -1.59%]
WTP /w Vol to NPV	-29.74%	32.55%	-2.90%	4.74%
	[-35.12% – -31.75%]	[22.85% – 34.06%]	[-10.65% – -8.79%]	[-22.61% – 7.22%]
WTP incr /w Vol	8.89%	9.65%	9.29%	9.47%
	[3.07% – 16.90%]	[2.81% – 16.60%]	[1.87% – 15.82%]	[8.95% – 12.51%]

Comparison of the present value savings from marginal 1 MPG improvement in fuel economy against the WTP for that same improvement in fuel economy from the demand model in Column (2) of Table 2. For each vehicle class, we compute the quarterly median price and fuel economy and match to mean fuel prices and implied volatility for that quarter. NPVs are computed assuming vehicles have a lifefime of 16.5 years, are driven 15,000 miles per year, and consumers discount future costs at a rate identical to the 10-year US Treasury bond rate at the time of purchase. NPVs and WTPs vary over time. The mean value is shown in the first row of each group, with the interquartile range in brackets below. The final three rows compare undervaluation of MPG not accounting for volatility, undervaluation accounting for volatility, and the percentage increase in the willingness to pay when accounting for volatility.

Table 6: Percentage Change in Sales and Fuel Economy

Nest	**Baseline**		**PI**		**QI**	
	Sales (millions) (1)	MPG (2)	% Δ Sales (3)	% Δ MPG (4)	% Δ Sales (5)	% Δ MPG (6)
All Vehicles	118.7	25.2	-6.4%	0.5%	-14.6%	1.2%
Convertible	1.0	24.1	-6.4%	0.3%	-14.7%	0.6%
Coupe	3.5	24.0	-6.3%	0.3%	-14.7%	0.7%
Hatchback	5.7	36.7	-4.4%	0.6%	-10.4%	1.3%
Passenger Vans	3.3	21.6	-7.0%	0.1%	-16.1%	0.3%
Pickups	14.9	18.0	-8.8%	0.2%	-19.5%	0.5%
Sedan	37.8	29.1	-5.2%	0.2%	-12.2%	0.5%
Sport Utility	50.7	23.4	-6.9%	0.3%	-15.4%	0.8%
Station Wagon	1.6	29.4	-5.7%	0.4%	-12.8%	0.7%
Van	0.3	23.2	-6.5%	0.2%	-15.0%	0.4%

This table contains the percentage change in sales and sales-weighted fuel economy under three scenarios. Baseline uses observed gasoline prices and future volatility. PI imposes a price instrument for GHG regulation with prices identical to the EU-ETS. QI imposes a quantity instrument for GHG regulation with prices and additional future uncertainty identical to the EU-ETS. The counterfactuals cover Q2 2010 through Q4 2019.

Table 7: Percentage Change in Sales and Fuel Economy, Select Years

(a) 2015

Nest	Baseline		PI		QI	
	Sales (millions) (1)	MPG (2)	% Δ Sales (3)	% Δ MPG (4)	% Δ Sales (5)	% Δ MPG (6)
All Vehicles	13.5	25.6	-4.4 %	0.3 %	-11.2 %	0.7 %
Convertible	0.1	24.7	-4.4 %	0.1 %	-11.3 %	0.4 %
Coupe	0.4	23.7	-4.6 %	0.2 %	-11.8 %	0.5 %
Hatchback	0.6	36.9	-3.1 %	0.3 %	-8.0 %	0.8 %
Passenger Vans	0.4	21.5	-5.0 %	0.0 %	-12.7 %	0.1 %
Pickups	1.6	18.6	-5.8 %	0.1 %	-14.6 %	0.2 %
Sedan	4.5	29.5	-3.7 %	0.1 %	-9.5 %	0.3 %
Sport Utility	5.6	23.6	-4.7 %	0.2 %	-11.8 %	0.5 %
Station Wagon	0.1	31.3	-3.6 %	0.2 %	-9.1 %	0.6 %
Van	0.0	24.3	-4.5 %	0.0 %	-11.4 %	0.1 %

(b) 2019

Nest	Baseline		PI		QI	
	Sales (millions) (1)	MPG (2)	% Δ Sales (3)	% Δ MPG (4)	% Δ Sales (5)	% Δ MPG (6)
All Vehicles	12.7	25.8	-12.7 %	0.9 %	-19.4 %	1.5 %
Convertible	0.1	25.7	-12.6 %	0.6 %	-19.1 %	1.0 %
Coupe	0.2	23.2	-13.8 %	0.6 %	-20.9 %	1.0 %
Hatchback	0.4	35.6	-9.5 %	1.0 %	-14.6 %	1.7 %
Passenger Vans	0.2	23.4	-13.7 %	0.7 %	-20.8 %	1.1 %
Pickups	1.9	19.2	-16.2 %	0.2 %	-24.4 %	0.3 %
Sedan	2.7	31.4	-10.3 %	0.6 %	-15.9 %	0.9 %
Sport Utility	6.8	24.8	-12.9 %	0.6 %	-19.7 %	1.0 %
Station Wagon	0.2	28.3	-11.2 %	0.2 %	-17.2 %	0.3 %
Van	0.0	25.1	-12.5 %	0.0 %	-19.1 %	0.1 %

This table contains the percentage change in sales and sales-weighted fuel economy for the price policy instrument (PI) and quantity policy instrument (QI) in 2015 and 2019. In both years, sales for non-passenger vans are fewer than 100,000.