Volatility and Uncertainty in Environmental Policy

by

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Environment

Duke University

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Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Environment in the Graduate School of Duke University

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ABSTRACT

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Abstract

Environmental policy is increasingly implemented via market mechanisms. While this is in many ways a great success for the economics profession, a number of questions remain. In this dissertation, I empirically explore the question of what will happen as environmental outcomes are coupled to potentially volatile market phenomena, whether policies can insulate environmental outcomes and market shocks, and policymakers should act to mitigate such volatility. I use a variety of empirical methods including reduced form and structural econometrics as well as theoretical models to consider a variety of policy, market, and institutional contexts. The effectiveness of market interventions depends on the context and on the policy mechanism. In particular, energy markets are characterized by low demand elasticities and kinked supply curves which are very flat below a capacity constraint (elastic) and very steep above it (inelastic). This means that a quantity-based policy that acts on demand, such as releasing additional pollution emission allowances from a reserved fund would be an effective way to constrain price shocks in a cap-and-trade system. However, a quantity-based policy that lowers the need for inframarginal supply, such as using ethanol as an oil product substitute to mitigate oil shocks, would be ineffective. Similarly, the benefits of such interventions depends on the macroeconomic impacts of
price shocks from the sector. Relatedly, I show that a liability rule designed to reduce risk from low-probability, high-consequence oil spills have very low compliance costs.
Dedication

To my parents who taught me why to work. To the scholars who taught me how to work. And to APS, who taught me to work broadly.
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1. Introduction

Environmental policy is increasingly implemented via market mechanisms. While this is in many ways a great success for the economics profession, a number of questions remain. In this dissertation, I empirically explore the question of what will happen as we couple environmental outcomes to potentially volatile market phenomena, whether policies can insulate environmental outcomes and market shocks, and whether they should. There are a number of potential causal mechanisms, including (but not limited to) financial phenomena in tradable permit markets driving pollution decisions, the ability of alternative energy sources to mitigate volatility in traditional fossil fuels markets, and basing investments in environmental protection on market decisions. I pursue each of these in turn.

1.1 Ethanol and Energy Security

This first essay examines the impact of ethanol on U.S. energy security. I construe energy security as resilience to world energy price shocks and thus ask whether ethanol can mitigate the impact of world oil market shocks on the US economy. I estimate the short-term increase in ethanol production induced by an increase in oil prices and the impact of that ethanol on gasoline prices. Ethanol production does not increase quickly enough or in large enough quantities to substantially offset oil price shocks. The small magnitude of the price effect is due to the extreme flatness of oil
refining supply curves, conditional on being below capacity constraints. The flatness of the oil refining curves implies that even if ethanol use does increase and offset oil product use, the reduction in oil product production does not substantially lower the spread between finished gasoline and crude prices.

Instead of mandating a minimum quantity of ethanol blending, an alternative policy of mandating precise quantities of ethanol blending would have substantially larger, but still small energy security benefits. This policy would effectively decouple the prices of ethanol and oil-based fuels.

1.2 The Effectiveness of Carbon Price Containment

In my second essay, I simulate the effectiveness and environmental impacts of a proposed policy to contain price risk in environmental markets. Economists have long recognized the value of market mechanisms for environmental policy. They have gained increasing salience as recent decades have increasingly seen market mechanisms supplanting traditional command-and-control or technological mandates for environmental policy. A number of countries now manage large fishing stocks with tradable quota. The acid rain program in the US reduced emissions at far lower costs than originally projected. The European Union, a consortium of northeastern states known as the Regional Greenhouse Gas Initiative, and the State of California now manage their greenhouse gas emissions via tradable allowances, and other states and provinces are considering similar policies. Switzerland recently introduced a hybrid
system in which companies can participate in a greenhouse gas cap-and-trade or opt out and pay a carbon tax. Australia has introduced a carbon tax (implemented as a cap-and-trade with unlimited allowances at a fixed price) which will transition to a traditional cap-and-trade system. Somewhat more broadly, government-controlled resource deposits are often allocated to private firms via auctions. And ecosystem services are often funded and allocated by either reverse auctions or market trading.

In a greenhouse gas cap-and-trade program, participants face uncertainty over future compliance costs. Participants can comply by either reducing (or abating) their own emissions or purchasing emissions allowances. However, the price of emissions allowances varies for a variety of reasons including uncertain abatement costs and volatile demand. Abatement costs are uncertain and allowance prices are determined by the marginal emissions abatement costs among all market participants (more precisely, the marginal abatement cost of the marginal participant). Energy demand (and therefore allowance demand) is stochastic, in part due to macroeconomic variation. This is important because greenhouse gas emitting industries are typically characterized by very large fixed costs of investment and long-lasting infrastructure which makes abatement planning difficult and vulnerable to inefficient stranded capital.

This suggests that allowance prices could rise or fall suddenly, with substantial distributional and efficiency impacts. Thus hybrid mechanisms have been proposed which would couple cap-and-trade systems with price floors and caps. These floors
(caps) would be implemented with by a commitment by the regulator to buy (sell) allowances at the target price. If this commitment is limited, prices could potentially fall below (above) the price floor (cap). Then the mechanism would be known as a soft price floor (cap). I develop a Monte Carlo model of the effectiveness of price containment mechanisms and their likely impact on aggregate emissions, showing that plausible policies would likely fully contain prices with moderate increases in emissions.

1.3 Measuring the Cost of an Oil Spill Liability Rule

In my third essay, I estimate the impact of making oil producers liable for damage caused by their spills. Oil production is an extremely large industry with worldwide production averaging approximately 89 million barrels per day in 2012. A number of large oil spills have occurred as a result, and in 1990 the US Congress passed the Oil Pollution Act (OPA) in response to the 1989 Exxon Valdez spill. The Act specified that oil and gas producers bear the risk of small and moderately sized spills into water. Any costs associated with this risk (safety measures, insurance premiums, etc) should be capitalized into the value of holding the rights to drill. I use a pseudo difference-in-difference estimator and show that there is no evidence that the oil spill liability rule imposed a substantial cost on producers. However, this estimate is limited by the statistical power of available data, leaving room for future refinement.
2. Ethanol and Energy Security

2.1 Introduction and overview

On May 3 2012, Secretary of Agriculture Tom Vilsack visited the Biofuels Center of North Carolina where he said “the Obama Administration has an ‘all-of-the-above’ [approach] to promoting domestic energy security, and increasing the percentage of ethanol to be blended with gasoline will help boost economic growth while lessening the nation's dependence on foreign oil” (USDA, 2012a). Vilsack’s statement was typical, with several distinct elements:

1) A high-level U.S. official stressed the importance of energy security,

2) He framed energy security as an economic issue,

3) He emphasized that ethanol can promote economic energy security.

Proponents of ethanol use suggest that it can increase domestic energy security. The implicit argument is that by refining domestically grown corn into ethanol and using that for transportation fuel, Americans will face lower energy prices, be insulated from shocks to world oil markets and lessen the financial transfers to foreign nations. While the military security literature has addressed physical supply continuity considerations (US DoD, 2011), the economic simulation literature has largely addressed ethanol’s potential equilibrium impact on energy prices and terms of trade (William H. [reference]).
Meyers et al., 2010), and a macroeconomic literature has explored the impact of oil
shocks on the macroeconomy (Ben S. Bernanke et al., 1997, James Hamilton, 1983, Lutz
Kilian, 2008, Steven E. Sexton et al., 2011), our understanding of ethanol’s ability to
mitigate oil shocks and thus potentially contribute to economic energy security is
limited.¹

This essay makes several contributions to the literature. First, I introduce a new
framework for modeling energy security in economic terms that describes energy
security in terms of energy prices and vulnerability to price shocks. While this is
certainly not a complete framework for analysis of energy security issues, it is a key
element underlying US policy debates. Second, I demonstrate the theoretical possibility
that an ethanol mandate, or a mandate for the construction of ethanol refining capacity,
could lower the gasoline price volatility that US consumers face and insulate consumers
from oil price shocks. Finally, I show that the current ethanol mandate does not

¹ Hamilton (1983) noted that “[all] but one of the U.S. recessions since World War II have been preceded …
by a dramatic increase in the price of crude petroleum”. For example, in the 1956 Suez Canal crisis, total
world oil production fell by 10.1%. This shortfall lasted for approximately 4 months, but lead to an 18%
decrease in US exports and subsequent recession. A variety of causal pathways have been proposed.
Energy is an input into production, so an increase in its price would be associated with a decrease in
production. On the demand side, consumers’ short-run demand elasticity for energy is low. Energy use is
largely associated with long-term decisions such as housing and vehicle choice. If consumers continue
purchasing energy at higher prices, purchases of other goods much fall. A third suggested pathway that an
increase in energy prices can drive up official inflation statistics, which leads to contractionary monetary
policy (Bernanke et al 1997). More recently, Sexton et al (2011) suggest that oil shocks can lower housing
values in outlying areas by driving up commuting costs, which can destabilize financial institutions that are
highly dependent on housing prices.
substantially lower gasoline price volatility or insulate against oil shocks in the current U.S. economic environment.

In this section I first discuss previous literature and the context. Section II develops a theoretical model of how the mandate minimum for ethanol use and blend wall, a maximum allowable level of ethanol use, can affect the price and quantity of ethanol on the blending market and how this affects retail gasoline prices. Section III adapts the theoretical model for estimation and places the model in the context of recent years, showing that neither the mandate nor the blend wall have been binding for short-term production decisions. Section IV discusses both structural (panel) and reduced form (GARCH-X) estimation and results. A series of policy analyses such as the tradeoff between cost and volatility and a calculation of the expected benefits of containing shocks follow in section V, while section VI offers policy conclusions and directions for future research.

2.2 Literature review

A series of papers pioneered by James Hamilton make the case that oil price shocks can cause recessions (Ben S. Bernanke, Mark Gertler and Mark Watson, 1997, Marc Gronwald, 2008, James Hamilton, 1983, 2003, Lutz Kilian and Dan Murphy, 2010, Knut Anton Mork, 1989, William D. Nordhaus, 2007). This has spawned a literature examining whether this is still the case, channels of causation, and the magnitude of the effect. One robust conclusion seems to be that both oil price levels and shocks to oil
prices impact the macroeconomy. Hamilton (2003) offers an overview of the literature, in particular noting that oil shocks can shift or defer consumer purchasing decisions for durable goods such as housing. Bernanke, Watson, and Gertner (1997) instead attribute much of the macroeconomic effects of oil shocks to central bank policy. Kilian and Murphy (2010) distinguish between supply shocks, demand shocks, and speculative behavior, and suggest that repeated unforeseen demand shocks drove the mid-2000’s increase in oil prices.

The macroeconomic literature on the importance of energy prices prompts the question of how agricultural markets and policies impact energy markets. There have been several strands of literature examining the impact of ethanol policies or the interaction of ethanol and oil markets. The largest literature has consisted of large-scale simulation models of the US agricultural sector which take world energy prices as exogenous inputs (Bruce A. Babcock, 2008). These models have played an important role in policy analysis, for example by forming the basis of the EPA’s analysis of the Renewable Fuels Standard (EPA, 2010). Related literature adds endogenous feedback to energy markets. This work tends to conclude that ethanol policy design does have substantial effects on the biofuels markets and agricultural land use but has limited impacts on broader energy markets (Madhu Khanna et al., 2011, Wyatt Thompson et al., 2009, Jarrett Whistance et al., 2010).
A number of other studies evaluate the interaction of ethanol and energy markets using an analytic modeling approach. Harry de Gorter and David Just develop an analytical model of the interaction of a mandate and subsidy, much like the combination of policies in place during the period of 2006 (when the mandate came into effect) to 2012 (when the direct subsidy expired) (Harry de Gorter and David R. Just, 2009). Like de Gorter and Just, Hertel and Beckman also show that if an ethanol quantity mandate is binding, oil price shocks do not propagate through to food markets (Thomas W. Hertel and Jayson Beckman, 2011). Oil price shocks do not change ethanol prices because the quantity of ethanol is fixed. This means that ethanol producers’ demand for corn feedstocks is not directly affected. Thus a binding mandate shields food prices from oil price shocks. However, a binding mandate can make ethanol prices more volatile because they are no longer damped by substitution with less-volatile oil-derived fuel prices. Other research considers the market equilibrium with flex-fuel vehicles, showing that increasing the amount of ethanol used in the primary gasoline market can drive up prices for E85 (transportation fuel comprised of 85% ethanol and 15% petroleum blendstock), reducing demand for flex fuel vehicles and increasing overall oil use (Cheng Qiu et al., 2011). However, these papers are typically based on plausible parametrizations instead of estimated values.

Structural econometric work largely focuses on long-term equilibrium relationships between a subset of policies, oil price levels, ethanol price levels, and
agricultural grain commodity prices. This literature has had mixed results, with some papers finding that ethanol lowers retail gasoline prices by as much as $0.89 per gallon (Xiaodong Du and Dermot J. Hayes, 2009), while other work finds no statistically robust effects (Christopher R. Knittel and Aaron Smith, 2012). Examinations of the relationships between volatility in ethanol and oil prices using financial time-series techniques have found that price levels and volatility do propogate between energy and agricultural markets because ethanol links them (Teresa Serra et al., 2011, Zibin Zhang et al., 2009). Financial time series approaches are excellent for estimating volatility in existing markets. However, it cannot answer questions about future ethanol markets under a strong mandate, which require a structural approach.

A broader literature tries to develop the idea of energy security. One line of research comes from the policy and political science communities in addition to economics. Michael Levi offers an excellent overview of energy security from a political science perspective, discussing the impacts of energy security concerns on international relations (Michael Levi, 2010). Economists typically focus more directly on direct costs, externalities, or other economic implications (S. Brown and H. Huntington, 2010). Some authors have tried to calculate the direct military expenditures related to maintaining international oil shipments (Paul N Leiby, 2008). Others have described an “oil premium”, using the framework of an externality in which consumer consumption of
oil products imposes risk and security costs on the rest of society (Ian W. H. Parry and Joel Darmstadter, 2003).

From the literature, we know that fuel prices and shocks matter for the economy, that ethanol can impact expected energy prices, and that the market and regulatory structure around ethanol industry impacts how oil prices propagate through related markets. Previous literature has not fully determined the interactions of oil price shocks, ethanol markets, and policy mechanisms.

2.3 Background on Ethanol Markets and Regulation

U.S. ethanol is produced from corn and other feedstocks, but primarily from corn grown in the U.S. Midwest. High shipping costs of inputs require refineries to locate near the corn fields. Ethanol is then shipped across the country by train and tanker truck. It is not shipped via pipeline because ethanol, unlike oil, will corrode pipelines if the pipeline has previously been used for oil. At rail terminals it is shipped via truck to blending terminals near the point of final sale where it is combined with oil-derived blendstock, typically called RBOB, and distributed to retail gasoline stations in the form of finished gasoline.

Ethanol is blended into gasoline for two purposes: as an oxygenate to enhance octane and reduce carbon monoxide formation, and as an energy source. Increased blending of ethanol as an oxygenate came with the phaseout of MTBE during 2000-2006. Oxygenates such as MTBE and ethanol make gasoline burn more completely, lower
emissions, increase fuel octane, and prevent engine knocking. MTBE was preferred due
to its lower cost. However, the discoveries that MTBE contaminated drinking water
supplies and is carcinogenic lead to MTBE bans in a number of states and a switch to
using ethanol as an oxygenate.

Since 2005, the minimum aggregate amount of blending has been set by a
national quantity mandate. This mandate was set by the Energy Policy Act of 2005 and
raised by the Energy Independence and Security Act of 2007. These laws required that
US gasoline include 4 billion gallons of ethanol in 2006, increasing to 12.6 billion gallons
of ethanol in 2011 and ultimately reaching 15 billion gallons in 2015. The standard also
includes mandates for other advanced biofuels such as cellulosic ethanol and requires a
total of 36 billion gallons of biofuels in 2022, comprised of a mixture of traditional corn-
based ethanol and other fuels. The actual compliance instrument is known as a
Renewable Identification Number, or RIN. One RIN is produced for each gallon of
ethanol produced. Compliance is achieved by requiring gasoline refiners and importers
to hold a certain number of RINS for each gallon of gasoline blendstock they produce or
import. If a party is required to blend ten gallons of ethanol in a given year,
operationally they have to acquire ten RINS for that year. If more ethanol is produced in

\footnote{Ethanol imports are also eligible to produce RINS, while ethanol exporters must surrender them. This
ensures that RINS reflect actual ethanol blended into gasoline in the U.S. – ethanol produced domestically
and exported does not count towards the mandate.}
a given year than is required, RINs can be banked for compliance the next year. This implies that the actual biofuel production in any given year may be higher or lower than the statutory mandate.

Blenders also face a 10% limit on the amount of ethanol that can be in any gallon of finished gasoline. This is known as the “blend wall”. There are two major reasons for the blend wall. First, vehicle manufacturers have expressed concern about damage to engines from ethanol blends above 10%. Second, finished gasoline with medium blends of ethanol (between approximately 20% and 80%) evaporates more volatile organic chemicals than low or high blends. Volatile organic chemicals can have both short- and long-run human health effects in the local area. Thus ethanol use has been capped at 10%.

Blenders have discretion on how much ethanol to add as long as they are at or above the mandate in aggregate and below the blend wall. Ethanol has similar albeit lower energy, so within this range ethanol and petroleum-based blendstock are substitutes.

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3 A maximum of 20% of the mandate can be met with banked RINS. This suggests the convergence of RIN prices across different RIN vintages may be limited if the total surplus of RINS in a year is more than 20% of the next year’s mandate.

4 The EPA has recently increased the limit to 15%, but blends between 10 and 15% are not yet in broad use. The limit was 10% during my period of study.
2.4 Source of Volatility

There are three primary channels for ethanol to lower the price volatility of finished gasoline. First, adding ethanol capacity in essence flattens the total supply curve for finished gasoline, making supply more price responsive. An increase in demand can be met by both increased oil-based fuel or ethanol-based fuel. Likewise, a shock to the supply of oil-based fuel from one source could be met with increased supply from both other oil sources or ethanol. This channel depends on the slope of the ethanol supply curve and on ethanol blenders being legally able to increase blending – on there not being a binding ethanol quantity cap.

Second, ethanol could lower fuel price volatility through portfolio diversification. Supply-side variation in oil blendstock prices is primarily driven by variation in international crude oil markets. Changes in world crude prices arise from demand changes, from geopolitical events, and from industry characteristics.

Ethanol supply volatility is instead primarily driven by variation in corn prices. Corn is traded on world grain markets, but the Midwestern United States is by far the largest producing region; thus the world corn market price is highly exposed to American weather variation. If ethanol has less supply-side volatility than oil blendstock, then increasing ethanol use and decreasing oil blendstock use would lower aggregate supply side volatility. Ethanol can lower gasoline price volatility even if it is more volatile than oil, as long as the supply side shocks are sufficiently uncorrelated.
Table 1 shows the correlations between the basic prices. While it first seems that corn and oil prices are strongly correlated, this is largely due to endogeneity. An exogenous shock to oil prices will also drive up ethanol prices because they are substitutes. When corn is instrumented with weather to focus on the relationship between exogenous inputs, we see that the correlation between corn and crude oil prices is less than 0.3, and with natural gas (a major energy source for refining corn into ethanol) is lower.

Table 1: Correlations among basic fuel input prices

<table>
<thead>
<tr>
<th></th>
<th>Crude oil</th>
<th>Corn</th>
<th>Instrumented corn</th>
<th>Natural gas</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude oil</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corn</td>
<td>0.66</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Instrumented corn</td>
<td>0.29</td>
<td>0.72</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Natural gas</td>
<td>0.23</td>
<td>-0.061</td>
<td>-0.16</td>
<td>1</td>
</tr>
</tbody>
</table>

The third way ethanol could potentially lower finished gasoline price volatility is volumetrically. If the ethanol quantity is fixed, then a change in oil prices will not result in a change in ethanol prices because the ethanol price is the price necessary to induce the fixed level of production. An ethanol quantity constraint decouples the ethanol and oil blendstock prices. This means that an increase in crude oil prices only increases a
portion of the finished gasoline price. The larger the fixed ethanol blend rate, the larger the impact of this volumetric factor on dampening the effects of crude price volatility on finished gasoline prices if the blend rate is binding.

2.5 Conceptual Framework

2.5.1 Energy Security Through the Lens of Energy Prices

Energy security is represented as a mean-variance value function taking into account the economy’s exposure to energy prices and energy shocks. This could be a risk-averse function of GDP or a regret-minimizing function of a decision-maker’s political goals, or a combination of both. Both energy price shocks and average energy price levels can have negative macroeconomic consequences, so an optimal energy policy should take into account both of these factors.

Consider a policymaker faced with choosing a parameter $\psi$ which represents the aggregate national ethanol capacity, which has implications for both the expected level and volatility of fuel prices. The policymaker maximizes a value function $V$, which may include income, risk aversion, environmental and distributional concerns. $V$ depends on both the random price of energy $P_{\text{Energy}}$ and exposure to random energy price shocks. Exposure to shocks is reflected by gasoline price volatility, later measured as variance.
Taking derivatives, we see that

\[ \frac{dV(P_{\text{Energy}}, \text{Vol}(P_{\text{Energy}}))}{d\psi} = \frac{dV}{dP_{\text{Energy}}} \frac{dP_{\text{Energy}}}{d\psi} + \frac{dV}{d\text{Vol}(P_{\text{Energy}})} \frac{d\text{Vol}(P_{\text{Energy}})}{d\psi} \]  \hspace{1cm} \text{(2.2)}

Setting the first order condition equal to zero suggests an optimality condition for the policymaker’s choice of \( \psi \)

\[ \frac{dV}{dP_{\text{Energy}}} \frac{dP_{\text{Energy}}}{d\psi} = \frac{dV}{d\text{Vol}(P_{\text{Energy}})} \frac{d\text{Vol}(P_{\text{Energy}})}{d\psi} \]  \hspace{1cm} \text{(2.3)}

Equation (2.3) shows that the policymaker faces a tradeoff between the average level and volatility of prices in choosing \( \psi \), and that the optimal choice depends on the relative impacts of prices and volatility on the macroeconomy. As reviewed earlier, the macroeconomic literature has focused on the direct impacts of energy prices and volatility (our \( \frac{dV}{dP_{\text{Energy}}} \) and \( \frac{dV}{d\text{Vol}(P_{\text{Energy}})} \) terms). The economic simulation literature has told us a lot about the impact of ethanol on expected energy prices (our \( \frac{dP_{\text{Energy}}}{d\psi} \) term). However, few have empirically studied the impact of ethanol on energy price volatility (our \( \frac{d\text{Vol}(P_{\text{Energy}})}{d\psi} \) term). I characterize this term for consumer finished gasoline prices.
2.5.2 A Model of Ethanol Blending for Transport Fuel

Finished gasoline sold at the retail pump is a combination of ethanol and petroleum blendstock. Assuming that retail sales are competitive and costless, the price of gasoline $P_G$ is a linear combination of the ethanol price $P_E$ and petroleum blendstock price $P_{BS}$,

$$P_G = \alpha P_E + (1-\alpha) P_{BS},$$  \hspace{1cm} (2.4)

where $\alpha$ is the blend ratio $\frac{E}{G}$ of the total quantity of ethanol $E$ and the total quantity of finished gasoline $G$.

Ethanol producers supply a quantity of ethanol $E$ as a function of the ethanol price $P_E$, available ethanol capacity $K$, and exogenous supply shifters $X$. These supply shifters include input prices. The quantity of ethanol for blending is constrained to be within the statutory range $[E, \bar{E}]$ where an underscore indicates a minimum aggregate quantity of ethanol blending and an overscore indicates an upper limit.

$$E = f (P_E, K, X) \hspace{1cm} s.t. \hspace{1cm} \underline{E} \leq E \leq \bar{E}$$  \hspace{1cm} (2.5)

Ethanol substitutes for petroleum blendstocks, so the ethanol price is set in equilibrium with the price of the petroleum blendstock $P_B$ unless the RFS mandate or blend wall are binding:

---

\(^5\) Appendix A. demonstrates that costly retail does not affect the volatility calculations.
From equation (2.6), we see that ethanol supply can only mitigate price spikes if neither the mandate nor the blend wall are binding. If the RFS is binding, ethanol production is independent of RBOB prices, so an oil price spike will not lead to an increase in ethanol production.

However, if the blend wall is binding and oil prices increase (decrease), the finished gasoline quantity will decrease (increase). This will lower (raise) the blend wall because it is defined as a percentage of the quantity of finished gasoline. This will lower (raise) the ethanol price, partially mitigating the shock to oil prices.

Renewable Identification Numbers, or RINs, are the basic compliance unit for the ethanol mandate. A blender can comply by either the required quantity of ethanol or, purchasing RINS from another blender who over-complied, or by a combination of both. A blender purchasing ethanol is actually purchasing both a unit of physical ethanol for blending and resale, and a unit of compliance with the mandate. Thus if the mandate is binding, RINs will trade at the difference between ethanol and RBOB prices. If the mandate is not binding, there will be more RINs available than gasoline blenders demand and the price will fall to zero (net of transactions costs). Alternatively if the blend wall is binding, the price of ethanol will be the price necessary to induce that
maximum level of production. The RIN price reflects the tightness of the mandate
(Harry de Gorter and David R. Just, 2009).

I show this graphically in Figure 1 and Figure 2. In Figure 1, I show the impact
of an ethanol mandate on the blending market. The length of the x-axis is the total
amount of gasoline demanded. While the figures show demand as a fixed quantity, this
is only for visual simplicity; the econometric estimation will allow the quantity of
gasoline demanded to be determined endogenously. The ethanol supply curve is E. The
petroleum blendstock supply curve B originates from the bottom-right corner. They
intersect at (P*, E*) which is the efficient market equilibrium. The price will be P*, the
ethanol quantity will be E*, and petroleum blendstock will supply the remainder. If a
low ethanol mandate \( E^1 \) is imposed, it will not be binding and will not affect prices or
quantities. However, if the mandate is raised to \( E^2 \), meeting the mandate will require
increasing production above the efficient level \( E^* \). This will drive ethanol prices up to
\( P^E \) and blendstock prices down to \( P^B \). The difference between them will be reflected in
RIN prices.

Figure 2 shows the impact of an ethanol cap on the blending market. The
supply curves and unconstrained market equilibrium are the same as in Figure 1. If
regulators impose a cap \( \overline{E} \) that is higher than \( E^* \), blenders continue to use \( E^* \) gallons of
ethanol, the cap will not bind, and prices will not change. However, if the cap is
lowered to $\bar{E}^2$, the quantity of ethanol will fall to $\bar{E}^2$ and its price will fall to $P^E_2$.

Petroleum blendstock supply will increase and its price will rise to $P^B_2$. Blenders would like to use more ethanol because it is less expensive, but cannot because of the blend wall.

![Figure 1: Ethanol Supply with a Mandate](image)

Figure 1: Ethanol Supply with a Mandate
Oil blendstock $B$ is produced based on the output price received for blendstock $P^B$, the input price for crude oil $P^O$, and refining supply shifters $Y$. Consumers in turn demand gasoline quantity $G$, which is a function of the price of finished gasoline $P^G$ and demand shifters $Z$.

$$ B = g(P^B, P^O, Y) \quad (2.7) $$

$$ G = h(P^G, Z) \quad (2.8) $$

I close the model by assuming that markets clear and noting that gasoline, ethanol, and blendstock prices are equivalent if neither the mandate nor the blend wall bind.

$$ G = B + E \quad (2.9) $$
\[ P^G = P^B = P^E \]  

(2.10)

I can now solve for the equilibrium gasoline price as a function of the fundamentals that determine the supply and demand curves and solve for the volatility (or variance) of this price. Inverting equation (2.7), yields

\[ P^B = g^{-1}(B, P^O) . \]

From equation (2.9) we know that \( B = G - E \). Thus

\[ P^B = g^{-1}(G - E, P^O) \]  

(2.11)

Rewriting equation (2.11) by noting that the price of oil blendstock \( P^B \) is equal to the price of finished gasoline \( P^G \) and plugging in the exogenous determinants of \( G \), \( E \), and \( P^O \) yields

\[ P^G = p(K, P^O, X, Y, Z). \]  

(2.12)

\[ \text{Var}(P^G) = \text{Var}(p(K, P^O, X, Y, Z)) \]

Note that the model does not include a corn supply curve. Equivalently, the model assumes a completely elastic corn supply curve. Quite to the contrary, the literature estimates grain supply curves to be quite inelastic (Michael J. Roberts and Wolfram Schlenker, 2009). Assuming the corn supply curve to be completely elastic will bias calculations to make corn-based ethanol look better than it actually is. If the corn supply curve were added, then an increase in oil prices would drive up ethanol prices, which would drive up the quantity of ethanol supplied, which would in turn raise the
price of corn. The increase in the price of corn would lower the ethanol supply curve (ie, it would reduce the amount of ethanol supplied at a given price), thus reducing the ability of ethanol to mitigate oil price spikes. Omitting this effect biases the model towards overestimating ethanol’s effect on gasoline prices.

2.6 Empirical Analysis

This section adapts the above theoretical model for estimation. The first subsection shows that the ethanol mandate and blend wall have not been binding, so the price equilibrium model holds.

2.6.1 The Ethanol Mandate and Blend Wall

This section shows that the ethanol mandate has not been binding on short-term production decisions (as opposed to long-term infrastructure capacity investment decisions) and that the blend wall was not binding during the period of analysis. This means that the supply curves of equations (2.13) and (2.14) hold.
First consider the ethanol mandate. I start by directly comparing the quantity of ethanol consumed to the mandate. Figure 3 shows US ethanol consumption (blue solid line), the statutory mandate (green dashed line), and the amount of ethanol needed to meet the compliance obligation – the mandate minus banked RINs (red dotted line). I construct the actual compliance obligation by assuming that all allowances which can be banked and used later are. The compliance obligation in a particular year is then the statutory mandate minus the lesser of the previous year’s excess production or 20% of that year’s mandate.\

In particular, the 2006 compliance obligation was the statutory mandate because it was the first year of the program and there were no banked allowances. Actual 2006 ethanol use was 4.8 billion gallons, 800 million gallons above the mandate of 4 billion. The 2007 mandate was 4.7 billion gallons, but 800 million 2006 RINS could be used in 2007, so the actual 2007 compliance obligation was 3.9 billion gallons. Production in 2007 was 6.5 billion gallons, 2.6 billion above the amount needed for compliance. Because the 2008 cap was 9 billion gallons and banked RINS can meet at most 20% of the cap, 1.8 billion 2007 RINS could be used in 2008 and the net compliance obligation was 7.2 billion gallons.

---

6 Firms are not allowed to meet at most 20% of their RFS obligation with banked RINS.
Ethanol use has been at least 21 percent above the level needed for compliance in every year and on average 34 percent above the compliance level. Without banking, the mandate would have been binding in 2008 and nearly so in 2009, but after including banking ethanol use has been at least 22% above the compliance level every year and has averaged 34% above this level. Thus the renewable fuel mandate was not binding in the short term during the period of analysis.

The blend wall was also non-binding. Ethanol consumption did seem to have neared the blend wall in many areas by the summer of 2011, but this is after the study period. This suggests that oil price increases in that period would lead to ethanol quantity decreases (as opposed to increases) because they would lead to decrease in the quantity of gasoline demanded, which would lead to a decrease in the total quantity of ethanol that could be blended. In principle this is a testable question, however using aggregated data from a single season would not be a robust test because the blend wall applies to every gallon of finished gasoline.

2.6.2 Developing a model for estimation

The amount of ethanol available for blending depends on the available production capacity. The average amount of ethanol consumed in each region i is assumed to be a fixed share of national capacity denoted as $V_{4i}$. The total ethanol capacity utilization rate is then $\sum_i V_{4i}$. The capacity utilization rate varies with corn
prices $P^C$, natural gas prices $P^N$, and ethanol prices which are assumed equal to gasoline prices $P^G$. Time is denoted with $t$ and $\epsilon$ describes an iid error term.

The quantity of petroleum blendstock supplied is assumed to move with the price of crude oil $P^O$, the price of finished gasoline $P^G$, a vector of supply shifters $Y$, an iid error $\delta$, and $\phi$ are parameters to be estimated. Gasoline demand $G$ is a function of a vector of demand shifters $Z$, the price of gasoline, and coefficient vectors $\eta$ and $\lambda$.

Population and income will serve as demand shifters.

Ethanol supply:
\[
E_t = v_0 + K_t \cdot (v_1 P^G_t + v_2 P^N_t + v_3 P^G_{t-i} + v_4 \epsilon_t) + \epsilon_t
\]  
(2.13)

Blendstock supply:
\[
B = \phi_0 + \phi_1 P^O_t + \phi_2 P^C_t + \phi_3 Y_{t-i} + \delta_{t-i}
\]  
(2.14)

Gasoline Demand:
\[
G_t = \eta Z_{t-i} + \lambda Z_{t-i} P^G_{t-i}
\]  
(2.15)

Price equilibrium:
\[
P^E_t = P^R_t = P^G_t
\]

Note that I omit the ethanol blending tax credit from equation (2.13). Others have ably studied the impact of the tax credit and shown that it increases production at substantial net cost to taxpayers (Harry de Gorter and David R. Just, 2009). However, it has little variation over my period of study. Appendix B. Including the Ethanol Production Tax Credit shows that including it does not substantially change the results. Appendix C: Fuel price equilibrium shows that the price equilibrium holds.

Solving the system for $P^G$ in terms of coefficients and observables yields

\[
P^G_{t-i} = D \cdot (v_0 + K_t \cdot (v_2 P^N_t + v_3 P^C_{t-i} + v_4 \epsilon_{t-i}) + \epsilon_{t-i} + \phi_0 + \phi_1 P^O_{t-i} + Y_{t-i} \phi + \delta_{t-i} - \eta Z_{t-i})
\]  
(2.16)
where \( D \equiv \frac{1}{(IZ_{it} - K, \nu_1 - \phi_1)}. \)

The volatility of \( P^G \), measured using its variance, has three major terms representing the impact of ethanol supply volatility, blendstock supply volatility, and diversification between ethanol and oil-based blendstocks respectively.

\[
Var(P^G) = D^2 (\text{eth} + \text{blend} + \text{div}) \tag{2.17}
\]

Where

\[
\text{eth} = K^2 \nu^2 \text{Var}(P^N) + K^2 \nu^2 \text{Var}(P^C) + \text{Var}(\epsilon)
\]

\[
\text{blend} = \phi^2 \text{Var}(P^O) + \phi^2 \text{Var}(Y) + \text{Var}(\delta)
\]

\[
\text{div} = 2K^2 \nu \nu \text{Cov}(P^N, P^C) + 2K\nu \phi \text{Cov}(P^N, P^O) + 2K\nu \phi \text{Cov}(P^C, P^O)
\]

Taking the derivative of (2.17) with respect to ethanol production capacity yields a relationship indicating the conditions when increasing ethanol production capacity will lower price volatility. The optimal ethanol capacity choice will occur in a range where this derivative is negative or zero.\(^7\)

\[
\frac{d\text{Var}(P^G)}{dK} = D^2 \left( \frac{d\text{eth}}{dK} + \frac{d\text{blend}}{dK} + \frac{d\text{div}}{dK} \right) - 2\text{Var}(P^G) \tag{2.18}
\]

Intuitively, increasing ethanol production capacity lowers variance as long as the portfolio diversification effect (the extent to which corn and natural gas shocks are uncorrelated with oil shocks) outweighs the increased exposure to corn and natural gas.

---

\(^7\) If the derivative is positive, that means that increasing capacity increases volatility. Alternatively, lowering capacity would lower volatility. This would also lower costs and would be preferred. Thus a positive derivative indicates a non-optimal capacity level.
shocks. Note that if no ethanol is blended, the variance of finished gasoline reduces to the variance from the blendstock supply factors: world oil prices $P_G$, blendstock shifters $Y$, and unobserved shocks.

### 2.6.3 Gasoline Price Endogeneity

Due to its endogeneity, I instrument for the price of gasoline $P_G$ in both the ethanol and blendstock supply equations. In the ethanol supply equation, the instrument for the price of gasoline is the price of crude oil. In the blendstock supply equation, the gasoline instruments are the crude price, crude oil inventories, ethanol production capacity, and ethanol production capacity interacted with instrumented corn and natural gas prices.

### 2.6.4 Corn Price Endogeneity

High levels of ethanol production may drive up corn prices. This phenomenon has led to the “food versus fuel” debate and entails real resource, efficiency, and distributional costs. It also presents an endogeneity problem for estimating the ethanol supply curve (equation (2.13)). I follow the work of Roberts and Schlenker and a substantial prior literature by using measures of current weather as a corn supply shifter to instrument for corn prices (Michael J. Roberts and Wolfram Schlenker, 2009). They also show that past seasons’ weather can be used as a demand shifter because a low (high) past harvest leads to lower (higher) grain stocks, thereby increasing (decreasing) current demand to replenish stocks.
The Roberts and Schlenker approach relied on annual weather measures to instrument annual average prices. To extend this to monthly data, we first generate a measure of national monthly heating and cooling degree days as they impact corn producing regions by weighting state-level monthly heating and cooling degree days with 2003 state-level corn production. We then construct each month’s average number of total heating and cooling degree days since the start of the growing season for that month of the year, deviation from average for the specific month, and deviation as a percent of the average. We use both the same-month and next-month heating and cooling degree percent deviations to instrument for corn prices. Inclusion of next-month weather allows for forward-looking agents. Because many of the same areas are used to grow winter wheat in the winter, this approach effectively instruments grain prices year-round. Figure 4 shows the actual and predicted corn prices.

Figure 4: Actual and Instrumented Corn Prices
Weather data is from the National Climatic Data Center, which provides state-month level average heating and cooling degree days. The cooling degree days measure for a single site on a single date is the daily average temperature in Fahrenheit minus 65, truncated at zero. If the daily average temperature is 77, that would be 12 cooling degree days, whereas a daily average temperature of 50 would be zero cooling degree days. Heating degree days are 65 minus the daily average temperature, again truncated at zero. A daily average temperature of 50 would then be 15 heating degree days, whereas a temperature of 77 would be zero. These single site-date measurements are then spatially averaged and aggregated to monthly levels.

Corn prices are monthly averages of the spot price from the S&P GSCI index on the Chicago Mercantile Exchange.

2.7 Data

2.7.1 Blendstock and Blendstock Input Prices

I use monthly PADD-level data from 2004-2010. Monthly wholesale gasoline prices, refiner acquisition costs for crude, and international crude benchmarks are from the Energy Information Administration (EIA) and are in dollars per gallon. The total finished gasoline quantity in thousand barrels per day is from the EIA.

---

8 PADDs, or Petroleum Administration for Defense Districts, are a standard way of dividing the country into regions to measure transportation fuel use. The five PADDs are the East Coast, Gulf Coast, Midwest, Rocky Mountains, and West Coast. I include a map of the PADDs in Appendix E.
2.7.2 Ethanol and Ethanol Input Prices

The quantity of ethanol blended into gasoline in thousand barrels per day is from the EIA, as are natural gas prices. National ethanol production capacity data is from the Renewable Fuels Association, the professional association of ethanol producers. Most ethanol produced in the U.S. (over 90 percent) is produced in PADD 2 (Midwest). It is then shipped throughout the United States, largely by rail. Thus PADD-level capacity and production data would not accurately measure our market.

All prices are in 2010 dollars, deflated with the BLS Current Price Index for All Urban Consumers (series CUUR0000SA0). Table 2 shows summary statistics for key variables. Key prices over time are shown in Figure 5 and Figure 6. The economic crash of 2008 jumps out in all prices, but there is also other variation in each. In particular, gas prices spiked in 2006 but have remained low after that with the onset of unconventional production. Corn prices remained in the early period, but spiked during the food crises of 2006-2007, 2008, and 2011-12 (after the study period). Figure 4 shows corn prices and predicted corn prices based on weather variables. Crude oil and finished gasoline prices also fluctuated throughout the period, largely moving together. Note that weather largely explains corn price movements in the early part of my analysis while ethanol production was low, but does not fully explain the price spike at the end of 2011 when ethanol production was high. Figure 7 shows aggregate US ethanol blending. Note the
dramatic increase with initial RFS implementation in 2006 and the subsequent continued increase over time.

Figure 5: Ethanol Blending Market Prices

Figure 6: Natural Gas Prices
Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std Dev</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>E (thousands of barrels per day per PADD)</td>
<td>88.2</td>
<td>76.9</td>
<td>420</td>
</tr>
<tr>
<td>K (thousands of barrels per day nationwide)</td>
<td>438</td>
<td>211</td>
<td>420</td>
</tr>
<tr>
<td>PC ($ per gallon)</td>
<td>2.05</td>
<td>0.493</td>
<td>420</td>
</tr>
<tr>
<td>PO ($ per gallon)</td>
<td>1.59</td>
<td>0.473</td>
<td>420</td>
</tr>
<tr>
<td>PC ($ per bushel)</td>
<td>3.56</td>
<td>1.07</td>
<td>420</td>
</tr>
<tr>
<td>PN ($ per ‘000 cubic feet)</td>
<td>7.75</td>
<td>2.12</td>
<td>420</td>
</tr>
</tbody>
</table>

Prices for gasoline, natural gas, and corn are demeaned for the ethanol supply equation. This implies that their coefficients represent the change in the PADD-level ethanol capacity utilization rate from a one dollar change in each price. The change in the U.S. aggregate utilization rate is then 5 times the coefficient, because there are five PADDs.
For the reduced form time-series estimation (described below) I use national monthly data from the same sources for the period 1986-2010. GARCH-X models can be computationally unstable and have better convergence properties with a long time period than with a shorter panel, and the full panel is not available for this longer period.

### 2.8 Panel IV and GMM

I estimate equations (2.13), (2.14), and (2.15) in levels and first differences with a standard panel instrumental variable approach and with a system GMM approach. While both are consistent, system GMM can improve estimation efficiency and allows the use of predetermined (as opposed to strictly exogenous) instruments. The
distinction is that a shock in period $t$ can affect the value of a predetermined variable in later periods, but cannot affect strictly exogenous variables in any period. Gasoline and corn price instruments are discussed below. The system GMM also estimates both the panel and first differences equations simultaneously and uses lagged values as instruments.

Panel data estimation relies on the data being stationary. I use the standard Im-Pesaran-Shin method to test for unit roots in panel data (K. S Im. et al., 2003). Table 3 shows results of these tests for our data series. The first column reports results for unit root tests in levels, the second for unit roots in levels after controlling for a linear time trend, and the third for unit roots in first differences. In each case, a “Y” indicates that the Im-Pesaran-Shin tests rejects the null of a unit root in each panel at the 5% confidence level. A “N” indicates that we cannot reject the null of unit roots in each panel.

Note that each data series is stationary in first differences, and that the dependent quantity variables are all trend stationary. This suggests that I can estimate the model in levels as long as we include a trend for ethanol quantities. I also estimate the model in first differences.
Table 3: Results of stationarity tests.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Stationary</th>
<th>Trend stationary</th>
<th>First differences stationary</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethanol quantity</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Blendstock quantity</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Gasoline quantity</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Ethanol capacity</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Gasoline price</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Crude oil price</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Corn price</td>
<td>N</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Instrumented corn price</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Natural gas price</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

2.9 GARCH-X Estimation

As a simple robustness check, I also directly estimate the impact of ethanol capacity on the variance of gasoline prices using a generalized autoregressive conditional heteroskedasticity process in which the variance of the error term also depends on observed covariates (GARCH-X). GARCH-X is a two-stage model. The first
stage (equation (2.19)) models the price of finished consumer gasoline as a linear function of the price of crude oil, with a mean zero iid error term (equation (2.20)).

The second stage models the volatility of the unobserved errors from the first stage as a function of past unobserved errors, the variance of past unobserved errors, and past observables as shown in equation (2.21). A positive estimate for $\alpha$ and $\beta$ indicates volatility clustering – distinct high and low volatility periods in which high volatility tends to follow high volatility, and low volatility follows low volatility. This can be thought of as a continuous version of regime shift models in which variance can be low or high depending on the (possibly endogenously determined) volatility regime. A negative and significant value for $\lambda_1$ would indicate that ethanol production effectively reduces gasoline price volatility. Equations (2.19) and (2.21) are estimated by maximum likelihood.

Note that the functional form relationship between K and gasoline price variance is exponential. This is a standard functional form for GARCH-X which is needed for computational reasons (other functional forms can take on negative values) but captures the essential flavor of concavity.

$P_t^g = \delta_0 + \delta_1 P_t^o + \delta_2 K_t + \epsilon_t$  \hspace{1cm} (2.19)

$\epsilon_t \mid \Omega_{t-1} \sim i.i.d \left(0, \sigma_t^2 \right)$  \hspace{1cm} (2.20)

$\sigma_t^2 = \sum_{k=1}^{m} \alpha_k \epsilon_{t-k}^2 + \sum_{f=1}^{n} \beta_f \sigma_{t-f}^2 + \exp(w + \lambda_1 * K_{t-1} + \lambda_2 * P_{t-1}^o)$  \hspace{1cm} (2.21)
Standard tests suggest a single time period for both the ARCH and GARCH terms \((m, n = 1)\).

### 2.10 Results

#### 2.10.1 Panel IV and GMM Results

Table 4 and Table 5 give results for estimation of blendstock (equation (2.14)) and ethanol (equation (2.13)) supply functions. In Table 4, specifications 1 and 2 show results for a standard panel IV. Crude prices are taken as exogenous, while gasoline prices are instrumented with crude prices, ethanol production capacity, and ethanol production instrumented with weather variables. Specification 2 also includes a linear time trend measures in months. Specification 3 is a dynamic panel model that uses the same instruments as well as lagged values for more efficient estimation estimated with GMM. Specification 4 is a log-log model, so the coefficients represent elasticities. We see that oil blendstock supply depends on input (crude) prices and output (gasoline) prices. We also see that the spread between blendstock prices and crude prices has been narrowing over time (from Specification 2), and that the blendstock supply is inelastic with regard to both input and output prices (from Specification 4).
Table 4: Regression Results for Blendstock Production in Levels, with standard errors in parentheses. ***, **, * denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Blendstock (Thousand barrels per day)</th>
<th>1 – Panel IV</th>
<th>2 – Panel IV with trend</th>
<th>3 - GMM</th>
<th>4 - Logs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline price ($ per gallon)</td>
<td>621***</td>
<td>417***</td>
<td>174***</td>
<td>0.235***</td>
</tr>
<tr>
<td></td>
<td>(70)</td>
<td>(81)</td>
<td>(11)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Crude price ($ per gallon)</td>
<td>-626***</td>
<td>-403***</td>
<td>-240***</td>
<td>-0.235***</td>
</tr>
<tr>
<td></td>
<td>(68)</td>
<td>(85)</td>
<td>(11)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Trend (months)</td>
<td></td>
<td>-1.30***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.35)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>1453***</td>
<td>1636***</td>
<td>1744***</td>
<td>7.12***</td>
</tr>
<tr>
<td></td>
<td>(473)</td>
<td>(436)</td>
<td>(184)</td>
<td>(0.0066)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>418</td>
<td>418</td>
<td>418</td>
<td>418</td>
</tr>
</tbody>
</table>
Table 5: Regression Results for Ethanol Production in Levels, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Ethanol (Thousand barrels per day)</th>
<th>1 – Panel IV</th>
<th>2 - GMM</th>
<th>3 - Logs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethanol capacity</td>
<td>0.198***</td>
<td>0.182***</td>
<td>1.30***</td>
</tr>
<tr>
<td>(Thousand barrels per day)</td>
<td>(0.013)</td>
<td>(0.0045)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Gasoline price ($ / gal)</td>
<td>0.0143*</td>
<td>0.00851***</td>
<td>0.202***</td>
</tr>
<tr>
<td>(0.01)</td>
<td></td>
<td>(0.0021)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Corn price ($ / bushel)</td>
<td>-0.0883*</td>
<td>-0.00351*</td>
<td>-0.109***</td>
</tr>
<tr>
<td>(0.0068)</td>
<td></td>
<td>(0.0018)</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Natural gas price ($ per ‘000 cubic feet)</td>
<td>-0.000106</td>
<td>-0.00152**</td>
<td>0.00241</td>
</tr>
<tr>
<td>(0.002)</td>
<td></td>
<td>(0.00064)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.63</td>
<td>8.18***</td>
<td>-3.89***</td>
</tr>
<tr>
<td>(35)</td>
<td></td>
<td>(2.0)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>418</td>
<td>418</td>
<td>418</td>
</tr>
</tbody>
</table>
Table 6: Regression Results for Gasoline Consumption in Levels, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Gasoline Consumption (Thousand barrels per day)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Population (thousands)</td>
<td>0.0360***</td>
</tr>
<tr>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Income (thousand $ per year)</td>
<td>-0.000291***</td>
</tr>
<tr>
<td>(0.0002)</td>
<td></td>
</tr>
<tr>
<td>Pop * price</td>
<td>0.00368***</td>
</tr>
<tr>
<td>(0.00036)</td>
<td></td>
</tr>
<tr>
<td>Income * price</td>
<td>-0.0000659</td>
</tr>
<tr>
<td>(0.000087)</td>
<td></td>
</tr>
<tr>
<td>Price ($ per gallon)</td>
<td>-27.4***</td>
</tr>
<tr>
<td>(9)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>207***</td>
</tr>
<tr>
<td>(40)</td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>418</td>
</tr>
</tbody>
</table>
Table 5 shows results for the estimation of the ethanol equation (2.13) using both the panel IV and GMM estimators. Specification 1 is a standard panel IV estimator. Gasoline prices are instrumented with crude prices. Corn prices are instrumented with weather measures. Specification 2 is a dynamic panel data that again uses the same instruments and lagged values to estimate more efficiently. Specification 3 is in logs so the coefficients can be interpreted as elasticities.

To interpret the ethanol coefficients, first recall that these coefficients are per PADD, while the capacity measure is nationwide and that the coefficients (excluding the constant) represent capacity utilization rates. This implies the coefficient of 0.198 on $K$ indicates on average capacity utilization rate of $5*0.198$ or 99%. A gasoline price coefficient of 0.143 implies that a $1$ increase in gasoline prices increases production by $0.0143*5$ or 7.15%. This highly inelastic production response is also indicated by the elasticities (approximately 0.2), or the coefficients in Specification 3. The quantity of ethanol blended is primarily driven by the available ethanol production capacity. The quantity of ethanol blended is also positively and statistically significantly responsive to crude prices and negatively and statistically significantly responsive to corn prices, although both of these effects are small in magnitude. While point estimates for natural gas price impacts are negative as expected, they are not statistically different from zero across many specifications. The finding of insignificant natural gas prices is consistent with a profitable gasoline-corn spread and low other variable costs.
However, the ethanol supply response to an increase in crude prices is not large enough to substantively mitigate the impact of crude price increases on gasoline prices. A one dollar per gallon exogenous increase in crude prices increases ethanol blending in each PADD by 1.43%. This lowers retail gasoline prices by about 2 cents, for a net gasoline price increase of 98 cents.

The gasoline demand equation results (in levels) imply a demand elasticity between -0.17 and -0.20, which is generally consistent with recent estimates in the literature (Martijn Brons et al., 2008, Jonathan E. Hughes et al., 2008). The primary purpose of this equation is to parameterize the volatility calculations; I would not suggest that this is the ideal way to estimate the elasticity gasoline demand.

Table 7, Table 8, and **Table 9** show panel instrumental variable results in first differences. While the point estimates are largely similar, they are less precise and generally not statistically different than zero. Additionally, point estimates of the impacts of ethanol on production are smaller, suggesting that ethanol production takes months to adjust to price shocks.
Table 7: Regression Results for Blendstock Production in First Differences, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Blendstock (Thousand barrels per day)</th>
<th>402</th>
</tr>
</thead>
<tbody>
<tr>
<td>Crude price ($ per gal)</td>
<td>402</td>
</tr>
<tr>
<td></td>
<td>(376)</td>
</tr>
<tr>
<td>Gasoline price ($ per gal)</td>
<td>-416</td>
</tr>
<tr>
<td></td>
<td>(403)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.38</td>
</tr>
<tr>
<td></td>
<td>(4.3)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>417</td>
</tr>
</tbody>
</table>


Table 8: Regression Results for Ethanol Production in First Differences, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Ethanol (Thousand barrels per day)</th>
<th>0.143* (0.07)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethanol capacity (Thousand barrels per day)</td>
<td>0.00588 (0.012)</td>
</tr>
<tr>
<td>Gasoline price ($ per gal)</td>
<td>-0.000156 (0.00080)</td>
</tr>
<tr>
<td>Natural gas price ($ per ‘000 cubic feet)</td>
<td>-0.00466 (0.0010)</td>
</tr>
<tr>
<td>Corn price ($ per bushel)</td>
<td>0.521 (0.75)</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>417</td>
</tr>
</tbody>
</table>
Table 9: Regression Results for Gasoline Consumption in First Differences, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Gasoline Consumption</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Population (thousands)</td>
<td>-0.110***</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
</tr>
<tr>
<td>Income (thousand $ per year)</td>
<td>-0.000279</td>
</tr>
<tr>
<td></td>
<td>(0.00028)</td>
</tr>
<tr>
<td>Pop * price</td>
<td>-0.0035</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Income * price</td>
<td>0.00013</td>
</tr>
<tr>
<td></td>
<td>(0.00011)</td>
</tr>
<tr>
<td>Price ($ per gallon)</td>
<td>-47</td>
</tr>
<tr>
<td></td>
<td>(84)</td>
</tr>
<tr>
<td>Constant</td>
<td>4.24</td>
</tr>
<tr>
<td></td>
<td>(2.3)</td>
</tr>
</tbody>
</table>
2.10.2 GARCH-X Estimation Results

Reduced form results are shown in Table 10. Specification 1 estimates the impact of ethanol supply on prices and residual volatility with production capacity (as it is written in (2.19)). Specification 2 replaces capacity actual ethanol production. Specification 3 uses ethanol production instrumented using ethanol capacity, crude prices, and weather variables. In each we see that that gasoline prices largely track crude prices (the crude coefficient is not statistically different than one) and that there is volatility clustering (alpha is positive and different than zero). We also see that ethanol lowers gasoline prices and gasoline volatility, but that the effect on each is very small.
Table 10: GARCH-X Estimation Results, with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Measure of ethanol quantity</th>
<th>K</th>
<th>E</th>
<th>E-hat</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Price</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.308***</td>
<td>0.334***</td>
<td>0.324***</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.020)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Crude ($ per gallon)</td>
<td>1.06***</td>
<td>1.02***</td>
<td>1.04***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.036)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Ethanol (Thousand barrels per day)</td>
<td>-6.12e-6**</td>
<td>-3.33e-6</td>
<td>-5.04e-6**</td>
</tr>
<tr>
<td></td>
<td>(2.6 e -6)</td>
<td>(2.1 e -6)</td>
<td>(2.0e-6)</td>
</tr>
<tr>
<td><strong>Variance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARCH</td>
<td>0.544***</td>
<td>0.625***</td>
<td>0.517***</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.16)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>GARCH</td>
<td>-0.220</td>
<td>-0.0315</td>
<td>-0.120*</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.10)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.85***</td>
<td>-5.78***</td>
<td>-5.54***</td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.42)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Ethanol (Thousand barrels per day)</td>
<td>-1.42e-4***</td>
<td>1.31e-4***</td>
<td>-1.29e-4***</td>
</tr>
<tr>
<td></td>
<td>(2.6e-5)</td>
<td>(2.6e-5)</td>
<td>(2.8e-5)</td>
</tr>
<tr>
<td>Crude ($ per gallon)</td>
<td>1.54***</td>
<td>1.88***</td>
<td>1.89***</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.38)</td>
<td>(0.37)</td>
</tr>
</tbody>
</table>
2.11 Policy analyses

This section considers a variety of alternative policy scenarios under the assumption that the estimated supply and demand curve parameters do not change. The first subsection considers a binding mandate – ie, a mandate that determines the ethanol production level either because it is above \( E^* \) or because it mandates a precise quantity of ethanol blending as opposed to the floor considered above.

The next subsection considers the impact of allowing the full 2022 Renewable Fuels Standard mandate of 36 billion gallons of alternative fuels to be met by corn-based ethanol, as opposed to the current legislation mandated 15 billion gallons of corn-based ethanol and 21 billion gallons of advanced biofuels. There are two major sources of instability in these dramatically out-of-sample projections: corn prices and oil refining capacity. At the time of this writing, the ethanol industry produces approximately 14 billion gallons of ethanol per year. Doing so consumes approximately 40% of U.S. corn production (USDA, 2012b). More than doubling current corn ethanol production would drive up corn prices substantially, thus also raising ethanol prices. Omitting the corn price impact will bias my calculations in favor of an ethanol increase. Similarly, the model assumes that oil refining capacity is exogenous and fixed. A long-term increase in non-oil based liquid fuels supply could result in reduced entry or increased exit. This would shift the blendstock supply curve in ways that are not currently accounted for in the model – in particular, if the long-run level of blendstock supply capacity were such
that supply was capacity constrained, the supply curve would be substantially steeper than was observed during the study period. This would substantially increase both the impact of oil price shocks and the effectiveness of ethanol at mitigating them.

I use results from panel IV estimations in levels for all policy analyses. These estimates find the largest impacts of ethanol. Panel IV estimates yield the largest impact of gasoline prices on ethanol production – it finds the steepest slopes for both the ethanol and blendstock supply curves. It is important to note that estimates of the ethanol supply curve in first differences find a 59% smaller slope of the ethanol supply curve. Using the panel IV estimates in levels may thus substantially overestimate ethanol’s ability to mitigate oil shocks and give an overly positive estimate of its volatility benefits.

2.11.1 Binding mandate

In this section I calculate ethanol’s ability to mitigate oil shocks under a binding quantity mandate. The key difference is that neither ethanol blending nor ethanol prices will increase if blendstock prices increase. As discussed previously, if the mandate is binding, the ethanol price is set by the price necessary to induce mandated production, which is above the blendstock price. This means that even if oil prices increase, ethanol prices (and thus production) will not increase unless blendstock prices increase all the
way to the ethanol price. If blendstock prices cannot spike that high, the mandate is tightly binding and the ethanol supply equation becomes

\[ P^E = f^{-1}(E) \]  \hspace{1cm} (2.22)

And the price equilibrium remains

\[ P^G = \alpha P^E + (1 - \alpha)P^B \]  \hspace{1cm} (2.23)

The variance of the price of gasoline is then

\[ \text{Var}(P^G) = \alpha^2 \text{Var}(P^E) + (1 - \alpha)^2 \text{Var}(P^B) + 2\alpha(1 - \alpha)\text{Cov}(P^E, P^B). \]  \hspace{1cm} (2.24)

Note that this is different from the variance equation if the mandate is not binding, because the quantities of the fuels do not change. Instead this expression more closely resembles classic financial portfolio theory analysis which assembles an aggregate portfolio from independent (but potentially correlated) securities.

I can solve for these terms separately.

Inverting the ethanol supply function (equation (2.13)) and plugging into equation (2.22), yields an expression for the ethanol price.

\[
P^E = \frac{E - \frac{v_0}{K} - \frac{v_2}{K}P^N - \frac{v_3}{K}P^C - v_4}{v_1}
\]  \hspace{1cm} (2.25)

Similarly, solving the blendstock supply equation (2.14) and gasoline demand equation (2.15) for the blendstock price yields
\[ P^B = \phi_0 + \phi_1 P^O + \phi_2 E + Y \varphi + \eta Z - \lambda Z \alpha f^{-1}(E) \]

(2.26)

Plugging (2.25) and (2.26) into (2.23), the gasoline price equilibrium becomes

\[ P^G = \alpha \left( \frac{E - \frac{V_0}{K} - V_2 P^N - V_3 P^C - V_4}{V_1} \right) + (1 - \alpha) \left( \phi_0 + \phi_1 P^O \varphi + Y \varphi + E - \eta Z - \lambda Z \alpha f^{-1}(E) \right) \]

And thus under a binding mandate, the variance of gasoline prices becomes

\[
\begin{align*}
\text{Var}(P^G) &= (2\alpha - \alpha^2) + \left( \frac{V_2^2}{V_1^2} \text{Var}(P^N) + \frac{V_3^2}{V_1^2} \text{Var}(P^C) + \frac{V_2 V_3}{V_1^2} \text{Cov}(P^N, P^C) \right) + \\
&\quad \frac{(1 - \alpha)^2}{(1 - \alpha)\lambda Z \phi_2} \left( \phi_1^2 \text{Var}(P^O) + \phi_2^2 \text{Var}(Y) - (\lambda Z)^2 \alpha^2 \left( \frac{V_2^2}{V_1^2 K} \text{Var}(P^N) + \frac{V_3^2}{V_1^2 K} \text{Var}(P^C) + \frac{V_2 V_3}{V_1^2 K} \text{Cov}(P^N, P^C) \right) + \\
&\quad \frac{V_2 V_3}{V_1^2 K} \text{Cov}(P^N, P^C) + 2\phi_1 \lambda Z \alpha \frac{V_3}{V_1} \text{Cov}(P^O, P^N) + 2\phi_1 \lambda Z \alpha \frac{V_3}{V_1} \text{Cov}(P^O, P^C) \right) + \\
&\quad (2\alpha - \alpha^2) \left( \phi_1 V_2 V_1 \text{Cov}(P^O, P^N) + \phi_2 V_3 V_1 \text{Cov}(P^O, P^C) \right)
\end{align*}
\]

Figure 8 shows the impact of increasing the ethanol blend percent (assuming production at the nameplate capacity level) for both binding (blue) and non-binding (red) mandates. While the benefits under a non-binding mandate are modest (less than 1% at current levels), a binding mandate can lower gasoline price volatility by up to approximately 10%. However, this is only because it decouples ethanol prices from crude prices. As indicated previously, if the mandate is binding, an increase in crude oil prices does not increase the price of ethanol because the price of ethanol is the (higher) price necessary to induce production at the mandated level.
Figure 8: Gasoline Price Volatility versus Blend Rate

2.11.2 Full RFS2 coverage

I also consider the price impacts if conventional corn-based ethanol were used to meet the full 36 billion mandate of the RFS2. If corn-based ethanol were used to meet the entire 36 billion gallon per year mandate, PADDs’ shares remained constant, nameplate capacity were 36 billion gallons per year and the mandate was not tightly binding, ethanol would lower variance by 1.2 percent.

However, a mandate at this level would likely bind production decisions in addition to infrastructure decisions. With this market structure, the variance would decrease by 14%. However, a binding mandate equivalent to current blend rates would lower volatility by an equivalent amount, and a binding mandate of 25 billion gallons would lower variance by 16%. Increasing the mandate beyond 25 billion gallons causes
variance to rise because the high variance of corn prices becomes more important than the volumetric effect.

Note that this analysis assumes that corn prices would remain at the average level as throughout the study period. However, such a dramatic increase in ethanol production would make corn prices both higher and more volatile. This would make ethanol production lower and more volatile. Thus this subsection likely overstates the benefit of using ethanol to meet the full RFS2 mandate.

The full RFS2 standard might also be met with a mixture of corn-based ethanol and advanced biofuels, as the statute is currently written. In this case, the volatility effects would also depend on the slope of the advanced biofuel supply curve (how much production increases when prices increase), the volatility of advanced biofuel supply costs, and their covariance with corn-based ethanol and oil blendstock supply shocks. If advanced biofuels are characterized by relatively high capital costs and a diverse set of input energy sources, their supply-side price volatility might be lower than that of corn-based ethanol. Advanced biofuels could thus lower the volatility of gasoline prices by more than conventional corn-based ethanol. However, the ability of advanced biofuels to mitigate oil price spikes would be constrained by the flatness of the blendstock supply curves, just as with corn-based ethanol.
2.11.3 Optimal Fuel Portfolio

This subsection develops a framework to consider optimal fuel portfolios from a price volatility perspective. To this point, the model of ethanol policy has focused on the short run. In the short term, the existence of ethanol production capacity lowers consumer gasoline price levels and can lower volatility. Figure 8 shows this effect. The red dotted line shows the variance in gasoline prices per gallon for different blend rates, including those observed (below 10%) and extrapolated (above 10%). At current blend rates, ethanol lowers gasoline price volatility by approximately 0.54%.

The blue line shows the variance with a binding mandate. This can be thought as an equal cap and floor such that the exact quantity of ethanol is fixed. Note that this is a modeling simulation based on our estimated supply curve, but is not directly observed. If the mandate were binding, at current blend rates it would lower volatility by approximately 12%. This is because the volumetric effect (oil price shocks do not raise prices on ethanol) is greater than the ability of ethanol production to increase in response to shocks. At blend rates above 17%, the variance increases again as the higher variance of corn prices becomes more important than the volumetric effect. This means that the optimal blend rate is less than 17%.

However, this does not consider the costs of building the ethanol capacity. Figure 9 shows gasoline price volatility versus the cost of building out ethanol.
production capacity. This is one way to think about the existing ethanol mandate – a de facto mandate to build capacity.

We can invert the short-term ethanol supply function to show that the short-term marginal cost of producing $E$ units of ethanol is $f^{-1}(E, K, X)$. If ethanol capacity can be built at a constant average cost of $P^K$, then the total and average costs of producing $E$ units of ethanol are

$$TC(E, K) = \int_0^E f^{-1}(e, K, X)de + P^K * K$$

$$AC(E, K) = \frac{1}{E} \int_0^E f^{-1}(e, K, X)de + P^K * \frac{K}{E}$$
Changing ethanol capacity and production also changes blendstock production. This makes the change in total production cost relative to having no ethanol capacity equal to

$$TC(K) = P^K * K + \int_0^{E(K)} f^{-1}(e, K, X)de + \int_{B(0)}^{B(0)} g^{-1}(b, P^O)db$$ (2.27)

where $g()$ is the blendstock supply curve from equation (2.14). Note that the second integral –the change in blendstock production cost - will be a negative number because ethanol production will displace blendstock production.

2.11.4 How much of an oil shock does ethanol prevent?

Based on estimation results, we can compute the degree to which ethanol capacity mitigates the impact of oil price shocks on gasoline prices. Differentiating $P^G$ with respect to $P^O$ in equation (2.16), we find that

$$\frac{dP^G}{dP^O} = \frac{\phi_1}{(\lambda Z - K)v_1 - \phi_2}$$

Using this relationship to compare the impact of a $1 per gallon rise in oil prices – with current ethanol capacity versus none – yields a 4¢ per gallon lower impact on gasoline prices due to ethanol capacity. Equivalently, the current ethanol industry mitigates about 4.2% of an oil price shock. Instead of causing prices to rise by $1 in the absence of an ethanol industry, an oil price shock would now only lead to a 95.8 cent price increase. Figure 10 shows the proportion of an oil shock that ethanol prevents for a range of blend rates. At a 9% blend rate, ethanol would mitigate approximately 0.038
dollars of every dollar of oil price increase. This amount, while seemingly small, could prevent some of the macroeconomic effects of oil shocks. We can think of avoided GDP losses as benefits and calculate them in the next section.

![Figure 10: Portion of an Oil Price Spike Mitigated by Ethanol](image)

2.11.5 Expected Benefits from Mitigating Oil Shocks

To calculate the expected benefits from mitigating oil-shock-related GDP losses, we need to understand both the likelihood of an oil shock and the GDP impacts of oil shocks (S. Brown and H. Huntington, 2010). Beccue and Huntington (2005) conducted an expert elicitation study of a range of events that could lead to oil shocks, as well as the probabilities and magnitudes of these shocks. Table 11 lists their results as annualized in Brown and Huntington (2010).
Brown and Huntington (2010) also calculate that the elasticity of world oil prices with respect to oil supply quantity interruption is approximately -0.136. Estimates of the elasticity of U.S. GDP with respect to world oil shocks vary substantially, from approximately -0.01 to -0.12 (D.W. Jones et al., 2004). Recent research finds somewhat lower elasticities and argue that previous papers overstated the impact of oil shocks on the economy (Olivier Blanchard and Jordan Gali, 2007). Due to this significant uncertainty, we use a range of estimates.

As noted in the literature review, a number of causal pathways have been proposed to explain the impact of oil shocks on GDP. Some attributed disproportionate impact to consumer gasoline prices, either because consumers purchase fewer new automobiles when gasoline prices are high and that the decrease in automobile sales reverberates through the economy, or who attribute GDP impacts to consumer wealth effects (J.D. Hamilton, 2009). Ethanol only directly mitigates shocks to gasoline, which accounts for approximately 45% of refined oil products (EIA). Indirect spillover effects into other oil product markets and their impacts are unclear, so we consider GDP impacts ranging from 45% to 100% of literature estimates.

Combining these terms yields equation (2.28) for the expected GDP savings from preventing oil shocks. The first three terms in the summation: the types of oil shock n, times the percentage size of the shock, times the elasticity of oil prices yield the set of oil price shocks. Multiplying this times the percent of oil shocks prevented by ethanol m(K)
yields the amount of oil shock mitigated, and multiplying this times the elasticity of GDP with respect to oil prices yields the avoided GDP loss. Finally, $\tau$ discounts the total to account for non-gasoline goods made from oil.

$$E[\text{GDP savings}] = \sum_n \text{prob}_n \cdot \frac{\Delta O_n}{O} \cdot \epsilon_{p^O,O} \cdot m(K) \cdot \epsilon_{GDP,p^O} \cdot \tau \quad \tau \in [0.45,1]$$

\[2.28\]

**Table 11: Probability of Oil Supply Shock. Based on Brown and Huntington (2010).**

<table>
<thead>
<tr>
<th>Disruption size (mmbd)</th>
<th>Probability</th>
<th>Oil price change</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.8439</td>
<td>0.00</td>
</tr>
<tr>
<td>1</td>
<td>0.0309</td>
<td>0.20</td>
</tr>
<tr>
<td>2</td>
<td>0.0325</td>
<td>0.39</td>
</tr>
<tr>
<td>3</td>
<td>0.0453</td>
<td>0.59</td>
</tr>
<tr>
<td>4</td>
<td>0.00216</td>
<td>0.79</td>
</tr>
<tr>
<td>5</td>
<td>0.00776</td>
<td>0.98</td>
</tr>
<tr>
<td>6</td>
<td>0.0103</td>
<td>1.18</td>
</tr>
<tr>
<td>7</td>
<td>0.0109</td>
<td>1.38</td>
</tr>
<tr>
<td>8</td>
<td>0.00764</td>
<td>1.57</td>
</tr>
<tr>
<td>9</td>
<td>0.00108</td>
<td>1.77</td>
</tr>
<tr>
<td>10</td>
<td>0.00156</td>
<td>1.97</td>
</tr>
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<td></td>
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<td>---</td>
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<td>11</td>
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<tr>
<td>12</td>
<td>0.00173</td>
<td>2.36</td>
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<td>13</td>
<td>0.000831</td>
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<td>14</td>
<td>0.0005111</td>
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<tr>
<td>15</td>
<td>0.000986</td>
<td>2.95</td>
</tr>
<tr>
<td>16</td>
<td>0.000119</td>
<td>3.14</td>
</tr>
</tbody>
</table>

At current levels of ethanol use, ethanol has expected benefits of 114 to 254 million dollars per year of avoided GDP losses from mitigating oil shocks. Figure 11 shows the expected annual benefits for a range of blend rates for both the base nonbinding case (solid line) and a binding mandate (dashed line) assuming 100% of literature estimates.
Future work is needed on several different issues: incorporating energy prices into the ethanol production function, endogenizing corn prices, considering kinked supply curves, and modeling oil refining industry entrance and exit.

First, the model currently does not directly incorporate diesel fuel costs into corn production. In particular, high (low) diesel fuel prices during the spring planting season would increase (decrease) farmers’ costs, resulting in less (more) corn planted and higher (lower) expected corn prices. However, diesel fuel prices are highly correlated with both contemporary and subsequent crude oil and blendstock prices due to their market equilibrium and autocorrelation. This makes isolating the effect of diesel prices shifting the supply curve versus blendstock prices as the price equilibrium along the
supply curve difficult. Moreover, spring diesel prices may be endogenously determined with corn planting decisions because agricultural use is one of the major demand sources for diesel fuel. These analyses are documented in Appendix E.

Second, as noted in section 2.5.2, corn supply curves can be quite inelastic. Furthermore, non-ethanol grain demand is primarily driven by food consumption, which is also inelastic. Adding the large inelastic demand source from the ethanol industry may make grain demand even more inelastic, in particular with respect to weather shocks. This suggests two distinct avenues of future work. The first avenue working out the implications of endogenous corn prices in this model. More broadly, this suggests an econometric analysis of the impact of the ethanol mandate on corn price levels (which a number of researchers have considered) and on corn price volatility (which few have). Preliminary analyses suggest that the ethanol mandate has indeed made corn prices more responsive to weather shocks.

Third, I will consider refining supply curves with capacity constraints. If an ethanol mandate moves blendstock production levels to below the capacity constraints, then that initial portion of the mandate may have a substantial benefit even while the remainder of it does not.

Fourth, a long-run mandate of 36 billion gallons, which over 25% of current consumption, could prompt oil refiner exit, reduced entry, or capacity reductions. Future work should consider the impact of biofuels on refiner capacity decisions.
2.13 Conclusions

Ethanol has been suggested as a solution to a number of policy problems, including explicitly energy security and implicitly gasoline price volatility. I show that the presence of ethanol production capacity can in principal reduce gasoline price volatility by increasing ethanol supply in response to oil price shocks. I then show that ethanol production does increase in response to oil price shocks and does lower the variance of gasoline prices. However, even with generous assumptions such as holding the correlation between corn and oil prices constant, ethanol’s ability to dampen gasoline price volatility is very small whether measured as the variance of gasoline price as a function of ethanol capacity or by ethanol production’s ability to prevent oil price spikes from reaching consumers. This suggests that ethanol is unlikely to be able to substantially lower the exposure of US energy consumers to volatility in international oil markets and thus unlikely to substantially contribute to a major aspect of energy security. This suggests that ethanol is unlikely to be able to substantially lower the exposure of US energy consumers to volatility in international oil markets and thus unlikely to substantially contribute to a major aspect of energy security.

A full welfare analysis would include a welfare measure of ethanol’s energy security benefits (as opposed to a GDP measure), a measure of impacts on other energy production sectors, environmental externalities, welfare impacts of induced food insecurity, and other factors beyond the scope of this study. The current ethanol policy
does have an expected energy security benefit of over a hundred million dollars annually. However, this is a small fraction of annualized capital costs. This juxtaposition does not suggest that the ethanol mandate clearly has positive net benefits.
3. The Effectiveness of Carbon Price Containment

3.1 Introduction

Economic instruments have become a more common way to regulate pollution since the prominent success of the sulfur dioxide trading program (Robert N. Stavins and Bradley Whitehead, 1997). More recently, the European Union has used a cap-and-trade system to meet its obligations under the Kyoto Protocol, a consortium of states in the northeastern U.S. have implemented a cap-and-trade system called the Regional Greenhouse Gas Initiative, California proceeds with implementation of a statewide cap-and-trade system under AB 32, and the provinces of Alberta and British Columbia have implemented carbon taxes. The primary alternatives are price-based instruments such as pollution taxes and fees, which fix the charge to pollute but allow total pollution to vary, and quantity-based instruments, which fix the total amount of pollution and allow trading of allowances at a market price. As discussed below, the tradeoffs between price and quantity instruments have been actively debated. But in the context of U.S. and E.U. climate policy, the quantity-based approach of cap-and-trade has been the dominant option.

The price uncertainty and volatility in carbon markets associated with cap-and-trade is a substantial concern in US policy discussions. To address this, Congress has added a soft price cap, termed a “strategic reserve fund”, to recent climate policy bills
(ACES 2009). This reserve fund would release a limited amount of additional permits at a target price cap, which would maintain that price as a ceiling if the reserve allowances are sufficient to meet demand, but would not if the market demanded more and bid the price up further.

Figure 12 shows example supply and demand curves for a strategic reserve. The cap is set at \( Q^* \), while the reserve price is somewhat higher. Some additional allowances are available at the reserve price, but once this limit is reached the supply curve is vertical. In Figure 13, we see the price containment mechanism in use. Realized prices are higher than expected, high enough that the market demands allowances from the reserve. The reserve is able to meet this demand by releasing additional allowances and market prices do not exceed the reserve price. In Figure 14, realized demand is higher still. The reserve is not large enough to meet demand at the reserve price. The reserve releases all the permits available and the market price is somewhat above the reserve price. However, it is still below the market price in the absence of a reserve fund. Thus
there are three policy variables: the reserve price, the annual reserve size, and the cumulative maximum reserve size.

This paper develops a novel simulation model for price containment mechanisms based on stochastic shocks Hotelling price paths. The shocks’ distributions are parameterized based on observed price changes in EU ETS markets as well as related energy markets. We then model the probabilistic effectiveness of price containment and the quantity of additional emissions.

Figure 12: A Strategic Reserve Fund with Expected Demand
Figure 13: A Strategic Reserve Fund with Expected Demand and Fully Contained Higher Realized Demand

Figure 14: A Strategic Reserve Fund with Expected Demand and Partially Contained Higher Realized Demand
3.2 Literature Review

An extensive literature discusses the merits of market-based mechanisms for pollution control (Marc J. Roberts and Michael Spence, 1976). These mechanisms can achieve pollution reductions at minimal costs by requiring firms to pay the external costs of their pollution and allowing firms to allocate emissions reductions to the least-cost sources. Weitzman’s seminal paper illustrated the distinction between price mechanisms and quantity mechanisms in the presence of abatement cost uncertainty (Martin L. Weitzman, 1974). More research has extended this analysis to the case of climate change and shown that, for climate change, price mechanisms dominate simple annual quantity mechanisms on efficiency grounds (Richard G. Newell and William A. Pizer, 2003). Keohane lays out a number of benefits to quantity mechanisms which are missing from these analyses (Nathaniel O. Keohane, 2009).

These benefits of quantity mechanisms have prompted interest in hybrid mechanisms, which would achieve some of the benefits of both price and quantity mechanisms. One prominent of hybrid mechanisms is the “safety valve”, or price cap. Another is the “price collar”, or combination of a price cap and a price floor. Both of these mechanisms couple the distributional flexibility of a quantity mechanism a high degree of price certainty. A price collar can be nearly as efficient as a tax, and more so than a simple price cap (Harrison Fell and Richard Morgenstern, 2011).
An allowance reserve is a generalization of the safety valve model in which a limited pool of allowances is available at a target price cap. This addresses dynamic concerns with a price cap and can potentially better replicate benefits of greenhouse gas emissions (Brian C. Murray et al., 2009). More recent work offers a numerical look at how an allowance reserve might work by using a two-period Monte Carlo model based on the MIT EPPA model (Alexander Golub and Nathaniel Keohane, 2011). Our work extends theirs by considering time more fully and considering price processes which are more consistent with past observed commodity prices.

A distinct literature has focused on understanding the dynamics of carbon pricing. This literature has largely focused on econometric analyses of the European Union’s Emissions Trading Scheme. One thread of this literature tests specific relationships and rationality of prices, while other authors model the price formation process (Emilie Alberola and Julien Chevallier, 2009, Eva Benz and Stefan Truck, 2009, A. C. Christiansen et al., 2005, Maria Mansanet-Bataller et al., 2007). Recent surveys provide excellent overviews of empirical work on the EU ETS (Frank J. Convery, 2009, A. Denny Ellerman et al., 2010). We use this literature to inform our model parameterization.

### 3.3 Simulation Model of Stochastic Carbon Allowance Prices and Price Containment

There are a number of energy-economic simulation models that can be used to understand the effect of climate and energy policy on the US economy (i.e., ADAGE,
IGEM, and EPPA). However, these models are deterministic equilibrium models, which means that they are not designed to consider random price fluctuations and the size of a reserve fund that would be needed to contain those fluctuations.

Instead of trying to replicate the large-scale CGE models used for climate policy, we use their outputs as a baseline – a most likely outcome – and add two forms of random variation described below. We use a Monte Carlo model to examine various scenarios and reserve sizes and consider the likelihood that a reserve will effectively constrain prices. Our Monte Carlo model directly simulate shocks in prices, instead of in abatement costs parameters as in some other models (Alexander Golub and Nathaniel Keohane, 2011 ). This allows us to simulate more complex price paths and directly compare our price volatility with historical data from related markets, but precludes us from directly examining the fundamental causes of cost variation.

3.3.1 Price Paths

Our model has three fundamental assumptions about price behavior: (1) expected prices rise exponentially according to a Hotelling price path, (2) they are subject to a random jump diffusion process reflecting changing expectations about underlying fundamentals, and (3) the elasticity of the price of carbon permits with

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1 ADAGE, IGEM, and EPPA are economywide computational general equilibrium models used to analyze the impacts of environmental policies. The models can produce estimates of allowance prices, sectoral prices, and commodity prices over time and are maintained by the Research Triangle Institute, Harvard, and MIT respectively. For more information see http://www.rti.org/page.cfm?objectid=DDC06637-7973-4B0F-AC46B3C69E09ADA9, http://www.hks.harvard.edu/m-rcbg/ptep/IGEM.htm, and http://globalchange.mit.edu/igsm/eppab.html.
respect to the allowance supply is constant. We further assume that allowance price shocks, mediated through oil prices, have macroeconomic impacts. We discuss each in turn.

In a jump diffusion framework, prices follow a near-continuous path (i.e., a random walk) in many periods with occasional large jumps. This is consistent with observed EU ETS prices.

Formally, we say that in the absence of a price-containment policy, prices follow

$$P_{i} = P_{i-1}^* ((1 + r) + \text{dojump}^* \text{jumpsing}^* N(\text{jumpsiz}e, \sigma_j))$$

(3.1)

The distributions of each random variable are iid.

The first term in the parentheses of (3.1), $1+r$, captures the familiar Hotelling model price growth at the discount rate $r$, which is consistent with how the economic models referenced above project prices when carbon allowances are transferable across time periods through banking and borrowing. The second term describes short-term price volatility (i.e., weather effects or random shocks in energy markets), also termed drift volatility, which is normally distributed with variance $\sigma_j$. The third term represents a discernible shock in market fundamentals that can shift prices substantially. The $\text{dojump}$ variable is one if there is a jump in that period and zero otherwise. The $\text{jumpsing}$ variable is one or negative one. Finally, $\text{jumpsiz}e$ is the average expected jump magnitude conditional on a jump occurring while $\sigma_j$ is the variance of jump magnitude.
An example of such an exogenous shock from the past is the first release of national emissions data in Europe after the trial phase of the ETS had already gone into effect. The emissions data suggested national emissions were generally lower than previous estimates and thus the EU ETS price dropped precipitously over a few day period in 2006 to reflect the suddenly realized drop in allowance demand. While this specific situation is unlikely to repeat itself if the U.S. were to commence a carbon market, because national emissions data already exist, one could imagine the release of information on technology availability, macroeconomic growth of developing countries, or other factors that could suddenly change market fundamentals in either direction. This third term is zero if there is no jump, but otherwise is a random size and direction.

### 3.3.2 Price Containment and Allowance Demand

The price containment mechanism releases a limited number of permits and lowers prices as follows.

\[
P_{\text{contained}}^t = P_{\text{uncontained}}^t \times (1 - \epsilon_p \times \frac{Q_{\text{released}}^t}{Q_{\text{total}}^t})
\]

**S.I.**

\[
P_{\text{uncontained}}^t \geq P_{\text{cap}}^t
\]

\[
Q_{\text{released}}^t \leq Q_{\text{max}}^t
\]

\[
\sum_{t=0}^{T} Q_{\text{released}}^t \leq Q_{\text{cum}}^t \leq Q_{\text{max}}^t
\]

Equation (3.2) models the price containment mechanism. \(Q_{\text{released}}\) is the quantity of allowances released by the price containment mechanism, and \(Q_{\text{total}}\) is the total
quantity of allowances in the program. The quantity released is constrained by both an annual maximum size $Q'_\text{max}$ and a cumulative maximum $Q^{\text{cum}}_\text{max}$. The percentage of total allowances released (or withdrawn if $Q_{\text{released}}$ is negative) by the price containment mechanism, which when multiplied by the inverse elasticity of allowance price with respect to allowance supply $\mathcal{E}_p$ yields the percentage change in allowance prices.

$P_{\text{uncontained}}$ is what the price would have been without a price containment mechanism. $P_{\text{contained}}$ is the price after the use of the price containment mechanism.

Additional allowances are released until either prices are contained to the target cap price, or until a quantity limit is reached. We assume full banking and borrowing. Golub and Keohane (2011) discuss the potential implications of a strategic reserve fund without full borrowing.

The constant elasticity of demand function (as in equation (3.3)) suggests a natural analytic location of volatility – the parameter $A$. Our multiplicative price shocks imply changes in $A$. Supply side shocks, such as statutory shifts in offset levels are modeled as scenarios. Equation (3.3) is the demand function for allowances.

$$Q_D = A \cdot P^{\frac{1}{\mathcal{E}}}$$  \hspace{1cm} (3.3)

\footnote{The elasticity is inverse because we have previously defined it as the quantity of permits required to effect a desired change in price.}
3.3.3 Model Caveats

This simple model omits a variety of dynamic and strategic second-order effects. First, a reserve fund would act to limit exposure to high allowance prices, reducing the need for firms to invest in abatement technologies and increasing expected prices. This model takes an expected input price which is independent of the price containment policy scenario. Second, a future price floor on a financial asset tends to raise its contemporary price, while a future price ceiling tends to lower (Paul R Krugman, 1991). Neither of these effects are accounted for in our price prices. Finally, under some conditions, firms which emit a large fraction of total emissions may find it advantageous to purchase allowances from the reserve at above-market prices to lower the market price on their other allowances (Andrew Stocking, 2012). This strategic behavior is not considered but would act to effectively loosen the emissions cap.

3.4 Methods

We conduct a Monte Carlo simulation with 5000 random instantiations. We parameterize the model based on a combination of empirical and simulation data and policy targets as described below.

We simulate a program with emission caps set at the levels in the Waxman-Markey bill. In that proposed legislation, the emission cap started at 4627 megatons (million metric tons) of carbon dioxide equivalent (CO2e), increasing with the addition of new sectors before decreasing to 1,035 million tons in the year 2050. The average cap
level over the period 2012 to 2050 is 3,354 million tons. See Figure 15 for a graphical representation.

![Graph showing annual emission cap from Waxman-Markey bill in million tons of CO\textsubscript{2} equivalent.](image)

**Figure 15: Annual Emission Cap from Waxman-Markey in Million Tons of CO\textsubscript{2} Equivalent**

We draw our initial expected prices on an EPA analysis of the Waxman-Markey bill (EPA, 2009). The EPA analyzed a number of different scenarios with different baseline scenarios with different assumptions about energy efficiency provisions, nuclear provisions, output-based rebates, and international offset supplies. We consider EPA’s Core and No International Offsets scenarios. These scenarios had starting prices of approximately $12 and $23 in 2012, increasing at 5% per year. In the Core Scenario, approximately one billion tons of international offset credits are available annually starting in 2012. Domestic offsets increase from 166 million credits in 2012 to 643 million
credits in 2050, for an average total of 1.4 billion credits per year over the course of the program. The lack of credit availability under the No International Offsets scenario drives up prices, increasing the supply of domestic offsets. Domestic offset supply starts at 300 million credits per year in 2012 and increases to 974 million for an average of 531 million credits per year over the life of the program, or about one-third of the unconstrained total.

We base the reserve fund trigger price and quantity parameters on legislative proposals. The Waxman-Markey bill proposed a reserve price of $28 per ton of CO$_2$e, initially increasing at 5% per year. The reserve fund would release a maximum of 5% of the annual allowance cap (10% after 2014). The Kerry-Lieberman bill specified an initial reserve price of $25 per ton of CO$_2$e, increasing at 5% per year, and releasing at most 5% of each year’s allowances to 2016 and 10% after that. We use an initial reserve price of $30, increasing at 5% per year. In our sensitivity analyses, we also consider initial prices of $25, 28, and $35.

We choose jump parameters to reflect our subjective estimates of the likelihood of regime-changing events (such as announcements about technologies such as carbon capture and storage (CCS) or vehicle electrification, policy shifts regarding nuclear energy, major shifts in macroeconomic growth trends) and their potential impacts on prices. The assumptions are a 20% random chance of a jump in any year, an expected

---

3 The Waxman-Markey reserve price shifted to 60% above the rolling 36-month closing price after 2015.
jump magnitude of 40% conditional on a jump occurring, and an equal probability of positive and negative jumps. Jumps of mean magnitude 40% are consistent with experience in past markets. In the EU ETS market, the April 2006 report that 2005 emissions had been lower than expected resulted in a EUA price decrease from 32 Euros to 18 Euros, or 44%. Figure 16 shows ETS prices for all vintages to date, showing that vintages typically move together, subject to banking constraints. US natural gas prices declined approximately 37% in the mid-1980, with larger and smaller shocks falling subsequently (see Figure 17).

In a similar spirit, EUA spot prices in 2009 (a fairly stable period without large regime-changing jumps) exhibited a daily volatility of 14%. We use 15% as a characteristic central value and again conduct sensitivity analyses for higher volatilities.

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4 Authors’ calculations.
The elasticity of price with respect to quantity is one of the primary factors determining the efficacy of the reserve fund. It captures the relationship between the number of allowance available and the market price. As more allowances are available, prices decline (and vice versa). We assume a constant value for elasticity, but in candor there is little reason to think that it is constant with respect to either quantity or time. However, reasonable estimates from broader economywide studies of cap-and-trade range from ~ -1.3 to ~ -3.5. Instead of choosing a more sophisticated demand function (which we believe would obscure the large uncertainty in the relationship between prices and quantity), we err on the size of transparency by maintaining a simple functional form and conduct a sensitivity analysis over plausible values from -1 to -3. We consider an elasticity of -2 to be a central case – i.e., a 10% increase in allowances reduces prices by 20%.
The simulation iterates over time, randomly drawing a new price for each yearly time step based on Equation (3.1). If the price is above the reserve price, we use our elasticity to calculate the number of permits demanded to maintain the reserve price. If that number is greater than the modeled statutory maximum, we calculate the constrained price, which may be higher than the reserve price (see equation (3.2)). A key point is the next period’s draw is based on the constrained price. This is because banking and borrowing will smooth out quantities to the new Hotelling price path and because the price-quantity elasticities are based on long-run quantity changes such as changes in total offset supplies.

3.5 Results

We find that a moderately sized annual reserve is likely to be sufficient to contain prices, and a total reserve of several billion tons is very likely to be sufficient. If large quantities of offsets are available then any price cap in the range assessed here is unlikely to be triggered. A low offset supply would raise prices and increase the likelihood of triggering the reserve, but the reserve is still likely to fully contain prices. In our central scenario, the reserve avoids 11.4 billion dollars worth of GDP losses in expectation, or 45 billion dollars worth of avoided GDP losses if it is ever triggered.

In our baseline scenario ($30 per ton reserve price, baseline volatility, EPA Core price scenario), we find that a 15% annual reserve tranche will fully contain prices to the reserve price with 95% confidence and will release fewer than 1 billion additional
allowance with 87% confidence. This is in large part because the reserve price is unlikely to be hit. In this scenario, the reserve is only triggered 26% of the time, and in those cases it contains prices 80% of the time.

We also consider a scenario with higher abatement, and thus higher expected prices, by modeling the EPA No International Offsets scenario. In this case we find that a 15% annual reserve tranche will fully contain prices to the reserve price with 85% confidence, will release fewer than 1 billion additional allowance with 69% confidence and will release fewer than 2 billion additional allowance with 85% confidence. The lower price containment rate and higher reserve demands are because the reserve is more likely to be used. In this case, it is triggered 62% of the time.

Figure 18: Probability of Price Containment versus Annual Reserve Size

We also consider sensitivity to both market fundamentals and to policy decisions. In Figure 18, we show the relationship between the reserve’s size and its
effectiveness at price containment. In Figure 19, we show the relationship between the reserve’s effectiveness at price containment and the elasticity of allowance prices with respect to the quantity of allowances released from the reserve. In each figure, the dashed line shows the probability that prices will be kept at or below the reserve price for the length of the program. The dash-dot lines show the probability that prices will be kept at or below the reserve price even if the reserve is triggered. This parameter is subject to considerable long-run uncertainty and could have substantial impact on any analysis.

![Graph showing probability of price containment versus elasticity](image)

**Figure 19: Probability of Price Containment versus Elasticity**

We also show that, while total reserve releases will likely be low, if offset supply is constricted then several more billion tons may be demanded from the allowance market. Figure 20 shows a CDF of permit demand. In this figure, the dashed line shows the probability that total reserve releases will be below a given quantity for our core
scenario. The dash-dot line shows the probability that a given quantity will be enough under our low offsets scenario.

![Graph](image)

**Figure 20: Cumulative Distribution Function of Tons Released from the Reserve**

### 3.5.1 Price Floors

We also model a price floor at $10 ton, rising at 5% annually. In this model, the regulator maintains the price floor by withdrawing allowances from the market. It has been suggested that allowances withheld at a price floor could be used to fill (or refill) a reserve fund. In Figure 21, we show a cumulative distribution function of allowances released from the reserve, and of allowances released net of allowances withheld at the price floor (i.e., the number of allowances released on that run minus the number that had previously been held back at a price floor on that run). We see that a price floor of this level is unlikely to effectively fill an emptied reserve fund. While both may be triggered,
it is unlikely for both large quantities of allowances to be withheld at the price floor and, at another time, large quantities of allowances to be demanded from the reserve. The price floor only saves large quantities of allowances when the reserve issues few.

Figure 21: Cumulative Distribution Function of Tons Released from the Reserve

3.6 Future Work

One advantage of this price-based model is that it is straightforward to change the modeled stochastic price process. Future work could update the model in light of more recent work on observed EU ETS prices and consider the robustness of results to other process models such as ARCH/GARCH models.

3.7 Conclusions

We simulate a price containment mechanism for a greenhouse gas cap-and-trade system consistent with past Congressional bills. We find that such a mechanism is likely to be effective at containing prices at a limited cost in increased emissions. We further
find that underlying fundamentals such as offset availability have a dramatic impact on
the effectiveness of a reserve fund in containing prices and that a price floor is unlikely
to counterbalance additional emissions from reserve allowances. However, this
modeling is limited by a fundamental lack of knowledge about the volatility dynamics
of projected allowance and about the market response to a potential release of additional
allowances. Further work in these areas would be greatly beneficial.
4. Measuring the Cost of an Oil Spill Liability Rule

4.1 Introduction

The 1989 Exxon Valdez oil spill in Prince William Sound, Alaska prompted public outcry and concern for conservation. Congress passed the Oil Protection Act of 1990 in response. The OPA imposed new costs on US oil producers and transporters. Changes included the imposition of liability up to $75 million for all spills into US waters, ban the restriction of some vessels from the Prince William Sound, the creation of a trust fund to cover damages beyond $75 million and imposition of a $0.05 per barrel tax and a requirement that potential spillers prove their ability to meet their liability in case of a spill.

The Deepwater Horizon spill of 2010 was the largest oil spill ever in US waters, releasing nearly 5 million barrels of oil into the Gulf of Mexico. There has been substantial political interest in a policy response, with a rapid reorganization of the federal oil production regulator, a national commission issuing recommendations, Congressional hearings, and ongoing Congressional discussions of new legislation. One prominent legislative proposal has been to increase the cap on oil spill liability. Representative Vern Buchanan (R-Fla) proposed lifting it entirely, while Senate Majority Leader Harry Reid called a $10 billion cap “inadequate” and Representative Begich and
Senator Landrieu have discussed increasing the cap from $75 million to $200 million. Congressmen from oil-producing states have claimed that lifting the cap would result in substantial job losses and would bankrupt many small businesses. However, empirical evidence of the effect of oil spill liability rules is lacking.

In this essay I estimate the ex ante private costs of oil spill liability on oil producers. I use observed bids from auctions for oil and gas rights to measure the expected present value of oil and gas production. These auctions took place before and after the liability cap was imposed, in areas where it was imposed and in areas where it was not. I can thus measure the private costs of the oil spill liability rule by comparing bids from after the OPA to those before it.

4.2 Previous Literature

There is a vast literature on estimating the damage costs of the Valdez spill, but there has been much less on the impact of the post-Valdez regulations on oil producing firms or on econometric estimates of spill risk. Similarly, there is a substantial literature on oil and gas rights auctions but the bulk of it has examined the Gulf of Mexico. Very little has used Alaskan auctions.

Hendricks and Porter coauthored a series of seminal papers on the econometrics of oil and gas auctions in the Gulf of Mexico (Kenneth Hendricks and Robert H. Porter, 1988, 1992, 1996). Subsequent research has found evidence of strategic interactions on
small spatial scales in production decisions in the Gulf of Mexico (Cynthia Lin, 2010).

One of the few papers written on Alaskan oil auctions showed that a 1998 policy shift meant to lower firms pre-auction research and exploration costs had the expected effects of lowering entry costs and encouraging participation by small firms.¹ (William Nebesky, 2007)

Mansur et al (1991) showed that the Valdez wreck immediately lowered oil equity values and lowered them in proportion to the firms’ exposure to the Trans Alaska Pipeline - Prince William Sound shipping route. This suggests that there were immediate expectations of future regulation because the regulatory risk was being priced into equities. We avoid the problem of identifying precisely when the expected regulation was reflected in bids because there were no auction between the spill and the passage of the OPA (Iqbal Mansur, Steven J. Cochran and John E. Phillips, 1991).

Brooks analyzed the firm structure impact of liability rules and showed that the OPA resulted in less external contracting with small firms as a response to those firms’ judgement-proof nature (Richard Brooks, 2002). Small firms were judgement-proof in that they would not have the resources to pay large penalties. If a small firm caused a large spill and received a large fine as a result, it could declare bankruptcy and avoid

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¹ In the previous regime, firms would request that the State of Alaska auction particular tracts. This advantaged firms with the resources to research which tracts they would prefer to be auctioned. In 1998, the State switched to areawide leasing, under which they would sequentially auction off portions of large pre-announced areas. This meant that firms could effectively participate in auctions with lower pre-auction research costs.
paying the fine. Larger firms feared that the fine would then be imposed on them.

Olmstead briefly surveys the literature on liability rules for water pollution, noting some results that liability rules can reduce pollution events but also result in regulatory avoidance behavior (Sheila Olmstead, 2010). This literature included documentation that OPA rules on oil shipping liability prompted marine transit companies to restructure to shield parent companies from potential liability (Inho Kim, 2002).

### 4.3 A Model of Firm Bidding in Oil and Gas Rights Auctions

This section develops a model of firms’ bidding behavior in auctions for oil and gas rights under State of Alaska administered tracts. Firms have common knowledge of the eventual cumulative production under the tract, location of the tract, and regulatory environment as an unobserved private signal of their own production costs. They then enter bids which are a strategic function of their own expected value for the rights as well as their beliefs about other firms. This section will relate the observed bids to firms’ values.

I model firms’ private value for a tract as the net present value of expected value of profits from that tract with independent, identically distributed private values as in equation (4.1). While revenues are common, firms have different operational capabilities and costs, thus justifying the paradigm of private values for tracts.
I observe tract-specific covariates $X_j$ (such as production and location) but do not observe the firms’ private signals. One covariate in $X_j$ is a dummy variable describing whether the tract is subject to OPA liability at the time of auction: true if it is offshore and auctioned after the OPA passage, false otherwise. $\beta$ is a vector of parameters to be estimated, and $\epsilon_{ij}$ is an unobserved private signal.

$$V_{ij} = X_j \beta + \epsilon_{ij},$$ or

$$V_{ij} \sim N(X_j \beta, \sigma) \quad (4.1)$$

Firm i’s problem bidding on tract j is then to maximize profit expected profits. The profit is the expected value of holding the rights minus the bid if the firm wins, and zero if the firm loses the auction. This can be represented as

$$\max_{b_j} (V_{ij} - b_j) \prod_{-i} F(b^{-1}(b_j, n)),$$ \quad (4.2)

where $F$ is the cumulative density function of values, $b^{-1}$ is the symmetric inverse bid function. The symmetric equilibrium strategy is then to bid the expected second highest value, conditional on having the highest value as written below where $Y^i$ denotes the highest value amongst other bidders. (Vijay Krishna, Auction Theory).

$$b(V_{ij}) = E[Y^i | Y^i < V_{ij}] \quad (4.3)$$
Intuitively, by bidding below her value, the bidder trades off the probability of winning the auction versus increased surplus from winning it. By shading down all the way to the expected value of the next-highest bidder (or that value plus a small epsilon), the maximizes the benefit in the case of the win. If the high-value bidder shaded down further, the second highest value bidder could defect and win the auction. If the high-value bidder shaded down less, she would be leaving surplus on the table. In principle equation (4.3) could be manipulated to find a likelihood function and estimate the parameters by maximum likelihood; however this both requires the assumption of a parametric form and is computationally difficult.

Instead I follow the insight of Guerre, Perrigne, and Vuong (2000) (hereafter GPV) that the system can be estimated nonparametrically. GPV show that values can be estimated from observed bids and the bid

\[ V_{ij} = b_{ij} + \frac{1}{\sum_{k \neq i} \frac{g_k(b_k)}{G_k(b_k)}} \]  

(4.4)

where \( G \) is the nonparametrically estimated bid cumulative distribution function and \( g \) is the attendant probability distribution function. ² Note that if the

² This assumes there is no reserve price or that it is not binding. Nearly all the bids near the reserve price are from a small group of bidders who do not seem to be bidding based on tract oil and gas deposits, instead they seem to be bidding speculatively with another goal. I remove these bids from my data.
probability distribution function $g$ is continuous, then private values are a continuous function of observed bids. In this model, firm $i$’s bid for tract $j$ $b_{ij}$ is

$$b_{ij} = V_{ij} - \frac{1}{\sum_{k \neq i} g_k(b_k)} .$$

Note that bids are generally not the expected value of holding the rights. If they were, firms would receive zero surplus. Instead firms strategically lower their bids, trading off more surplus if they win versus a lower probability of winning.

### 4.4 Data

The data covers bids for Alaskan oil and gas rights before and after the Valdez and OPA. These bids are from three areas: the Cook Inlet, the North Slope and northern foothills, and the Beaufort Sea. Tracts in the Beaufort Sea and Cook Inlet are located offshore, while tracts surrounding the Cook Inlet and on the North Slope are located onshore. Thus I have tracts that are onshore and offshore, before and after the OPA, in northern and southern Alaska. Figure 22 shows the location of the oil and gas producing regions in Alaska at a large scale. Figure 23 shows the producing areas of northern Alaska in greater detail. The yellow squares and rectangles are tracts auctioned by the State of Alaska in State of Alaska controlled waters, i.e. waters out to three miles from shore. The peach squares and rectangles are tracts auctioned by the State on land. Light blue shapes denote participating areas, a regulatory feature of oil
fields meant to address common pool problems, while the shapes above them are oil fields as measured by the EIA. Table 12 shows the number of bids for on- and off-shore tracts before and after the OPA. This variation identifies the OPA impact, while Table 13 shows summary statistics.

Figure 22: Locations of oil and gas producing regions in Alaska
Figure 23: Map of oil and gas producing areas in northern Alaska auctioned by the State of Alaska

Table 12: Number of bids for tracts before and after the OPA, on- and off-shore

<table>
<thead>
<tr>
<th></th>
<th>Onshore</th>
<th>Offshore</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before OPA</td>
<td>531</td>
<td>827</td>
</tr>
<tr>
<td>After OPA</td>
<td>1068</td>
<td>1586</td>
</tr>
</tbody>
</table>

All three regions hold large quantities of oil and natural gas. However, due to the difficulty of year-round sea navigation off Alaska’s northern coast, all of the oil
produced from the North Slope and Beaufort Sea is exported via the Alaska Pipeline to
the port of Valdez, where it is shipped out via the Prince William Sound. Gas from the
North Slope is generally either used locally or not extracted, although there has been
long-running discussion of a natural gas pipeline from the North Slope. Oil from Cook
Inlet is shipped out via Cook Inlet. Gas from Cook Inlet is shipped via pipeline for local
use in manufacturing and energy generation, shipped out via Cook Inlet, or flared.

We have bidding data for auctions for oil and gas rights run by the State of
Alaska from 1983 to 2009. These are primarily for lands controlled by the State of
Alaska including state-owned lands and offshore oil and gas within 3 miles of the
shoreline. There are also a limited number of tracts on land controlled by Native
American groups. This comprises approximately 4000 bids from over 3000 auctions.
These data are from by the State of Alaska Department of Natural Resources’ Division of
Oil and Gas (DOG). We drop 12 outlying bids of over $5,000,000.

These bid data are supplemented with production data from the Alaska Oil and
Gas Conservation Commission, which regulates oil and gas production and royalties.
Production data is reported as monthly barrels per well, and wells are tied to tracts.
With that I can tie the production data to the tract it was drilled on. Production is
discounted at 5% per year back to the auction date and summed to measure the present

---

3 We also have data for auctions before 1983. However, from 1979-1982 the State of Alaska experimented
with alternative auction formats. We omit these auctions.
value of future production. I assign a zero value to tracts that neither produce nor 
underlie producing pools.

Table 13: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>Mean</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bonus Bid</td>
<td>$35,886</td>
<td>$104,971</td>
<td>4020</td>
</tr>
<tr>
<td>Oil Production</td>
<td>0</td>
<td>$27,300,000</td>
<td>4020</td>
</tr>
<tr>
<td>is after OPA</td>
<td></td>
<td>0.66</td>
<td>4020</td>
</tr>
<tr>
<td>is offshore</td>
<td></td>
<td>0.37</td>
<td>2572</td>
</tr>
<tr>
<td>has OPA liability</td>
<td></td>
<td>0.18</td>
<td>2572</td>
</tr>
<tr>
<td>is Northern Alaska</td>
<td></td>
<td>0.69</td>
<td>4020</td>
</tr>
</tbody>
</table>

Most production in Alaska is unitized. In unitization, a number of tracts 
overlying a common source of oil are operated jointly, with revenues divided according 
to prenegotiated rates (personal communication, Jennifer Hainey, DOG). I do not 
observe these negotiations. However, they are generally based on the share of oil 
underlying the tract. To approximate unitization shares, GIS data from the US Energy
Information Administration showing the boundary of each pool. I use ArcGIS to calculate each tract’s portion of its encompassing unit (the area of the unit) and participating area and assume that the tract’s proportion of the total revenue for the unit.  

Drilling cost information is available from the American Petroleum Institute in annual reports for a number of geographic areas. However, this data series does not go back to the beginning of the data, and I could not purchase access to it. Thus I assume that drilling incurs fixed and variable costs, and that variable costs are proportional to total depth drilled.

Oil and gas prices are from the Wharton Research Data Service. Natural gas production is omitted for tracts in northern Alaska because there is no economically viable way to transport it from the site.

---

4 From Alaskan statues governing unitization (11 ACC 83.356), a unit “must encompass the minimum area required to include all or part of one or more oil or gas reservoirs, or all or part of one or more potential hydrocarbon accumulations.” A participating area may include only the land reasonably known to be underlain by hydrocarbons and known or reasonably estimated and known or reasonably estimated through the use of geological, geophysical, or engineering data to be capable of producing or contributing to production of hydrocarbons in paying quantities.” The distinction is that a unit is not necessarily expected to be fully underlain by oil or gas.

5 In expectation, estimates of revenue shares are likely overestimated because operating interests may receive a share of revenues without necessarily controlling any tracts. However, this has long been the case and thus should not bias our dummy variables of interest for this essay.
4.5 Results

Table 14 shows the results of regressing bids on covariates as in equation (4.5).

Recall that bids are a continuous function of values (i.e., expected profits). This implies that a coefficient of zero in bids will also have a zero coefficient on values.

\[ b_{ij} = X_j \beta + \epsilon_{ij} \]  \hspace{1cm} (4.5)

Note that there is no statistically significant impact of the OPA liability rule (as estimated by the OPA impact term). However, also note the low coefficients on oil revenues and the low explanatory power.
Table 14: Bid regression coefficients with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Oil and Gas revenue</th>
<th>Oil Revenue</th>
<th>Oil Revenue with Liability Dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil Revenue ($ '000)</td>
<td>0.0698*** (0.0099)</td>
<td>0.0698*** (0.0099)</td>
<td>0.0686*** (0.012)</td>
</tr>
<tr>
<td>Gas Revenue ($ '000)</td>
<td>0.396 (0.374)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>isAfterValdez (dummy)</td>
<td>-10351 (9858)</td>
<td>-10220 (9826)</td>
<td>-20316 (17666)</td>
</tr>
<tr>
<td>OPA liability rule exposure (dummy)</td>
<td></td>
<td></td>
<td>4479 (24883)</td>
</tr>
<tr>
<td>is North Slope (dummy)</td>
<td>86838*** (10462)</td>
<td>86398*** (10447)</td>
<td>55880 (43317)</td>
</tr>
<tr>
<td>is Beaufort Sea (dummy)</td>
<td>109713*** (13123)</td>
<td>109397*** (13117)</td>
<td>70894* (43493)</td>
</tr>
<tr>
<td>Constant term</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>r-squared</td>
<td>0.04</td>
<td>0.04</td>
<td>0.01</td>
</tr>
<tr>
<td>N</td>
<td>4020</td>
<td>4020</td>
<td>2572</td>
</tr>
</tbody>
</table>
4.5.1 Reduced Sample

Many auctioned tracts neither produced oil nor were part of oil-producing units. Dropping these from the sample leaves a total of 92 observations. Summary statistics are given in Table 15.

Table 15: Reduced sample summary statistics

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>Mean</th>
<th>Number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bonus Bid ($$)</td>
<td>88378</td>
<td>266,789</td>
<td>92</td>
</tr>
<tr>
<td>Oil Production ($$$)</td>
<td>19,750,200</td>
<td>101,430,000</td>
<td>92</td>
</tr>
<tr>
<td>is after OPA</td>
<td>0.793</td>
<td></td>
<td>92</td>
</tr>
<tr>
<td>is offshore</td>
<td>0.467</td>
<td></td>
<td>92</td>
</tr>
<tr>
<td>has OPA liability</td>
<td>0.359</td>
<td></td>
<td>92</td>
</tr>
<tr>
<td>is Northern Alaska</td>
<td>0.956</td>
<td></td>
<td>92</td>
</tr>
</tbody>
</table>

Reestimating equation (4.5) on the reduced sample yields Table 16. There is little evidence that the OPA impacts bidding decisions. More confusingly, there is little evidence that future oil revenues impact bidding decisions as the oil revenue coefficient is near zero.
Table 16: Linear results on reduced sample with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Oil and Gas revenue</th>
<th>Oil Revenue</th>
<th>Oil Revenue with Liability Dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil Revenue ($ ‘000)</td>
<td>0.0655***</td>
<td>0.0655***</td>
<td>0.0662***</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Gas Revenue ($ ‘000)</td>
<td>20.3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(343)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>isAfterValdez (dummy)</td>
<td>95821</td>
<td>95815</td>
<td>131265</td>
</tr>
<tr>
<td></td>
<td>(171941)</td>
<td>(170953)</td>
<td>(184606)</td>
</tr>
<tr>
<td>OPA liability rule exposure (dummy)</td>
<td></td>
<td></td>
<td>-77716</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(148813)</td>
</tr>
<tr>
<td>is North Slope (dummy)</td>
<td>168783</td>
<td>139772</td>
<td>113171</td>
</tr>
<tr>
<td></td>
<td>(586975)</td>
<td>(319153)</td>
<td>(324502)</td>
</tr>
<tr>
<td>is Beaufort Sea (dummy)</td>
<td>66160</td>
<td>37101</td>
<td>24012</td>
</tr>
<tr>
<td></td>
<td>(614720)</td>
<td>(367180)</td>
<td>(369572)</td>
</tr>
<tr>
<td>Constant term</td>
<td>-37609</td>
<td>-8552</td>
<td>14257</td>
</tr>
<tr>
<td></td>
<td>(37609)</td>
<td>(353260)</td>
<td>(357424)</td>
</tr>
<tr>
<td>r-squared</td>
<td>0.08</td>
<td>0.08</td>
<td>0.16</td>
</tr>
<tr>
<td>N</td>
<td>92</td>
<td>92</td>
<td>92</td>
</tr>
</tbody>
</table>
However, it seems that bids are distributed lognormally. Figure 24 shows a histogram of logged bids versus a normal distribution. More formally, standard skewness and kurtosis tests reject the null that bids are normal, but are not able to reject the hypothesis that logged bids are normal. Therefore, I investigate a specification of log bids as a function of logged revenues and other variables.

![Histogram of logged bids, with a normalized normal distribution](image)

**Figure 24: Histogram of logged bids, with a normalized normal distribution**

Table 17 describes estimation results for equation (4.6), where $\delta_j$ is distributed lognormally. Note that oil revenues are decomposed into production and price at the
time of auction. This is a decomposition of the logged revenues from previous specifications without loss of generality.

Oil production does indeed have substantial and significant impact on oil prices, with an elasticity between 0.22 and 0.3. Oil and gas production are highly correlated in this data set, thus while they can both be profit centers, they are difficult to estimate independently. We also see some evidence of oil prices being reflected in bids. However, again we see little effect from the Oil Pollution Act. In this case it is not clear whether the low statistical power is merely an artifact of the low sample size.

$$\log(b_{ij}) = \log(X_{ij}) \times \beta + \delta_{ij}$$

(4.6)

Specification one includes both oil and gas. However, they are highly collinear and thus gas is omitted in specifications 2-4. In each we see evidence that bids do indeed reflect ex poste oil revenues, with a strongly significant coefficient on production and a positive but insignificant coefficient on price. The weakness of the coefficient on price could reflect the fact that bidders may rely on long-term price projections instead of contemporary short-term price signals. If bidders rely on long-term price projections that are consistently above short-term projections, then their bidding could be consistent with rational expectations (ie, could reflect all future expected revenues) while the coefficient would be biased towards zero.
Table 17: Logged results on reduced sample with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Oil and Gas revenue</th>
<th>Oil Revenue</th>
<th>Oil Revenue with Liability Dummy</th>
<th>Oil Revenue with Liability Dummy and Time Trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log oil production (log thousand barrels)</td>
<td>0.240*** (0.339)</td>
<td>0.226*** (0.0866)</td>
<td>0.220*** (0.0873)</td>
<td>0.301*** (0.0846)</td>
</tr>
<tr>
<td>Log oil price (log $ per gallon)</td>
<td>-0.0486 (0.699)</td>
<td>0.132 (0.641)</td>
<td>0.209 (0.652)</td>
<td>0.732 (0.626)</td>
</tr>
<tr>
<td>Log gas production (log thousand cubic feet)</td>
<td>-0.00955 (0.281)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log gas price (log $ per thousand cubic feet)</td>
<td>1.34 (1.89)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>isAfterValdez (bool)</td>
<td>0.889 (0.493)</td>
<td>-0.0656 (0.364)</td>
<td>-0.151 (0.386)</td>
<td>-2.39*** (0.712)</td>
</tr>
<tr>
<td>OPA liability rule exposure</td>
<td></td>
<td></td>
<td>0.225 (0.325)</td>
<td>-0.015 (0.311)</td>
</tr>
<tr>
<td>is North Slope</td>
<td>-0.475 (0.756)</td>
<td>-0.385 (0.739)</td>
<td>-0.298 (0.298)</td>
<td>-0.753 (0.713)</td>
</tr>
<tr>
<td>is Beaufort Sea</td>
<td>-0.540 (1.04)</td>
<td>-0.0948 (0.804)</td>
<td>-0.044 (0.810)</td>
<td>-2.08** (0.940)</td>
</tr>
<tr>
<td>Time trend (years)</td>
<td></td>
<td></td>
<td></td>
<td>0.305***</td>
</tr>
</tbody>
</table>
since 1980) | 7.18*** | 7.73*** | 7.50*** | (0.0837)  
| Constant term | (2.61) | (2.46) | (2.49) | (2.57)  
| r-squared | 0.08 | 0.08 | 0.08 | 0.21  
| N | 92 | 92 | 92 | 92  

### 4.6 Potential for Further Work

Future work will proceed in two directions: attempted to improve estimates of the OPA’s impact, and exploring why so many bidders entered substantial bids for tracts that did not produce oil.

An ideal first step to improving estimates of the OPA’s would be to use bidders’ ex ante predictions of potential production instead of ex poste measures. However, the data requirements for this analysis (internal analyses for every potential bidder) are likely to be insurmountable. I will also explore alternative measures of oil price projections. Additionally, I will switch to using a two-stage model, estimating bidders’ private values for bids and estimating the OPA’s impact on estimated values instead of directly estimating the OPA’s impact on bids.

This work also suggests the question of why bidders purchase so many tracts which do not produce oil. Figure 25 shows a log-log scatter plot of bids versus oil production. For graphical purposes, tracts that do not produce oil have an assigned x-
axis value of 0. The histogram along the vertical axis describes the distribution of all bids, while the histogram along the horizontal axis describes the distribution of production from all tracts. As before, only 92 of the 3821 bids were for tracts which produced oil. Amongst those 92, there does seem to be a clear positive relationship between ex post oil production and bids amongst producing tracts (as found in the above results section). However, there were also many large bids for non-producing tracts – of the 3729 bids for non-producing tracts, the median bid was $33966 and the mean bids was $132165. Further, 1364 (or 44%) of the bids for non-producing tracts were higher than the median bid for producing tracts while 991 were above the $266789 mean bid for producing tracts.

Taken together, this evidence suggests two different explanations. First, bidders may have some prior signal of the amount of oil that will come from a tract, but that these signals are very noisy. Future research can explore why the bidders’ projections of oil production are so imprecise. Alternatively, bidders may know that the likelihood of a tract producing is low, and are in essence bidding on the option value of the tract in case it actually has oil. This “option value” theory would have a variety of testable predictions, including the presence of spatial information spillovers in exploration and development (Cynthia Lin, 2010). Future work can develop a model of bidding for option value in which bidders know that many tracts do not produce and test that
model. Estimating an option value auction model could also help estimate the impact of
the OPA liability rule.

Figure 25: Bids versus oil production in log-log space, with histograms for each

4.7 Conclusions

This paper attempts to estimate the cost of the Oil Pollution Act of 1990’s
imposition of liability for oil spills into US water on oil producers. It develops a model
relating this ex ante cost to the expected profits from holding the rights to produce oil
and relates expected profits to observed bids for those rights. It develops a novel data

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set of auctions for oil and gas rights conducted by the State of Alaska and estimates the model on that data. However, I find no evidence that the Oil Pollution Act’s liability rule imposed costs on oil producers. This may be due to the small sample size of tracts auctioned by the State which actually produced oil and resultant low statistical power.
Appendix A. Relaxation of Assumption that Retail Gasoline Markup is Zero

Let us instead model finished gasoline prices as a markup $c$ from input prices:

$$P^G = \alpha P^E + (1 - \alpha)P^B + c = P^B + c$$

Recall my blendstock supply equation:

$$B = \phi_0 + \phi_1 P^G_\mu + \phi_2 P^B_\mu + Y_\mu \varphi + \delta_\mu$$

Substituting in $P^G - c$ for $P^B$, we see that

$$B = \phi_0 + \phi_1 P^G_\mu + \phi_2 (P^G_\mu - c) + Y_\mu \varphi + \delta_\mu$$

$$B = \phi_0 - \phi_2 c + \phi_1 P^G_\mu + \phi_2 P^G_\mu + Y_\mu \varphi + \delta_\mu$$

Thus if finished gasoline retail is not costless, the cost will be reflected in the constant term which does not show up in volatility calculations. An analogous calculation holds for the ethanol model

$$E = v_0 + v_1 P^K + v_2 (P^G - c) K + v_3 P^K K + v_4 K$$

$$E = v_0 + v_1 P^K + v_2 P^K + v_3 P^K K + (v_4 + v_5 c) K$$

In this case, the finished gasoline retail cost will bias the average capacity utilization coefficient. Again, this term drops out when I take the variance. Thus assuming costless retail does not affect my volatility and shock mitigation calculations.
Appendix B. Including the Ethanol Production Tax Credit

If I add a constant ethanol blending tax subsidy to the model, the price equilibrium becomes

\[ P^E = P^B + \tau \]

Substituting that into the ethanol supply function and rearranging, we see that

\[ E = v_0 + v_1 p^N K + v_2 (P^B + \tau) K + v_3 p^C K + v_4 K \]

If \( \tau \) is constant, this becomes

\[ E = v_0 + v_1 p^N K + v_2 P^B K + v_3 p^C K + (v_4 + \tau) K \]

Thus, omitting the tax subsidy does bias the estimate of the baseline utilization rate. However, as in Appendix A. Relaxation of Assumption that Retail Gasoline Markup is Zero this drops out from volatility and shock mitigation calculations.
Appendix C: Fuel price equilibrium

In this appendix I show that the price equilibrium assumed to hold in the conceptual and empirical models does indeed seem to hold when appropriate constants and energy equivalence are considered. I show in Appendices A and B that the model can accommodate the constant terms, and the energy equivalence is a matter of units.

I obtained daily national average ethanol wholesale prices, spot petroleum blendstock prices (NYMEX RBOB) and daily average retail gasoline price from January 1, 2007 through Dec 31 2010. These are shown in Figure 26. Visually it certainly appears that wholesale gasoline and RBOB prices track one another with a roughly constant offset. While the correlation is somewhat weaker, ethanol prices also roughly track RBOB prices. Ethanol prices did depart somewhat from RBOB prices in the summer of 2010 due to an unusually and unexpectedly large U.S. corn harvest. We can also test these relationships a bit more formally.
A cointegrating relationship between data series indicates that they (or their sums) track one another. Standard trace statistics suggest the presence of potentially two cointegrating relationships between gasoline, ethanol, and RBOB prices. Table 18 shows these cointegrating relationships. All cointegrating coefficients are significant at the 1% level and are marked with ‘***’. 

Figure 26: Transportation Fuel Prices
Table 18: Transportation fuel price cointegration with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th>Fuels</th>
<th>Cointegrating equation 1</th>
<th>Cointegration equation 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gasoline ($ per gallon)</td>
<td>1 (fixed)</td>
<td></td>
</tr>
<tr>
<td>RBOB ($ per gallon)</td>
<td>-0.984*** (0.015)</td>
<td>-0.729*** (0.17)</td>
</tr>
<tr>
<td>Ethanol ($ per gallon)</td>
<td></td>
<td>1 (fixed)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.744</td>
<td>-0.464</td>
</tr>
</tbody>
</table>

The first cointegration equation describes the price equilibrium between the RBOB and gasoline markets and implies that a $1 increase in the gasoline price is associated with an increase of 0.984 dollars in the RBOB price. This estimate is not significantly different than exactly 1. The second cointegrating equation describes the RBOB and ethanol substitution markets. It implies that a $1 increase in the RBOB price is associated with an increase of 0.729 dollars in the ethanol price. This is not significantly different from the ratio of the energy in a gallon of ethanol to the energy in a gallon of petroleum-based fuel and suggests that substitution is on an energy-equivalent basis.
Note that there is a constant offset of approximately 74 cents per gallon of gasoline between the gasoline and RBOB prices. As shown in Appendix 1, this may bias coefficient estimates but will not affect my volatility calculations. Similarly, the ethanol blending tax credit is reflected in the constant of $0.464. As shown in Appendix 2, this may also bias a coefficient estimate but will not affect my volatility and mitigation calculations.
Appendix D: Map of Regional Petroleum (PADD) Districts
Appendix E: The Impact of Diesel Fuel Prices on Ethanol Supply

In this appendix I show that spring diesel prices do seem to impact corn farmers’ costs, and that because they are highly correlated with subsequent blendstock prices it is difficult to distinguish their impact from the impact of output (blendstock) prices. I obtain average diesel prices for the Midwest from the US EIA and use the April price for the remainder of the year and next January, February, and March, calling this “spring diesel”. The correlations between the spring diesel price, spring (April) Brent price, Brent price, and blendstock prices are shown in Table 19.

Table 19: Correlations Between Spring Diesel and Brent Prices and Later Prices

<table>
<thead>
<tr>
<th></th>
<th>Spring Diesel</th>
<th>Spring Brent</th>
<th>Brent</th>
<th>Gasoline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spring Diesel</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spring Brent</td>
<td>0.99</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brent</td>
<td>0.86</td>
<td>0.856</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Gasoline</td>
<td>0.80</td>
<td>0.78</td>
<td>0.93</td>
<td>1</td>
</tr>
</tbody>
</table>

The correlation between the spring diesel price, which farmers consider when making planting decisions, and the gasoline price, which is the output price ethanol producers receive for their product, is 0.8.
First we include the spring diesel price (instrumented with spring brent) as an instrument for corn prices in addition to the weather instruments discussed in section 2.6.4. This increases the explanatory power of the instruments from an $R^2$ of 0.42 to 0.71. The new predicted corn prices are shown in the green short dashed line in Figure 27, as well as corn prices predicted with only the weather instruments (red long dashed line) and observed corn prices (blue solid line).

![Actual and predicted corn prices](image)

**Figure 27: Actual and Instrumented Corn Prices**

However, using these new instrumented corn prices to estimate the ethanol supply curve yields counter-intuitive results. Table 20 provides estimation results for panel IV and GMM estimation of the ethanol supply curve using both diesel and
weather instruments for corn and only using weather instruments. In the new specifications, estimates of the impact of contemporary output (gasoline) prices become negative and insignificant (instead of positive and significant as in previous specifications. Further, the corn price point estimate becomes insignificant in both specifications and positive in one. This suggests that the diesel instrument is also proxying for the effect of the output (gasoline) price.
Table 20: Ethanol Supply Curve using Diesel as an Instrument for Corn Prices with standard errors in parentheses. *, **, *** denote 10%, 5%, and 1% Confidence Levels.

<table>
<thead>
<tr>
<th></th>
<th>Including diesel in corn instruments</th>
<th>Only using weather in corn instruments</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ethanol (Thousand barrels per day)</strong></td>
<td><strong>Panel IV</strong></td>
<td><strong>Panel IV</strong></td>
</tr>
<tr>
<td></td>
<td><strong>GMM estimator</strong></td>
<td><strong>GMM estimator</strong></td>
</tr>
<tr>
<td>Ethanol capacity</td>
<td>0.227*** (0.040)</td>
<td>0.198*** (0.011)</td>
</tr>
<tr>
<td>(Thousand barrels per day)</td>
<td></td>
<td>0.198*** (0.013)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.182*** (0.0045)</td>
</tr>
<tr>
<td>Gasoline price</td>
<td>-0.00266 (0.0144)</td>
<td>-0.00539** (0.0022)</td>
</tr>
<tr>
<td>($ / gal)</td>
<td></td>
<td>0.0143 (0.01)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.00851*** (0.0021)</td>
</tr>
<tr>
<td>Corn price</td>
<td>-0.00359 (0.00728)</td>
<td>0.00216 (0.00158)</td>
</tr>
<tr>
<td>($ / bushel)</td>
<td></td>
<td>-0.0883*** (0.0068)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.00351* (0.0018)</td>
</tr>
<tr>
<td>Natural gas price</td>
<td>0.00219 (0.00290)</td>
<td>0.000205 (0.000682)</td>
</tr>
<tr>
<td>($ per ‘000 cubic feet)</td>
<td></td>
<td>-0.000106 (0.002)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.00152** (0.00064)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.85 (33.5)</td>
<td>-2.48 (3.19)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.63 (35)</td>
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<td></td>
<td></td>
<td>8.18*** (2.0)</td>
</tr>
<tr>
<td>Number of</td>
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</table>
References


____. 2012b. "Corn: Background,"


Biography

Peter Maniloff, born and raised in North Carolina, holds bachelor’s degrees in physics and computer science as well as a master’s degree in environmental science and management. All are from Duke. GTHC.