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Policy Shocks and Market-Based Regulations: Evidence from the Renewable Fuel Standard

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Abstract

The Renewable Fuel Standard (RFS2) is a US federal policy that mandates large increases in biofuel consumption and is implemented using a market for tradeable compliance credits. We develop a dynamic model of compliance with the RFS2 in which firms face uncertainty about future relative fuel prices and future enforcement of the mandate. Our model shows how changes in expected future enforcement can have dramatic effects on the price of compliance credits and thereby have large effects on the current cost of compliance. To illustrate, we estimate empirically the effect of three 'policy shocks' that reduced the expected 2014 mandates and introduced significant uncertainty regarding future compliance schedules. We estimate that one shock, the release of the 2013 Final Rule in which the Environmental Protection Agency suggested it would likely reduce the 2014 mandate, decreased the value of the subsidy (tax) provided by the RFS2 to the biofuel (fossil fuel) industry in 2013 by nearly $8 billion. Similar shocks followed with two subsequent events that released preliminary versions of the 2014 mandate reductions. We conclude that the goals of the RFS2 would be better served through active management of compliance-credit markets.

JEL Codes: Q42, Q50, H23

Keywords: tradeable credits, policy design, quantity mechanisms, renewable fuel standard

1 Introduction

Environmental regulations implemented using tradeable credits are less costly than command and control policies (Coase, 1960; Crocker, 1966; Dales, 1968). For example, instead of instituting firm level pollution control requirements, closing a fishery after the catch has reached a given quota, or giving a few firms exclusive rights to a restricted activity, a regulator allows an industry flexibility in meeting a policy's objectives by limiting the total level of an economic activity and creating a credit system that allows regulated parties to trade the right to that activity. In the absence of barriers to trade, economic theory suggests that trading credits will lead to an efficient market outcome in which marginal compliance costs are equalized across regulated parties (Montgomery, 1972).

Tradeable credits have recently been used to implement policies that require costly uncoordinated investments in environmental services and the development of new technology. The most notable of these policies are found in the energy sector. For example, several states have passed Low Carbon Fuel Standards requiring significant reductions in the carbon intensity of fuel sold in the the state (National Low Carbon Fuel Standard Project, 2014), and Renewable Portfolio Standards requiring increasing shares of electrical generation be derived from renewable sources (Department of Energy, 2014). In addition, one of the two preferred policy instruments under the EPA Clean Power Plan proposed in the summer of 2014 is a rate based standard limiting CO_2 emission rates of fossil-fuel fired electric generation plants (Environmental Protection Agency, 2014).

In this paper, we study perhaps the most ambitious and longest standing of these policies, the US Renewable Fuel Standard (RFS2), and its associated market for tradeable credits, known as Renewable Identification Numbers (RINs). The RFS2 mandates large increases in biofuel use, reaching 25% of predicted US transportation fuel consumption by 2022. Prior to 2015, the RFS2 allowed the mandate to be met almost entirely with ethanol produced from corn, which is typically the least expensive biofuel, but it generates a small estimated greenhouse gas emission reduction. After 2015, the policy requires a large and increasing proportion of biofuel to be derived from so-called advanced sources, which generate larger greenhouse gas emission reductions than corn ethanol and include ethanol made from sugarcane, biodiesel made from vegetable oil, and ethanol made from the inedible parts of plants. Thus, meeting the RFS2 mandates requires large increases in biofuel production and consumption capacity, particularity for advanced biofuels.

We focus on the RIN market because it reveals the marginal cost of compliance with the policy. We derive market clearing RIN prices in a dynamic model in which firms face uncertainty about future relative fuel prices and future enforcement of the mandate. Consistent with the previous literature, we show how the RFS2 can be conceptualized as revenue-neutral subsidy to the biofuel industry financed by a tax on petroleum fuels (Lapan and Moschini, 2012). Our model also shows how changes in expected future enforcement can have dramatic effects on the price of compliance credits and thereby have large effects on the current cost of compliance. These effects can be large when the marginal compliance cost curve is steep. To test whether observed RIN prices are consistent with our model, we provide a test of RIN market efficiency using a new method developed in the time series econometrics literature. We cannot reject the null hypothesis of efficient RIN markets.

To elucidate the effects of changes in expected future enforcement, we estimate historical RIN price drivers from late 2012 through mid-2014. We pay particular attention to estimating the effect of three events on RIN markets. We find that the three events, which we characterize as 'policy shocks', were responsible for large, statistically significant decreases in RFS2 compliance costs. The first event is the release of the 2013 Final Rule, in which the EPA indicated it would likely reduce the 2014 mandate but gave little guidance as to what the reductions would be or how future compliance paths would be affected. The 2013 Final Rule was followed by a subsequent Reuters news article leaking a draft of the proposed cuts, our second event. The final event is the release of the 2014 Proposed Rule in which the EPA officially proposed the cuts. We estimate that the 2013 Final Rule led to a nearly \$8 billion decrease in the value of the subsidy (tax) provided by the program for the biofuel (fossil fuel) industry for the 2013 compliance year alone. Similar losses on the order \$0.1-\$1 billion were observed following the subsequent two policy shocks.

Given the large, sudden shifts in the value of the RFS2 around the three events, we study effects of the shocks on commodity markets and stock prices of publicly trade biofuel firms. We show that prices of oil, ethanol, and other biofuel feedstocks did not experience significant abnormal returns following the events; however, soybean oil prices experienced a significant, abnormal loss around 2% following the publication of the Reuters article. The result is consistent with a prediction of our model that biodiesel, which is predominantly produced from soybean oil, was the marginal fuel for the overall biofuel mandate in 2013.

RINs incentivize the production of fuels that would be unmarketable without the RFS2. As a result, unexpected changes to the policy pose an acute threat to firms with high production costs, primarily advanced biofuel producers. Consistent with this, we show that stock prices of corn ethanol producers were largely unaffected by the events, but that companies that produced or had large investments in advanced biofuels experienced large and significant losses around the three policy shocks.

Through its announcements, the EPA both reduced the incentive to produce advanced biofuels and introduced a substantial degree of uncertainty in fuel markets regarding future compliance schedules.[1] The uncertainty in turn creates an option value to delaying investments in biofuel production capacity (Dixit and Pindyck, 1994). This in turn undermines the policy's goals and increasing future compliance costs if large scale production of advanced biofuel remains a long run policy objective (Miao et al., 2012).[2]

[1]Consistent with our findings, a recent report by the International Energy Agency states that unanticipated changes to renewable energy incentives represent a 'key challenge to deployment' of renewables (International Energy Agency, 2014).

[2]Similarly, uncertainty regarding future tax, fiscal and monetary policy is also an often cited issue hampering long-term economic investments (Baker et al., 2013).

Our findings suggest that the RFS2 has reached a steep portion of the short-run marginal compliance cost curve. As a result, small changes to the expected future mandates have large effects on RIN prices. Our paper illustrates the importance for regulators using quantity-based mechanisms to provide a stable price signal when compliance costs are uncertain and volatile. As such, we propose alternative policy designs that address these shortcomings through more active management of compliance credit markets.

The paper proceeds as follows. Section 2 provides a background on the Renewable Fuel Standard and RIN Markets. Section 3 reviews the relevant literature. Section 4 presents a dynamic model of an industry facing a RFS over time under uncertainty to motivate our study of RIN markets and to enable us to better understand dynamics that have arisen in the markets to date. Section 5 discusses historical RIN prices and other relevant data used in our subsequent analysis, and presents a test of market rationality for RIN markets. Section 6 estimates historical cost drivers of RIN prices, focusing on the effect of the three policy shocks on RIN prices. In addition, we study the effect of the shocks on relevant commodity market prices and biofuel stock market prices. Section 7 discusses the results, and section 8 concludes.

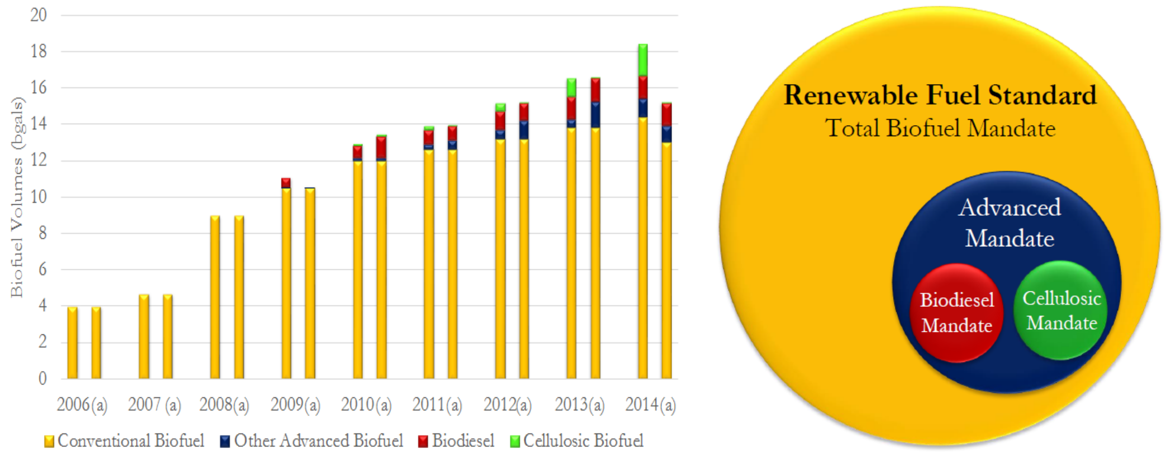
2 The RFS2 and the Market for RINs

The Renewable Fuel Standard was created by the Energy Policy Act of 2005 and expanded under the Energy Independence and Security Act (EISA) of 2007, creating the RFS2. The program sets ambitious standards for biofuel consumption, with the goal of expanding consumption to 36 billion gallons (bgal) of renewable fuels per year by 2022. The Environmental Protection Agency (EPA) administers the program, and while EISA provides specific biofuel consumption targets, the EPA is allowed discretion in setting each year's mandates.

The RFS2 distinguishes between categories, or types, of biofuel and sets separate mandates for each. These categories are differentiated by their estimated greenhouse gas emissions relative to petroleum fuels. The biofuel categories are: (i) cellulosic biofuel, which can be produced from wood, grasses, or the inedible parts of plants; (ii) biodiesel, predominantly produced from soybeans or canola in the US; (iii) advanced biofuel, or fuels with life-cycle greenhouse gas (GHG) emissions at least 50 percent below a threshold set by the law; and (iv) renewable fuel, including all previous categories as well as ethanol derived from corn. The mandates are nested so that cellulosic biofuel and biodiesel count toward the advanced biofuel mandate, and all biofuels count toward the overall renewable fuel mandate.

Figure 1a graphs the EISA and Final Rule mandates for 2006-2014 and Figure 1b illustrates the nested structure of the RFS2. The program is designed so that compliance in early years can be met mostly with ethanol derived from corn, with increasing requirements for categories (i)-(iii) later in the program. For example, in 2013 the total renewable fuel mandate was 16.5 bgal, of which 13.8 bgal could be met with corn

Figure 1: The Renewable Fuel Standard*



(a) RFS2 Mandates

(b) Nested Mandate Structure

*Note: The left figure graphs the RFS2 mandates from 2006-2014. The left bars graph the EISA mandates and the right bars represent the mandates from the EPA's Final Rules. In 2014, the right bar reflects the 2014 Proposed Rule. The right figure graphs the nested structure of the mandate. Yellow, blue, red, and green correspond to corn, advanced, biodiesel, and cellulosic ethanol, respectively.

ethanol. In contrast, in 2022 the overall renewable fuel mandate is set at 36 bgal, of which corn ethanol is limited to 15 bgal (Environmental Protection Agency, 2013b). Thus, the program relies on the speedy development of a large advanced biofuel industry, especially after 2015.

To enforce the RFS2, every gallon of approved renewable fuel produced in or imported into the United States from a registered producer is associated with a Renewable Identification Number (RIN). Whenever a gallon of renewable fuel is blended into the US fuel supply, the RIN is 'detached' and allowed to be sold. Obligated parties, predominantly oil refiners and importers, comply with the RFS2 by turning in a quantity of RINs equal to their prorated portion of the RFS2 mandate. Thus, parties maintain compliance with the program by either blending renewable fuel into their product or by purchasing RINs generated by other firms.

The EPA allows limited banking and borrowing of RINs across compliance years. RINs from the previous compliance year are allowed to constitute up to 20% of any firm's current year compliance obligation. In addition, firms are allowed to carry a deficit, but may only do so for one year (Environmental Protection Agency, 2007). As a result, the industry as a whole is able to carry a net deficit or net surplus from one compliance period to the next, but is limited to the extent it may do so.

To enforce the nested mandates as well as banking and borrowing restrictions, RINs are differentiated by fuel type and vintage year. RIN types correspond to the biofuel categories with conventional (D6)

RINs applying towards the total renewable fuel mandate; advanced biofuel (D5) RINs applying towards the advanced and renewable fuel mandates; and biodiesel (D4) RINs applying towards the biodiesel, advanced, and renewable fuel mandate.[3]

The success of the RFS2 in expanding US biofuel consumption faces two major challenges: (i) the blend wall, and (ii) the lack of development of a viable cellulosic biofuel industry.

The blend wall is the notion that it is expensive to maintain compliance with the RFS2 past a 10% ethanol-gasoline blend. Ethanol has historically been blended with gasoline at two levels: 10% ethanol, referred to as E10; and 85% ethanol, referred to as E85.[4] E10 has been approved by the EPA for decades and makes up more than 99% of ethanol-blended gasoline sales.[5] The volumes specified by EISA were set under the assumption that gasoline consumption in the United States would increase each year. Instead, gasoline and diesel consumption has declined since 2007. Thus, to maintain compliance with the RFS2 past a 10% ethanol-gasoline blend refiners must either sell greater volumes of E85 or increase biodiesel consumption where blending constraints are less binding. Both compliance options are costly and require high RIN prices to overcome price differences between high ethanol blend fuels and lower blend fuels to 'break' the blend wall.

Additional compliance problems have arisen because the levels of advanced biofuel production envisioned in 2007 have yet to materialize. This is especially true with cellulosic biofuels. As of May 2014, there were six cellulosic biofuel plants expected to produce fuel in 2014 (Adler et al., 2014), though little production has taken place and all companies are experiencing technical and financial problems.

These challenges are increasingly reflected in the EPA's rulings. Prior to each compliance year, the EPA is required to release a Proposed and Final Rule. Until 2013, the EPA accounted for the lack of advanced

[3]We do not consider cellulosic ethanol RINs in this paper because little cellulosic biofuel has been produced to date despite the mandate for its production.

[4]The Clean Air Act Amendments (CAAA) of 1977 prohibit any fuel additive from being blended into the US gasoline supply unless the EPA grants a waiver for the fuel. In order to obtain a waiver, parties must demonstrate the additive will not lead to higher emissions of key criteria pollutants (Clean Air Act Section 211(f)). Waivers are difficult to obtain for low blends of ethanol because at lower blends, ethanol increases the volatility of fuels, which can violate Reid Vapor Pressure (RVP) requirements under the CAAA of 1990.

[5]In 2010, the EPA granted a partial waiver for E15 blends, or gasoline containing up to 15% ethanol; however, the waiver was only approved for model year vehicles 2001 and newer due to concerns of increased corrosion from higher blend gasoline in older vehicles (Environmental Protection Agency, 2011). The E15 waiver also maintains strict RVP limits, limiting the allowed volatility of fuel sold in areas of the US. This effectively restricts E15 from being sold in many urban regions of the United States in the summer when more stringent air quality standards are in effect. As a result, little E15 has been sold in the US to date.

[6]In addition, the biodiesel mandate deviates from the volumes set out in EISA. The total amount of biodiesel required under the initial law has been met, however, as the 2009 requirements were shifted to 2010 obligations.

[7]Initially, the EPA allowed firms to purchase paper credits in lieu of credits generated from cellulosic biofuel production; however, the legality of paper credits have been questioned in a number of court cases. As a result, the option is not used currently.

biofuel production by exercising the flexibility under EISA to reduce the cellulosic biofuel mandate and increase the advanced biofuel mandate.[6,7] In its 2013 Final Rule, released nine months behind schedule in August 2013, the EPA changed course by stating that it may reduce the overall biofuel mandate for 2014 (Environmental Protection Agency, 2013a). In its 2014 Proposed Rule, released in November 2013, the Agency called for a significant cut to the overall biofuel mandate. Figure 1a illustrates the proposed 2014 standards. As can be seen, the levels represent a large decrease relative to both the EISA standards as well as the 2013 mandates.

3 Prior Literature

A growing literature studies the economics of biofuel mandates and carbon intensity standards such as California's Low Carbon Fuel Standard. Early work by de Gorter and Just (2009) studies the market effects of biofuel mandates. Lapan and Moschini (2012) develop a general equilibrium, open economy model to compare biofuel mandates with other policy instruments such as subsidies and fuel taxes. Other papers compare the welfare and markets effects of the RFS2 and intensity standards to taxes and cap and trade programs (Rajagopal et al., 2011; Holland et al., 2009, 2013, 2014; Rajagopal and Plevin, 2013; Lemoine, 2013a; Bento et al., 2014), and explore unintended consequences of the RFS2 such as leading to lower costs per vehicle mile traveled (Khanna et al., 2008). Lade and Lin (2015) study the potential efficiency gains from strategically setting a price ceiling on RIN prices with fuel mandates such as the RFS2.

Few empirical papers on the RFS2 have been written to date. Anderson (2012) estimates demand for E85 in Minnesota. He finds that demand is relatively elastic compared to regular gasoline, but that preferences are heterogeneous and a small constituent of consumers are willing to pay a premium for E85. A number of subsequent papers study demand for high blend ethanol and alternative fuel vehicles in the United States and Brazil, but find mixed results regarding consumers' preferences for biofuels (Du and Carriquiry, 2013; Salvo and Huse, 2013; Babcock and Pouliot, 2013; Pouliot and Babcock, 2014c). In addition, a small but growing literature studies the impacts of the RFS2 on fuel prices and find that the impacts on retail fuel prices are likely small to date (Du and Hayes, 2009; Pouliot and Babcock, 2014a,b; Knittel and Smith, 2014).

McPhail et al. (2011) and Verleger (2013) provide thorough primers on institutional features of RIN markets and discussions of factors driving RIN prices. In addition, several authors regularly publish commentaries and working papers on the RFS2 and RIN markets (see e.g., Thompson et al. (2010, 2012); Babcock (2012); Babcock and Pouliot (2013); Irwin (2014b)).

Our paper also contributes to the broader literature comparing price versus quantity mechanisms under economic regulations. The literature studying quantity versus price mechanisms under compliance cost uncertainty dates to Weitzman (1974). Roberts and Spence (1976) first proposed a hybrid policy mechanism that limits a pollutant or effluent using tradeable permits supplemented by a fixed abatement subsidy and non-compliance penalty to ensure compliance costs remain in a given range. The authors argue such a mechanism reduces the expected social cost of a policy when a regulator is uncertain about compliance costs and benefits. Such hybrid price-quantity policies have been more recently studied by Pizer (2002), Newell et al. (2005), Burtraw et al. (2010), and Lade and Lin (2015) among others.

4 A Dynamic Model of Compliance

In a static model of a biofuel mandate with no uncertainty, RIN prices reflect the current marginal compliance cost, and are a function of the difference between the marginal renewable fuel used to meet the standard and the price of conventional fossil fuel (Lade and Lin, 2015). Static models of the RFS2, however, omit two important features relevant to our study of RIN markets. First, the RFS2 is applied over many years and firms are allowed to bank and borrow credits from one year to the next. Second, regulated parties are uncertain about future fuel costs, market prices, and - since 2013 - the future stringency of the policy.

To understand RIN prices, we develop a dynamic model of compliance with the RFS2 under uncertainty. The model is motivated by Schennach (2000), who studies SO_2 permits under the Clean Air Act Amendments of 1990, and Rubin (1996) and Holland and Moore (2012, 2013), who study permit markets under cap and trade programs.

We begin with a stylized model in Section 4.1 where there is only one renewable fuel and a single compliance period. In Appendix A, we present two important extensions. First, we discuss a scenario with a single renewable fuel and two compliance periods, and restrict the amount of banking allowed between the compliance periods. The model allows us to understand the relationship between RIN prices for different vintages of the same RIN type. Second, we present a model with two renewable fuels, a single compliance period, and a nested mandate structure. The model allows us to understand the relationship across RIN types for the same compliance year. We discuss the results from the two extensions in Section 4.2.

4.1 Model

Consider a competitive industry composed of N firms complying with the Renewable Fuel Standard. Suppose firm i produces fuel Q in each period t using one conventional and one renewable input, and that inputs are perfect substitutes in production such that $Q_{i,t} = q^c_{i,t} + q^r_{i,t}$.[8] Assume fuel is sold in each period at market clearing price P_t, and that the firm's cost function is separable in the inputs such that $C_{i,t}(q^c_{i,t}, q^r_{i,t}) =$

[8] We abstract from details regarding fuel quality differences between renewable and conventional fuels such as differences in octane levels. Energy content differences between the fuels can be accommodated in the model by assuming the fuels units are specified in gasoline gallon equivalents (GGE).

$C^c_{i,t}(q^c_{i,t}) + C^r_{i,t}(q^r_{i,t})$, with $C^{j'}_{i,t}(\cdot) > 0$ and $C^{j''}_{i,t}(\cdot) > 0$ for $j = c, r$ and all t. Under the RFS2, every unit of the renewable input generates a tradeable credit $c_{i,t}$ that can be sold to other firms and used for compliance in lieu of physically blending renewable fuel. Firms can purchase or sell credits in each period at market clearing price r_t.[9]

Uncertainty enters each firm's maximization problem through several avenues. In each period, firms may experience a common price (demand) shock, a common cost (supply) shock, and a common policy shock. We denote the tuple of shocks by Θ_t, and assume all shocks are realized at the beginning of each period before firms make their production decisions. Thus, firms make production decisions knowing the current value and history of all shocks, but not the value of future shocks. We assume every firm knows the distribution of the parameters and is able to form consistent, rational expectations given a realized history of shocks.

Suppose there is one compliance period, T, and firms make production decisions for $t = 1, 2, ..., T$. We write the RFS constraint for each firm as requiring the total volume of renewable fuel produced and the number of credits purchased over the period to be greater than or equal to the standard α times the total volume of conventional fuel produced. Specifically, the policy requires:

$$\sum_{t=1}^{T}(q^r_{i,t} + c_{i,t}) \geq \alpha \sum_{t=1}^{T} q^c_{i,t}. \tag{1}$$

The right-hand side of the inequality above is referred to as the firm's Renewable Volume Obligation (RVO). Summing equation (1) over all firms yields the industry's RVO, equal to the total volume of renewable fuel mandated by the program.

We rewrite the policy constraint in a compact form by defining the state variable $B_{i,t}$ as the volume of 'banked' credits held by firm i in period t. The variable evolves over time according to:

$$B_{i,t+1} = B_{i,t} + q^r_{i,t} + c_{i,t} - \alpha q^c_{i,t},$$

for $t = 1, \cdots, T$. Assume the bank is empty in the first period such that $B_{i,1} = 0$. We now rewrite the policy constraint (1) as:[10]

$$B_{i,T+1} \geq 0.$$

for each firm i.

Given the setup above, we write each firm's Bellman equation in each period as:

$$V_{i,t}(B_{i,t}; \Theta_t) = \max_{\substack{q^c_{i,t}, q^r_{i,t} \geq 0, \\ c_{i,t}}} P_t(q^c_{i,t} + q^r_{i,t}) - C^c_{i,t}(q^c_{i,t}) - C^r_{i,t}(q^r_{i,t}) - r_t c_{i,t} + \beta \mathbb{E}_t[V_{i,t+1}(B_{i,t+1}; \Theta_{t+1})] \tag{2}$$

[9] We allow $c_{i,t}$ to be positive or negative, with the convention that firms purchase credits on net whenever $c_{i,t} > 0$ and sell credits whenever $c_{i,t} < 0$.

[10] To see this, note that $B_{i,T+1} = B_{i,T} + q^r_{i,T} + c_{i,T} - \alpha q^c_{i,T} = \sum_{t=1}^{T} \left(q^r_{i,t} + c_{i,t} - \alpha q^c_{i,t} \right)$

$$\text{subject to} \quad B_{i,t+1} = B_{i,t} + q^r_{i,t} + c_{i,t} - \alpha q^c_{i,t}$$
$$B_{i,T+1} \geq 0$$
$$B_{i,1} = 0.$$

Given the finite time horizon, the problem is solved recursively. We assume there is no scrap value to having a positive bank in the final period T, therefore the value function for $T+1$ is zero. The Karush-Kuhn-Tucker (KKT) conditions for each period are given by:[11]

$$q^c_{i,t} \geq 0 \quad \perp \quad P_t - C^{c'}_{i,t}(q^c_{i,t}) - \beta^{(T-t)}\alpha \mathbb{E}_t[\lambda_{i,T}] \leq 0, \tag{3}$$

$$q^r_{i,t} \geq 0 \quad \perp \quad P_t - C^{r'}_{i,t}(q^r_{i,t}) + \beta^{(T-t)} \mathbb{E}_t[\lambda_{i,T}] \leq 0, \tag{4}$$

$$- r_t + \beta^{(T-t)} \mathbb{E}_t[\lambda_{i,T}] = 0, \tag{5}$$

$$B_{i,T+1}\lambda_{i,T} = 0, \tag{6}$$

where $\lambda_{i,T}$ denote the firm's Lagrange multiplier on the RFS constraint $B_{i,T+1} \geq 0$, and '$\perp$' denotes 'is complementary to' for all optimality conditions, implying that at least one equation binds with equality.

In each period, the number of credits sold must equal the number of credits purchased. A price sequence $\{r_1, r_2, ..., r_T\}$ defines an equilibrium if all firms optimally choose the number of compliance credits purchased or sold in each period and the following holds:

$$r_t \left[\sum_{i=1}^{N} c_{i,t} \right] = 0, \qquad t = 1, \cdots, T. \tag{7}$$

Equation (7) is a flow condition, requiring that in each period a credit purchased by one firm must be generated by another firm.

Because all shocks are realized before time T production decisions are made, firms are certain about compliance costs in the final period, and the problem is a static constrained optimization problem with no

[11] To see this, note that in any period the firm's optimality conditions can also be expressed as:

$$\left(P_t - C^{c'}_t(q^c_t) + \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \frac{\partial B_{t+1}}{\partial q^c_t} \right) q^c_t = 0$$
$$\left(P_t - C^{r'}_t(q^r_t) + \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \frac{\partial B_{t+1}}{\partial q^r_t} \right) q^r_t = 0$$
$$\left(-r_t + \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \frac{\partial B_{t+1}}{\partial c_t} \right) c_t = 0.$$

For convenience, we suppress the i subscripts in this footnote. The second term in each condition reflects the effect of the choice variables on the future periods' value function. Consider the second term in the conventional fuel optimality condition. Substituting forward:

$$\begin{aligned} \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \frac{\partial B_{t+1}}{\partial q^c_t} &= -\alpha \beta \mathbb{E}_t \frac{\partial V_{t+1}}{\partial B_{t+1}} \\ &= -\beta^{(T-t)} \alpha \mathbb{E}_t[\lambda_T] \end{aligned}$$

The first equality follows from the fact that $(\partial B_{t+1}/\partial q^c_t) = -\alpha$. The second equality follows from forward substituting due to the fact that increases (decreases) in the firm's bank does not affect the firm's value function until the final period. In the final period, we know $\lambda_T = r_T$, yielding our desired result. Similar arguments follow for the other optimality conditions.

uncertainty. This implies that, in the final period, each firm will choose the fuel mix such that $\lambda_{i,T}$ equals the RIN price, i.e., $r_T = \lambda_{i,T}$. If the policy constraint binds, then $B_{i,T+1} = 0$ for all i, and equations (5) - (7) imply $r_T \geq 0$ in equilibrium. If the policy does not bind, then $B_{i,T+1} > 0$ for at least some firms and the equilibrium price $r_T = 0$.

Prior to the final period, firms face uncertainty about whether the policy will bind. If the policy will bind with positive probability, then $\mathbb{E}_t[r_T] > 0$, and equations (3) and (4) imply that the policy taxes the conventional fuel and subsidizes the renewable fuel. To see this, note that in an interior solution, producing one unit of conventional fuel in t increases expected future compliance costs by $\alpha\mathbb{E}_t[r_T]$, the RVO associated with conventional fuel production, while producing one unit of renewable fuel reduces the discounted future expected compliance costs by $\mathbb{E}_t[r_T]$.

Each period, firms trade in the credit market until their individual compliance costs are equalized. Equation (5) states that the firm will buy or sell compliance credits until the discounted expected future marginal compliance cost equals the market clearing credit price in that period. Thus, RIN prices in a rational expectations equilibrium must satisfy:

$$r_t = \beta^{(T-t)}\mathbb{E}_t[r_T] \tag{8}$$

for $t \in [1, T]$. Furthermore, using equations (3) and (4) we can show as in Lade and Lin (2013) that the following holds:

$$r_T = \frac{1}{1+\alpha}\max\left(C_T^{r'}(q_T^r) - C_T^{c'}(q_T^c), 0\right), \tag{9}$$

where $C^{j'}(q^j)$ is the market supply curve for $j = c, r$ evaluated at market clearing quantity $q_T^j = \sum_i q_{i,T}^j$. Thus, RIN prices derive their value from the expected differential in the costs between the renewable and conventional fuels in the compliance period.

4.2 Implications and Extensions

The model has important implications germane to our study of RIN prices. First, the model illustrates that RIN prices follow Hotelling's rule, growing over time at the rate of interest in expectation.[12] Second, equations (8) and (9) state that RIN prices reflect expected future compliance costs, and increase (decrease) in the expected cost of the renewable (conventional) input. Because RIN prices adjust in each period as the market incorporates new information, any unanticipated shock changing the expected future stringency of the policy will immediately be reflected in RIN prices.

[12] To see this, let $\delta = \frac{1-\beta}{\beta}$ denote the discount rate. From equation (8), the change in RIN prices from one period to the next is given by:

$$\frac{\mathbb{E}_t[r_{t+1}] - r_t}{r_t} = \delta.$$

A third insight that can be inferred from the firms' optimality conditions in (3) and (4) is that a binding RFS2 has an equivalent price-based mechanism, namely instituting a revenue neutral tax on conventional fuels used to fund a subsidy for biofuels. The result is analogous to the equivalence between cap and trade programs and an emissions tax. We use this insight to quantify the value of changes in RIN prices due to the policy shocks in Section 6.

In Appendix A we extend the model along two dimensions. First, to understand the implications of the banking and borrowing restrictions, we allow for two compliance periods, T_1 and T_2, and restrict the amount of credits that can be banked or borrowed for compliance in the second period such that $\underline{B} \leq B_{T_1+1} \leq \overline{B}$.[13] We impose the RFS2 over both compliance periods by including the constraint $B_{T_2+1} \geq 0$, analogous to the constraint presented in the model in Section 4.1. Because the fuel industry has over-complied with RFS2 mandates to date, we give particular attention to the effect of banking restrictions on RIN prices. Given a binding banking restriction in the first compliance period, we show that market clearing RIN prices are equal to:

$$r_t = \begin{cases} \beta^{(T_2-t)}\mathbb{E}_t[r_{T_2}] - \beta^{(T_1-t)}\mathbb{E}_t[\overline{\Phi}] & \text{if } t \in [1, T_1] \\ \beta^{(T_2-t)}\mathbb{E}_t[r_{T_2}] & \text{if } t \in [T_1+1, T_2], \end{cases} \tag{10}$$

where $\overline{\Phi}$ is the Lagrange multiplier associated with the banking restriction and is greater than or equal to zero when the banking restriction binds. A binding banking restriction creates a wedge between RIN prices of the two compliance periods. While firms would like to produce more biofuel in the first compliance period, they are unable to fully arbitrage higher expected future compliance costs because of the restriction. Thus, a binding banking restriction limits arbitrage between compliance periods and creates an option value to RINs that can be used in future periods. The result is similar to Schennach (2000) and Pindyck (1993) for the case of SO_2 permits and commodity futures prices, respectively.

Equation (10) is written such that RINs in the second compliance period trade in $t \in [T_1+1, T_2]$. In reality, multiple RIN vintages trade concurrently. Thus, equation (10) implies that if future vintages trade at a premium to current vintages for the same RIN type, we can infer that the market expects the banking restrictions to bind.

Second, to analyze a nested mandate, we consider a model with two renewable inputs, $q^r_{1,t}$ and $q^r_{2,t}$. We assume there is an overall biofuel mandate and a nested mandate for $q^r_{2,t}$. For simplicity, we assume there is only one compliance period. We show that RIN prices for the overall mandate $r_{1,t}$ and RIN prices for the nested mandate $r_{2,t}$ are given by:

$$r_{1,t} = \beta^{(T-t)}\mathbb{E}_t[r_{1,T}] \quad \text{for } t \in [1, T] \tag{11}$$

$$r_{2,t} = \beta^{(T-t)}\left(\mathbb{E}_t[r_{1,T}] + \mathbb{E}_t[r_{2,T}]\right) \quad \text{for } t \in [1, T]. \tag{12}$$

[13] In this section, we suppress the i subscript for brevity.

Equations (11) and (12) state that RIN prices for the nested biofuel $q^r_{2,t}$ can never be less valuable than RIN prices for the overall biofuel mandate. This occurs because RINs for the nested mandate are used for compliance towards both mandates. Thus, if we observe a convergence between RIN types for the same vintage year such that $r_{1,t} = r_{2,t} > 0$, we can infer the industry is over-complying with the nested mandate in order to meet the requirements of the overall renewable fuel mandate. This insight allows us to explain the convergence in RIN prices across biofuel types in 2013.

5 Data

In this section, we discuss the data used for our empirical study of RIN prices. We also provide context around the three 'policy shocks' of interest. Last, to test whether RIN prices are consistent with predictions from our model presented in Section 4, we present results from a test of market efficiency.

5.1 Historical RIN Prices and Fuel Cost Data

The Oil Price Information Service (OPIS) is a main source of RIN prices.[14] OPIS determines prices through daily surveys of active market participants and reports a low, high and average price for each RIN type and vintage.[15] Prices for conventional RINs have been reported since April 2008, advanced RINs have been reported since January 2011, and biodiesel RINs have been reported since June 2009.

Figure 2 plots the average price for each RIN type from 2008-2014. Conventional RINs traded at relatively low prices in the program's early years. The highest observed price before 2013 was observed January 2009 when conventional RINs traded for $0.18/gal.[16] In January 2013, prices of all RINs rose sharply, reaching around $1.40/gal by July 2013. After this, prices fell sharply to around $0.40/gal the following year.

Prices of advanced and biodiesel RINs have been relatively high over their entire trading history. Both series experienced price run-ups in mid-2011 following increases in commodity market prices during the period, after which prices fell steadily. As with conventional RIN markets, both series experienced large increases beginning in January 2013 as well as fell sharply in August 2013.

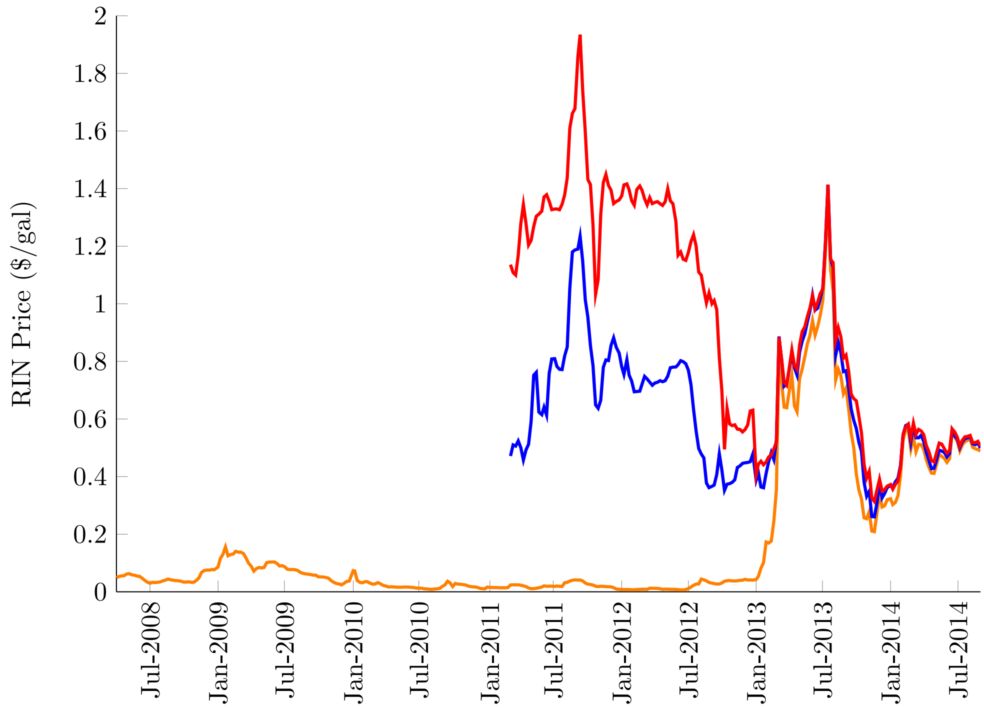
In late 2012 and early 2013, many market participants questioned why prices of conventional RINs were not higher. That year, more than 80% of US farmland was experiencing drought conditions (USDA Economic

[14]Phone conversations with an executive at a major oil refinery confirm OPIS is regularly cited and used as a basis when negotiating RIN sales and purchases.

[15]For more information on the methods used by OPIS to collect its data, see Oil Price Information Service (2014).

[16]This occurred as oil prices fell from their July 2008 high of over $140/barrel to around $40/barrel while other commodity market prices such as ethanol and corn remained relatively stable.

Figure 2: Historical RIN Prices*



*Note: The figure graphs average conventional (orange), advanced (blue), and biodiesel (red) RIN prices across all RIN vintages trading at the time. (Source: OPIS).

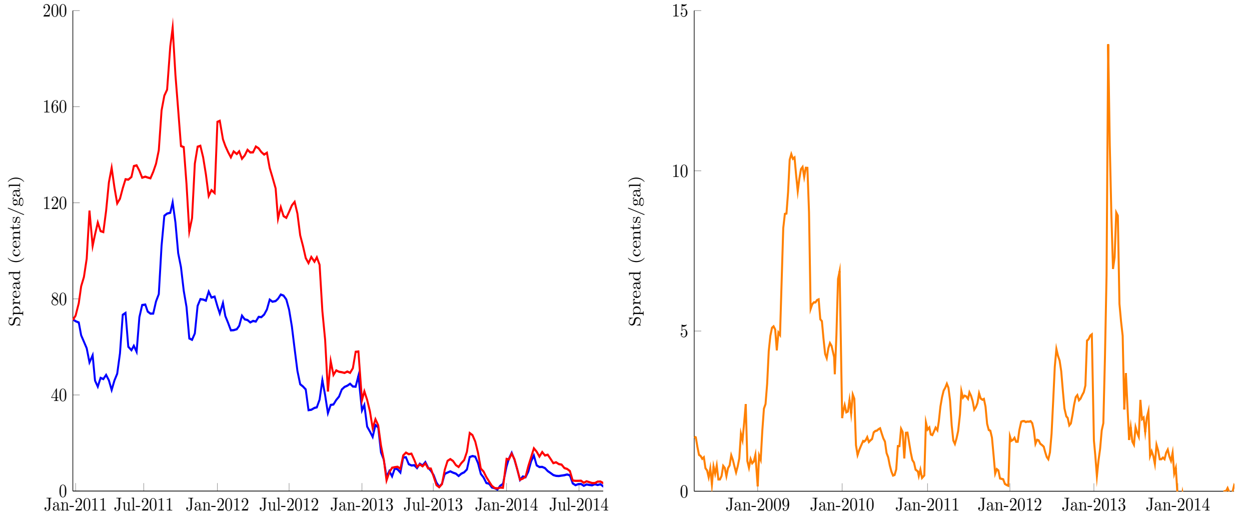
Research Service, 2013). In addition, the statutory 2013 EISA mandates were expected to exceed the blend wall for the first time. Both factors should have put upward pressure on conventional RIN prices in 2012.

Several explanations for this lack of movement were proposed. Thompson et al. (2012) suggest that the fuel industry may have expected the EPA to waive a portion of the 2013 total biofuel mandate. At the time, the release of the 2013 Proposed Rule had been delayed, which may have been perceived as a signal that the Agency was considering altering the statutory requirements. Others have argued that the market may have misperceived the increase in compliance costs beyond the blend wall.

The sharp increase in RIN prices in January 2013 corresponded closely to the release of the 2013 Proposed Rule, which maintained the overall EISA mandates for the year. The increase supports the hypothesis that the market interpreted the delayed release of the Rule as a signal that the EPA may waive a portion of the overall biofuel mandate. We do not include the 2013 Proposed Rule in our subsequent event study because interpreting the 2013 Proposed Rule as a 'policy shock' is less straightforward than the subsequent announcements.

Following the increase in RIN prices in January 2013, biodiesel, advanced, and conventional RIN prices converged. This is illustrated in Figure 3a, which graphs the spread between advanced and conventional

Figure 3: Relationship Across Biofuel Types and Vintages*



(a) Advanced and Biodiesel to Conventional Spread

(b) Front-Prior Conventional Spread

*Note: The left figure graphs the spread between front year biodiesel and conventional RIN prices (red) and advanced and conventional RIN prices (blue). The right graphs the spread between front and prior year RIN prices for conventional RINs.

RIN prices and biodiesel and conventional RIN prices. The spread decreased sharply in early 2013, with conventional RINs trading at nearly the same price as advanced and biodiesel RINs from 2013 through 2014. As discussed in Section 4.2, the convergence in RIN prices suggests that as the industry expected to over-comply with the biodiesel mandates in order to comply with the overall biofuel mandate as the mandate moved beyond the blend wall.

Our model predicts that if the banking restriction binds, prior year vintage RINs will trade at a discount to front (or current) year RINs. Figure 3b graphs the spread between conventional front and prior year RIN prices. From 2008 through the middle of 2013, the spread fluctuates and reaches as much as \$0.14/gal. The spread fell sharply in early 2013. This suggests that in the absence of the RFS2 banking restriction, the fuel industry would have blended more corn ethanol and carried a larger bank of RINs in early years.

In section 6, we study 2013 conventional, advanced, and biodiesel RIN prices. From our model, RIN prices should reflect expected future compliance costs. Future compliance costs are a function of both expected future fuel costs as well as expectations regarding the future stringency of the policy. To control for expected future fuel costs, we collect futures prices on July 2014 contracts for ethanol, soybean oil, and WTI crude, all from the Commodity Futures Exchange.[17] We choose July 2014 contracts because the series have traded over the entire observation period, and July contracts are typically among the most heavily traded. Results

[17]Ideally, we would observe a futures price series for biodiesel; however, such a series is not currently trading on a major exchange. As a result, we use soybean oil, the dominant feedstock for biodiesel in the United States, to control for biodiesel prices.

Table 1: Summary Statistics for Price Data (cents/gal)

	Mean	Std. Dev.	Min	Max	N
2013 Conventional (D6) RINs	44.92	33.37	4.75	145.5	423
2013 Advanced (D5) RINs	59.89	26.52	22	146.5	423
2013 Biodiesel (D4) RINs	71.74	26.86	23.5	146.5	423
July 2014 WTI Oil Futures	222.38	7.65	202.33	242.93	423
July 2014 Ethanol Futures	196.25	20.39	159	240.8	423
July 2014 Soybean Oil Futures	360.69	37.36	290.29	427.74	423

do not meaningfully change using other contracts. Table 1 presents summary statistics of the price series used in our analysis.

5.2 Policy Announcement Dates

We estimate the effect of three 'policy shocks' that led to large, unexpected reductions in the 2014 RFS2 mandates on RIN prices. The first event is the release of the 2013 Final Rule in August 2013. In the Rule, the EPA upheld the 2013 standards from the 2013 Proposed Rule; however, the Agency acknowledged for the first time the challenges with meeting the standard for 2014 and beyond, including the following language:

> *As described in the [Notice of Proposed Rule Making (NPRM)], we recognize that...for 2014 the ability of the market to consume ethanol as E15 [and] E85 is constrained in a number of ways. We believe that it will be challenging for the market to consume sufficient quantities of ethanol...and to produce sufficient volumes of non-ethanol biofuels...to reach the mandated 18.15 bill gal for 2014.* ***Given these challenges, EPA anticipates that adjustments to the 2014 volume requirements are likely to be necessary based on the projected circumstances for 2014****... EPA will discuss options and approaches for addressing these issues, consistent with our statutory authorities, in the forthcoming NPRM for the 2014 standards.*[18] [emphasis added]

Note that while the EPA implied it would likely reduce the mandates in the future, it gave no guidance as to what those adjustments would be. Subsequently in October 2013, a news article was published in Reuters leaking an early version of EPA's 2014 Proposed Rule. The article included the following discussion:

> *With two words, the US environment regulator may be handing oil refiners the biggest win of a long battle to beat back the seemingly inexorable rise of ethanol fuel.* ***In a leaked proposal that would significantly scale back biofuel blending requirements next year,*** *the US*

[18]The 18.15 billion gallon number corresponds to the overall biofuel mandate specified under EISA for 2014.

> *Environmental Protection Agency (EPA) says the blend wall - the 10 percent threshold of ethanol-mixed gasoline that is at the crux of the lobbying war - is an "important reality"....Regardless, according to an August 26 draft proposal seen by Reuters, the waiver has enabled the* ***EPA to cut the amount of corn-based ethanol that would be required in 2014 to 13 billion gallons. That is about 6 percent less than this year and well short of the 14.4 billion gallons required under the 2007 law,*** *but it is in line with a waiver request from two oil groups to cap the ethanol volume at 9.7 percent, about 12.88 billion gallons.* (Podkul, 2006) [emphasis added]

The article was the first insight into the EPA's coming cuts to the 2014 standard, and revealed that the EPA was considering reducing the overall standard not only below statutory levels, but below the 2013 mandates.

Our final event of interest is the release of the 2014 Proposed Rule in early November 2013 in which the EPA officially proposed reducing the overall biofuel standard.[19] In the Rule, the EPA proposed deep cuts to the overall biofuel standard, reducing the overall biofuel mandate 2.94 bgals below the EISA mandates and 1.34 bgals below the 2013 level. The proposed cuts are graphed in the right two columns of Figure 1a.

5.3 Testing the Efficiency of RIN Markets

To ascertain whether historical RIN prices have acted in a manner consistent with our theory model, we test the efficiency of RIN markets. There are some reasons to believe that RIN markets may fail to exhibit full price discovery. Proper reporting of RIN prices may be a concern given that RINs do not trade on a formal exchange and OPIS collects the data through daily surveys. In addition, several industry participants have called into question the efficiency of RIN markets (Morgenson and Gebeloff, 2013).

A key prediction from our model is that for each RIN type and vintage, prices from t to $t+1$ should satisfy:

$$r_t = \beta \mathbb{E}_t[r_{t+1}]. \tag{13}$$

Because we observe daily RIN prices and there is presumably no cost to storing RINs, it is reasonable to assume $\beta \approx 1$. Thus, equation (13) implies the following testable hypothesis:

$$H_0 : \mathbb{E}_t[\mathbf{x}_t(r_{t+1} - r_t)] = 0. \tag{14}$$

[19]The 2013 RFS2 Final Rule was released to the public on 08/06/2013, the Reuters article leaking an advanced version of the 2014 RFS2 Proposed Rule was published on 10/11/2013, and the 2014 RFS2 Proposed Rule was released on 11/15/2013. Dates for the Final and Proposed rules were determined by the date the EPA's news releases, which are often published a week or two in advance of the Rules' publication in the Federal Register.

Equation (14) states that in a rational expectations equilibrium, RIN prices should follow a random walk. A key implication of this is that RIN price changes from t to $t+1$ should be uncorrelated with any variables $\mathbf{x}_t$, i.e., RIN price movements should be unpredictable.

Testing equation (14) amounts to a test of market efficiency in the sense of Fama (1965), and is related to tests of the efficiency market hypothesis common in the finance literature (Lo and MacKinlay, 1988, 1999; Malkiel, 2005). It is important to note that unpredictability represents a necessary but not sufficient condition for market efficiency. If we find significant predictability in RIN markets, however, there would be reasonable cause for concern in proceeding with our empirics.

We test equation (14) using a forecasting exercise. Specifically, we construct a Model Confidence Set (MCS) comparing a large number of forecast models of RIN prices using the methods developed by Hansen et al. (2011). Here, we discuss the intuition behind the procedure and our findings. Appendix B provides a detailed description of the methods and results.

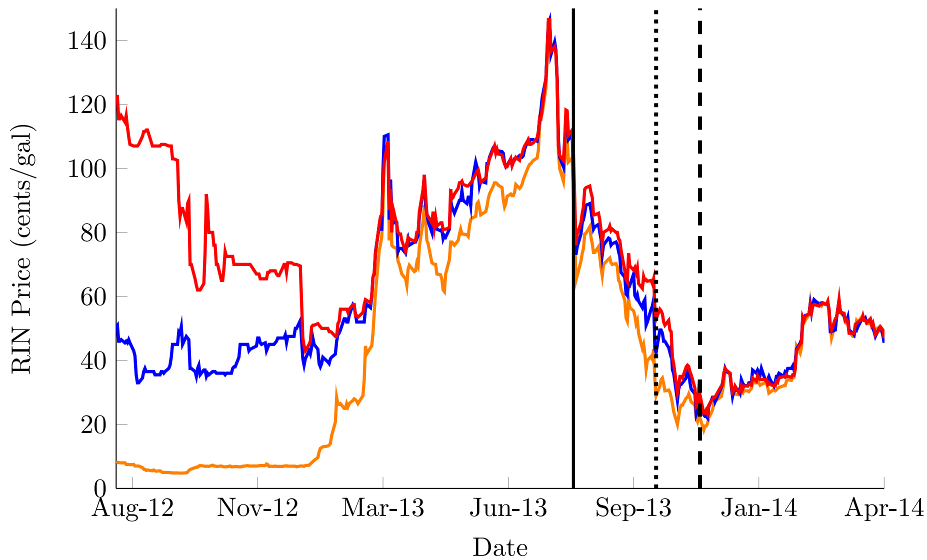
Given a set of predictors, $\mathbf{x}_t$, we construct and evaluate a large number of competing forecasts of RIN prices using combinations of $\mathbf{x}_t$. The Model Confidence Set identifies the best performing forecast model and estimates the set of models (the MCS) whose performance are statistically indistinguishable from it. Our objective is to evaluate the relative performance of the random walk forecast. If we find that the random walk forecast does not lie in the MCS, we would have significant cause for concern that RIN price movements have been predictable.

We construct the MCS for each RIN type and vintage, as well as a number of combined RIN series. In all cases, the random walk forecast is among the top performing models, and is never excluded from the MCS at conventional confidence levels. For advanced and biodiesel RINs, top competing models in several instances contain lagged differenced RIN prices, suggesting the series may exhibit price drift. The gains from using lagged RIN prices, however, dissipate when evaluating RIN price forecasts from week to week. This suggests there may be timing issues with daily reported RIN prices with some reported RIN prices reflecting previous day transaction prices. Alternatively, some of the early markets for advanced and biodiesel RINs may have been relatively illiquid from day to day. Overall, however, the exercise supports modeling RINs as a random walk, suggesting the market exhibits proper price discovery. This implies that the event study techniques used in the next section are suitable for our analysis.

6 Estimating Historical RIN Price Drivers

We now study historical drivers of RIN prices, focusing on the effect of the three policy shocks discussed in Section 5.2. Because the EPA's banking restrictions were binding for early conventional RIN vintages, aggregating RINs across all vintage years may induce non-linearities in the series (Smith, 2005). Thus, we

Figure 4: 2013 Vintage RINs*



*Note: The figure graphs 2013 conventional RIN prices (orange), advanced prices (blue), and biodiesel prices (red). The vertical solid line corresponds to the 2013 Final Rule release date, the dotted line is publication date of the Reuters article, and the dashed line is the 2014 Proposed Rule release date (Source: OPIS).

study only 2013 conventional, advanced, and biodiesel RIN vintages. Figure 4 graphs the series and the timing of the three policy shocks. As can be seen, the series traded prior to the large run-up in conventional RIN prices as well as during the subsequent decreases in prices in the latter half of 2013. On all three event dates, particularly the release of the 2013 Final Rule, all RIN prices appear to have experienced sharp decreases.

For all price series we conduct Dickey-Fuller GLS unit root tests using data from August 2012 through April 2014 (Elliot et al., 1996). The results are presented in Table 2. We cannot reject the presence of a unit root for any RIN series, suggesting that prices follow a random walk. The results are consistent with both our theoretical model and our findings from the Model Confidence Set exercise.

6.1 Estimation Strategy

To estimate the effect of fuel price changes and the three policy shocks on RIN prices, we adopt an event study framework. Other authors have used similar methods to estimate the effect of policy announcements on stock and commodity markets (Linn, 2010; Lemoine, 2013b; Bushnell et al., 2013). Our main specification is given by:

$$\Delta \log(r_t) = \alpha + \Delta \log(x_t)\beta + \sum_{m=1}^{3} \sum_{s=s_{m,0}}^{S} \gamma_{m,s}\tau_{m,s} + \varepsilon_t, \tag{15}$$

Table 2: Dickey-Fuller GLS Test Results*

	Lags		
Price Series	1	5	10
2013 RIN Series			
Conventional RINs	-0.869	-1.009	-1.193
Advanced RINs	-1.545	-1.468	-1.455
Biodiesel RINs	-1.819	-1.659	-1.560
July 2014 Commodity Futures Series			
Oil	-3.048*	-2.821	-2.757
Ethanol	-0.917	-0.863	-0.731
Soybean Oil	-2.339	-2.309	-2.441
S&P-GS Commodity Index	-3.161*	-3.076*	-3.322*

*Note: The table presents DF-GLS test statistics allowing for a time trend (Elliot et al., 1996). 5% critical values for lags 1, 5 and 10 are -2.88, -2.87 and -2.85, respectively. * denotes significance at 5%.

where $\Delta\log(r_t)$ are differenced log RIN prices, $\Delta\log(x_t)$ is a vector of differenced log prices for all energy and commodity market data, $\tau_{m,s}$ is an indicator for event m on trading day s, and $s \in [s_{m,0}, S]$ is the event window. We estimate equation (15) separately for conventional, advanced, and biodiesel RINs for the period August 2012 to April 2014, allowing the events and energy and feedstock price shocks to have differential effects on each RIN type.

In traditional event studies of firm stock market prices, normal returns are specified as a mean daily return and a return due to the stock price's co-movement with a market index (MacKinlay, 1997). Motivated by our model in Section 4, we specify normal returns for RINs as a mean daily return α plus returns to due changes in expected future fuel costs $\Delta\log(x_t)$. For our main specifications, we use commodity futures prices for WTI crude oil, ethanol, and soybean oil in x_t. In Appendix C we explore specification using other control variables for normal returns.[20]

Abnormal return estimates $\hat{\gamma}_{m,s}$ correspond to price changes during event m on day s that cannot be explained by changes in commodity and feedstock prices or the estimated average daily return. To see this, note that:

$$\hat{\gamma}_{m,s} = \Delta\log(r_t) - \hat{\alpha} - \Delta\log(x_t)\hat{\beta}$$

for all m and s. Thus, to the extent that commodity markets were also affected by our events of interest, $\hat{\gamma}_{m,s}$ estimates the returns outside of those due to adjustments in RIN prices to changes in commodity market prices.

Abnormal returns are attributable to event m so long as no other events outside of movements in x_t affected RIN markets on the dates of interest. Because we observe daily RIN prices, the assumption is less

[20]We also estimated specification using spot market prices. Results are not sensitive to the contract used.

restrictive than it would be for low frequency RIN prices. To control for other potential confounding factors, we also estimate specifications that include day of week effects, month of year effects, and control for a flexible polynomial of time.[21] The latter specification is analogous to a regression discontinuity design with time as the running variable and multiple breaks.

For each event, we calculate the cumulative abnormal returns (CARs) from the event over the window $s \in [s_{m,0}, S]$ as:

$$CAR_{m,S} = \sum_{s=s_{m,0}}^{S} \hat{\gamma}_{m,s},$$

for $m = 1, 2, 3$. If RIN markets do not fully internalize the change in expected future compliance costs on the event day, $CAR_{m,S}$ will capture adjustments in RIN prices due to event m over time horizon S. We consider two event windows: (i) a 2-day event window accounting for 2 trading days after each event; and (ii) a 5-day event window accounting for 5 trading days after the event.

Traditional inference about the hypothesis $H_0 : \gamma_{m,s} = 0$ may be inappropriate in event study settings (Conley and Taber, 2011; Gelbach et al., 2013). Because abnormal returns are estimated based on a single observation, asymptotic arguments do not apply, and t- and F- statistics may exhibit poor size and power properties. As a result, we use the sample quantile (SQ) test proposed by Gelbach et al. (2013) for our inference about all estimated abnormal returns.[22] The test uses the distribution of $\hat{\varepsilon}_t$ for all non-event days to estimate empirical critical values from the density of the residuals. As long as the error process is stationary, the distribution of the residuals and empirical critical values will converge to the true null distribution of abnormal returns as $T \rightarrow \infty$.

Given that the EPA's announcements resulted in substantial cuts to the RFS2 mandate, we also study the effects of the events on other markets. Because the RFS2 provides a major source of demand for biofuels and biofuel feedstocks, announcements changing expected future demand for biofuels may affect feedstock markets. We test this hypothesis by studying commodity futures markets following each event.

We use a similar estimation technique as equation (15) to test for abnormal returns in commodity markets. For all commodity prices except WTI crude oil prices, we specify $\Delta\log(x_t)$ as the S&P Goldman Sachs (S&P-GS) Commodity Index, traded on the Chicago Mercantile Exchange. The index is composed approximately 24 commodities, including a wide range of commodity futures prices with heavy weights for energy commodity futures prices. Abnormal return estimates therefore represent those returns that cannot be explained by a commodity specific mean daily return as well as corresponding movements in the S&P-GS

[21] We use a sixth order polynomial of time. More flexible functions do not change the results.

[22] Similar methods are used by Lemoine (2013b) to study commodity market movements after negotiations for a comprehensive climate bill in the US Senate ended unexpectedly.

[23] Given the importance of the RFS2 in driving demand for biofuel feedstocks, it is likely that large cuts to the RFS2 would cause adjustments in multiple markets. To the extent that non-feedstock prices were affected by the events, our results are downward biased.

Commodity Index. To the extent that the S&P-GS index was unaffected by the EPA announcements, the regression allows us to identify abnormal returns in the futures series most directly affected by the announced RFS2 cuts relative to other commodity markets that are less affected by the EPA announcements.[23] Because crude oil prices constitute a large share of the S&P-GS commodity index, we specify normal returns for WTI contracts as those due to a mean daily return and co-movement with the Russell 3000 stock market index.

We also test for abnormal stock market returns for publicly traded biofuel companies. We specify normal returns as a firm specific mean daily return and the covariance of the firm's returns with a broad market index, the Russell 3000 index. We estimate a joint model of average abnormal returns for biofuel firms and allow for differential effects for advanced, biodiesel, and cellulosic biofuel firms. The estimated equation is:

$$\Delta\log(R_{it}) = \alpha_i + \Delta\log(x_{it})\beta + \mathbf{1}_\kappa \sum_{m=1}^{3} \sum_{s=s_{m,0}}^{S} \gamma_{m,s}\tau_{i,m,s} + \varepsilon_{it} \tag{16}$$

where i denotes the firm, $\Delta\log(R_{it})$ are differenced log stock prices, $\Delta\log(x_{it})$ are differenced log prices for the stock market index, $\tau_{i,m,s}$ are indicators for event m for firm i on trading day s, and $\mathbf{1}_\kappa$ is an indicator equal to one if firm i produces or has large investments in biofuel category κ. In our regressions, κ includes conventional, advanced, and biodiesel producers. For both commodity returns and stock returns, we include specifications using flexible time controls as in our RIN price regressions.

6.2 Results: RIN Returns

Table 3 presents our estimation results for 2013 conventional, advanced and biodiesel RINs. All reported standard errors for normal return estimates are computed using the Newey-West estimator allowing for arbitrary autocorrelation in the residuals. No normal returns are statistically significant, however, the sign of all point estimates are consistent with our theory model. The estimates suggest a one percent increase in WTI prices decrease RIN prices between 0.3%-0.46%, a one percent increase in ethanol prices increases RIN prices by 0.02%-0.25%, and a one percent increase in soybean oil prices increases RINs between 0.22%-0.66%. The results suggest little variation in RIN prices over the sample period was due to movements in commodity markets, which were relatively stable in 2013.

Abnormal return estimates find large and significant movements in all three series around the three events, especially following the release of the 2013 Final Rule. The day the 2013 Final Rule was released, conventional RINs experienced a 11%-13% abnormal loss, advanced RINs decreased between 12%-13%, and biodiesel RINs lost approximately 6% of their value.

Figure 5 graphs cumulative abnormal returns for each series following the events. Within two trading days after the release of the Rule, conventional RIN prices fell 40%-47%, and advanced and biodiesel RINs fell between 35%-42%. Cumulative abnormal returns recover slightly for a 5-day window, with losses ranging from 18% to 36% across the series.

Table 3: Regression Results - Dependent Variable: Log 2013 RIN Price Changes*

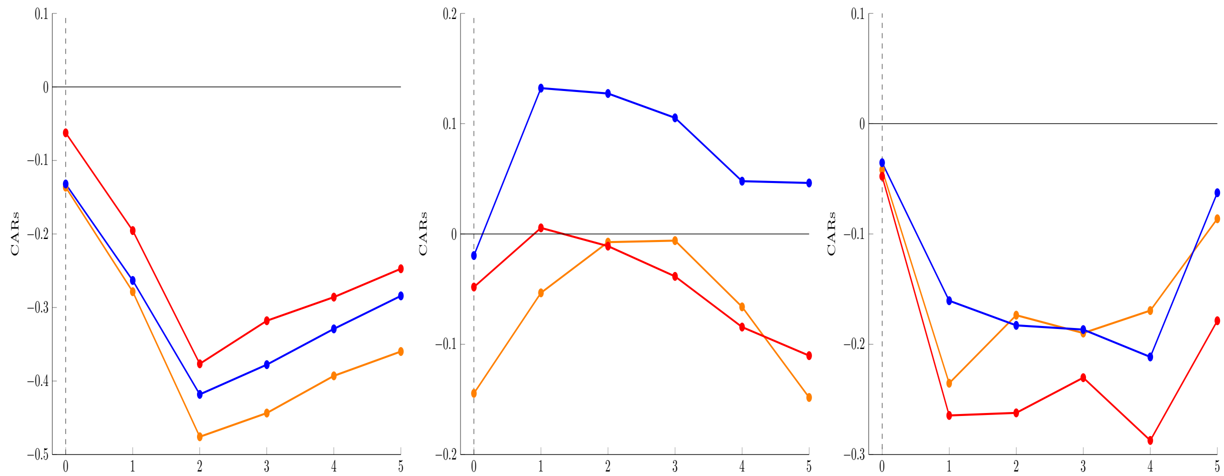
		Conventional RINs		Advanced RINs		Biodiesel RINs	
		(1)	(2)	(1)	(2)	(1)	(2)
Normal Returns							
Oil Futures		-0.460	-0.455	-0.361	-0.340	-0.313	-0.294
		(0.369)	(0.364)	(0.345)	(0.352)	(0.342)	(0.351)
Ethanol Futures		0.259	0.202	0.084	0.025	0.226	0.153
		(0.219)	(0.228)	(0.276)	(0.278)	(0.248)	(0.250)
Soybean Oil Futures		0.569	0.602	0.218	0.280	0.664	0.677
		(0.336)	(0.351)	(0.399)	(0.405)	(0.390)	(0.402)
Constant		0.006	0.069	0.001	-0.031	-0.001	-0.006
		(0.004)	(0.043)	(0.003)	(0.037)	(0.003)	(0.037)
Abnormal Returns	Day						
2013 Final Rule	0	-0.136**	-0.113**	-0.131*	-0.113*	-0.061	-0.053
	1	-0.142**	-0.125**	-0.131*	-0.116*	-0.133**	-0.127**
	2	-0.197**	-0.173**	-0.155**	-0.131*	-0.181**	-0.163**
	3	0.030	0.051	0.038	0.055	0.057	0.066
	4	0.050	0.067	0.047	0.058	0.030	0.045
	5	0.031	0.060	0.043	0.063	0.037	0.047
Reuters Article	0	-0.144**	-0.135**	-0.019	0.013	-0.047	-0.034
	1	0.091	0.096	0.151	0.177	0.053	0.070
	2	0.046	0.061	-0.004	0.030	-0.017	-0.002
	3	0.001	0.010	-0.023	0.008	-0.029	-0.016
	4	-0.060	-0.045	-0.057	-0.018	-0.046	-0.024
	5	-0.083*	-0.071	-0.003	0.028	-0.027	-0.012
2014 Proposed Rule	0	-0.042	-0.020	-0.035	-0.025	-0.047	-0.045
	1	-0.193**	-0.177**	-0.124*	-0.121*	-0.216**	-0.211**
	2	0.061	0.088	-0.022	-0.011	0.002	0.004
	3	-0.015	0.004	-0.003	0.005	0.032	0.033
	4	0.019	0.046	-0.027	-0.011	-0.059	-0.047
	5	0.083	0.104	0.149	0.155	0.108	0.110
Flexible Time Controls		No	Yes	No	Yes	No	Yes
N		422	422	422	422	422	422
SQ 5% Critical Values		-0.0786	-0.0804	-0.0997	-0.0935	-0.0682	-0.0722
SQ 1% Critical Values		-0.1001	-0.0999	-0.1412	-0.1374	-0.1309	-0.124

*Note: Standard errors in parentheses are Newey-West errors with 5 lags. Inference for abnormal returns are based on SQ critical values. The lower tail SQ critical values are given at the bottom of the table. Stars denote significance with * $p<0.05$ and ** $p<0.01$.

CARs are more varied following the Reuters article and 2014 Proposed Rule. Following the publication of the Reuters article, conventional RIN prices decreased initially, recovered over a 2-day horizon, but fell again over a 5-day horizon. Biodiesel RINs followed a similar trajectory. Advanced RIN prices do not appear to have been affected by the release of the Reuters article. Following the release of the Proposed Rule, all RIN categories followed a similar trajectory initially, decreasing by approximately 30% over 2 trading days before slightly recovering over a 5-day horizon.

Figure 5: RIN Cumulative Abnormal Returns*

(a) 2013 Final Rule Release (b) Reuters Article (c) 2014 Proposed Rule Release



*Note: The figure graphs cumulative abnormal returns (CARs) for conventional RINs in orange, advanced RINs in blue, and biodiesel RINs in red. The event day is normalized to day 0.

One way to measure the impact of the abnormal losses is to calculate the change in the value of the subsidy (tax) provided by the program for the biofuel (fossil fuel) industry in 2013 due to the event. This is equal to the value of the 2013 Renewable Volume Obligation (RVO).[24] To estimate this, we multiply the 2013 RVO mandate volumes by the abnormal return estimates for each event and mandate.

Results are presented in Table 4.[25] The largest losses occur after the 2013 Final Rule was released. On the day the 2013 Final Rule was released, the estimated abnormal return corresponds to a decrease in the value of the 2013 RVO of between $1.97-$2.4 billion. Within the two subsequent trading days, the cumulative abnormal returns correspond to a loss in value of the 2013 RVO between $7.4-$8.5 billion. Losses are smaller following the release of the Reuters article and 2014 Proposed rule. Event day losses following the publication of the Reuters article are significant and on the order of $600-$830 million. Cumulative losses recover over a 2 day horizon, but fall over a longer event horizon. Following the release of the 2014 Final Rule, event day

[24]The RVO is given by the right-hand side of equation (1) summed over all firms for each fuel type.

[25]To calculate the change in the value of the RVO and corresponding standard errors, we estimate a fully interacted panel analogue of equation (15) so that estimates correspond to those in specification (1) for each RIN type. We cluster standard errors at the month to allow for arbitrary serial correlation and correlation across RIN types. For each event and horizon, we convert the abnormal return estimates the $/gal and multiply the value by the 2013 mandate volumes for each biofuel type. The mandated biofuel volumes for 2013 were 13.8 bgals, 0.83 bgals, and 1.92 bgals for conventional biofuel, advanced biofuel and biodiesel, respectively.

[26]To give a sense of magnitude of the losses, nameplate capacity construction costs for a typical Iowa ethanol and biodiesel plant are around $2/gal (Hofstrand, 2014). Thus, the cumulative 5 day losses following the release of the 2013 Final Rule could have been used to increase biofuel production capacity between 14%-20% (Nebraska Energy Office, 2014; Biodiesel Magazine, 2014).

Table 4: Change in Value of the 2013 Renewable Volume Obligation*

Event	Event Window	Δ in 2013 RVO Value ($ bil)	95% Confidence Interval
2013 Final Rule	Event Day	-$2.185**	[-$2.398, -$1.971]
	2 Day	-$7.960**	[-$8.490, -$7.431]
	5 Day	-$5.994**	[-$6.870, -$5.118]
Reuters Article	Event Day	-$0.7303**	[-$0.828, -$0.633]
	2 Day	$0.001	[-$0.149, $0.151]
	5 Day	-$0.802**	[-$1.082, -$0.522]
2014 Proposed Rule	Event Day	-$0.169**	[-$0.216, -$0.122]
	2 Day	-$0.746**	[-$0.861, -$0.630]
	5 Day	-$0.396**	[-$0.589, -$0.203]

*Note: The table presents the change in the value of the 2013 Renewable Volume Obligation (RVO) due to each event. To calculate the change in the value of the 2013 RVO, we estimate a panel version of equation (15), allowing for differential effects of each event and energy variable for each RIN type. Standard errors are clustered by month to control for serial correlation in each RIN series as well as correlation across RINs. For each event window, we calculate the change in the value of the RVO and corresponding confidence interval by converting the point estimates for each event, window, and type of RIN to $/gallon and multiplying each loss by the corresponding RVO for each biofuel category.

loss estimates range between $120-$215 million, and increase over a 2 and 5 day horizon.[26]

6.3 Results: Commodity and Biofuel Stock Returns

Table 5 presents abnormal return estimates and SQ critical values for WTI crude oil, ethanol, soybean oil, corn, and sugar futures contracts. Overall, we find little movement in these commodity markets around the events. Few abnormal return estimates in each event window are statistically significant, and most significant returns occur several days after the events and are therefore unlikely to be attributable to them. The one exception occurs in soybean oil markets on the day the Reuters article was published, where we estimate an abnormal loss of -1.9%.

The loss in soybean oil markets can be rationalized by recalling that the Reuters article revealed for the first time that the overall biofuel mandate would likely be set below 2013 levels. Before the release of the 2013 Final Rule, the convergence of RIN prices across biofuel types indicated that biodiesel was the marginal compliance fuel for the overall biofuel mandate (Irwin, 2014a,b). The cuts discussed in the Reuters article, however, signaled that the 2014 standards would be set below the blend-wall, effectively reducing demand for biodiesel as the marginal compliance fuel for the overall mandate.

We also estimate abnormal and cumulative abnormal returns for the 12 publicly traded biofuel producers listed in Table 6.[27] For each producer, we classify them as a producer or investor in conventional ethanol,

[27] There are many more biofuel producers, however, most are privately owned.

Table 5: Commodity Market Abnormal Return Estimates*

	Day	WTI Crude		Ethanol		Soybean Oil		Corn		Sugar	
		(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
2013 Final Rule	0	-0.006	-0.009	0.006	0.003	-0.008	-0.011	0.000	-0.004	0.001	0.001
	1	-0.002	-0.004	-0.008	-0.009	-0.007	-0.010	-0.000	-0.003	0.016	0.017
	2	-0.008	-0.012	0.002	0.002	0.001	-0.001	0.007	0.006	-0.001	-0.001
	3	0.012	0.009	-0.036**	-0.040**	-0.007	-0.008	-0.015	-0.017	0.006	0.005
	4	0.006	0.002	0.000	-0.003	0.017	0.016	0.019	0.015	0.004	0.004
	5	0.005	0.003	-0.019	-0.021	0.005	0.002	-0.033*	-0.037*	0.002	0.003
Reuters Article	0	-0.006	-0.006	-0.008	-0.010	-0.019*	-0.017*	-0.009	-0.007	0.011	0.011
	1	0.000	0.000	0.001	-0.001	0.003	0.004	0.007	0.006	0.005	0.006
	2	-0.002	-0.001	0.012	0.011	0.009	0.008	0.016	0.015	-0.015	-0.013
	3	0.003	0.005	0.007	0.007	0.015	0.014	-0.004	-0.003	0.012	0.015
	4	-0.019*	-0.019*	-0.007	-0.006	-0.001	-0.001	0.003	0.007	0.002	0.003
	5	0.002	0.003	-0.002	-0.004	0.012	0.013	-0.004	-0.001	0.014	0.014
2014 Proposed Rule	0	-0.003	-0.003	-0.006	-0.008	-0.013	-0.011	-0.014	-0.013	-0.000	0.000
	1	-0.007	-0.007	0.004	0.003	-0.007	-0.004	-0.020	-0.021	0.009	0.010
	2	-0.000	0.001	-0.001	-0.002	-0.001	-0.001	0.013	0.011	-0.001	0.000
	3	0.003	0.005	0.026*	0.026*	0.007	0.007	-0.004	-0.004	0.003	0.005
	4	0.010	0.009	0.004	0.006	0.024*	0.025*	0.007	0.009	-0.001	0.000
	5	-0.004	-0.004	-0.012	-0.014	-0.007	-0.006	-0.001	0.001	-0.006	-0.006
Flexible Time Controls		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N		422	422	422	422	422	422	422	422	422	422
Sample Quantile Critical Values											
95%	Lower	-0.018	-0.019	-0.021	-0.023	-0.016	-0.015	-0.024	-0.026	-0.018	-0.018
	Upper	0.017	0.017	0.023	0.023	0.019	0.018	0.024	0.024	0.022	0.020
99%	Lower	-0.030	-0.028	-0.030	-0.029	-0.021	-0.021	-0.041	-0.038	-0.027	-0.027
	Upper	0.024	0.025	0.033	0.032	0.030	0.027	0.049	0.047	0.027	0.026

Note: SQ test critical values are estimated from the empirical residual distribution. Abnormal returns represent those that cannot be explained by corresponding movements in the S&P-GS Commodity Index, or in the case of WTI crude, the Russell 3000 Index, and a daily mean return. * denotes the hypothesis is rejected at the 5% empirical critical value and ** denotes the hypothesis is rejected at the 1% empirical critical value.

Table 6: Biofuel Producers and Categories*

Firm	Ticker	Categories
Archer Daniels Midland	ADM	Conventional, Biodiesel
Andersons Inc.	ANDE	Conventional
Cosan, Ltd.	CZZ	Advanced
FutureFuel Corp	FF	Biodiesel
Gevo, Inc.	GEVO	Advanced
Green Plains Renewable Energy	GPRE	Conventional
Methes Energies International	MEIL	Biodiesel
Neste Oil	NTOIY	Biodiesel
Pacific Ethanol	PEIX	Conventional, Advanced
Renewable Energy Group, Inc.	REGI	Biodiesel
Solazyme, Inc.	SZYM	Biodiesel

*Note: Categories reflect whether firms either produce or have significant investments in a particular advanced biofuel category. If a firm has no assigned category, the firm predominantly produces conventional corn-based ethanol.

advanced ethanol, or biodiesel. We then estimate equation (16) using the indicators for each category. Thus, reported abnormal returns represent average abnormal returns for all companies within a given category. Table 7 summarizes the abnormal and cumulative abnormal return estimates, and presents p-values for a F test of H_0: $\sum_{s_{m,0}}^{S} \tau_{m,s} = 0$ for each event m and event window S. Separate event study estimates by firm are presented in Appendix C.

Conventional ethanol producers did not experience significant abnormal returns following any of the three events. Advanced ethanol producers, however, experienced large, statistically significant losses on the order of 3%-12% following the release of the 2013 Final Rule, and small but insignificant cumulative losses following the release of the Reuters article. Abnormal returns for advanced producers are positive but statistically insignificant following the release of the 2014 Proposed Rule.

Biodiesel producers experienced small, insignificant abnormal losses following the release of the 2013 Final Rule that recover over a 2 or 5 day horizon. Event day losses following the release of the Reuters article are on the order of 1%-1.2% and statistically significant. The losses increase over a 2-5 day horizon to over 2% on average, but are statistically insignificant. The results are consistent with our findings in soybean oil markets, suggesting the revelation that the mandates would be below 2013 levels led to decreases in expected biodiesel demand. Returns are negative but insignificant following the release of the 2014 Proposed Rule.

7 Discussion and Implications

We find the announcement by the EPA that it would likely reduce the 2014 mandates and the two subsequent events confirming the cuts were responsible for large decreases in RIN prices in 2013. In addition, we find evidence that the events had adverse impacts on advanced biofuel firms and soybean oil markets, but did not

Table 7: Cumulative Abnormal Returns: Biofuel Companies*

		Conventional Producers		Advanced Producers		Biodiesel Producers	
		(1)	(2)	(1)	(2)	(1)	(2)
2013 Final Rule	Event Day	-0.0032	-0.0081	-0.0247*	-0.0317*	-0.0038	-0.0115
		(0.7059)	(0.3848)	(0.0185)	(0.0116)	(0.7572)	(0.4319)
	2 Day	0.0030	-0.0075	-0.0706*	-0.0853**	0.0157	-0.0007
		(0.9047)	(0.7414)	(0.0109)	(0.0055)	(0.5939)	(0.9836)
	5 Day	0.0068	-0.0135	-0.0941*	-0.1223**	0.0332	0.0017
		(0.8696)	(0.7155)	(0.0117)	(0.0065)	(0.3308)	(0.9692)
Reuters Article	Event Day	-0.0045	-0.0024	-0.0055	-0.0026	-0.0122**	-0.0090*
		(0.5610)	(0.7585)	(0.5143)	(0.7390)	(0.0084)	(0.0184)
	2 Day	-0.0073	-0.0023	-0.0045	0.0025	-0.0287	-0.0208
		(0.5621)	(0.8455)	(0.7916)	(0.8933)	(0.1426)	(0.3368)
	5 Day	-0.0253	-0.0135	-0.0311	-0.0145	-0.0213	-0.0028
		(0.2445)	(0.5087)	(0.3047)	(0.6292)	(0.1373)	(0.8154)
2014 Proposed Rule	Event Day	-0.0225	-0.0206	0.1211	0.1238	-0.0057	-0.0028
		(0.2543)	(0.3138)	(0.0952)	(0.0910)	(0.7021)	(0.8570)
	2 Day	-0.0435	-0.0393	0.0465	0.0523	-0.0462	-0.0398
		(0.2154)	(0.2498)	(0.1273)	(0.1084)	(0.2713)	(0.3931)
	5 Day	0.0425	0.0517	0.0963	0.1091	-0.0682	-0.0540
		(0.2629)	(0.2260)	(0.1144)	(0.1132)	(0.1240)	(0.3107)
Flexible Time Controls?		No	Yes	No	Yes	No	Yes
N		3685	3685	3685	3685	3685	3685

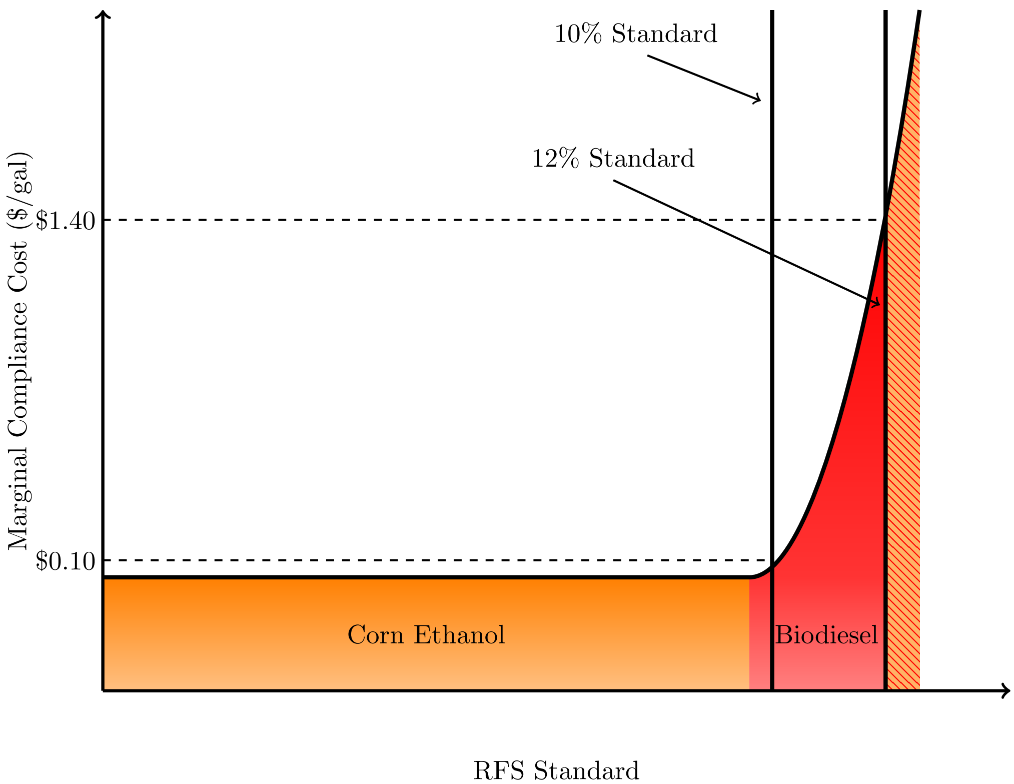
*Note: Stars denote significance with * p<0.05 and **p<0.01. Abnormal return p-values in parentheses are computed for the F test with 10 degrees of freedom of H_0: $\sum_{s_{m,0}}^{S} \tau_{m,s} = 0$ for each event m and event window S. Model (1) estimates normal returns as a mean constant return and those due to returns in the aggregate stock market index. Model (2) includes flexible time controls.

affect the stock price of conventional biofuel producers or other commodity markets. Our findings suggest that the short-run marginal compliance cost curve for the overall biofuel mandates are relatively flat until mandate reaches the blend wall, after which it increases sharply.

Figure 6 graphs a hypothetical marginal compliance cost curve in the spirit of our findings. In the Figure, until the RFS2 standard reaches 10%, marginal compliance costs are below \$0.10/gal, and the industry complies with the overall biofuel standard by increasing blending of conventional corn ethanol. As the standard moves beyond 10%, the marginal fuel used to meet the overall biofuel standard is biodiesel, which is much costlier due to both higher feedstock costs as well as binding production capacities. Beyond a 12% standard, marginal compliance costs continue to increase sharply and the industry complies through

[28] Because RIN prices reflect expected future compliance costs due to the ability of firms to bank compliance credits, the anticipation of moving beyond 10% would lead to large increases in RIN prices.

Figure 6: Hypothetical Marginal Compliance Curve*



*Note: The figure graphs a hypothetical short-run marginal compliance cost curve for the RFS2 consistent with observed movements in the market in 2013. Above a 10% standard, the industry must move to more costly compliance options, increasing biodiesel production. Beyond a 12% standard, the industry increases high blend ethanol and biodiesel.

increasing sales of high blend ethanol and increasing biodiesel production.[28]

Our paper highlights a policy that may substantially benefit from the inclusion of an alternative compliance mechanism such as a non-compliance penalty or the availability of compliance credits through a credit window. Both mechanisms would ensure compliance costs do not exceed untenable levels, and would modify the program from being a pure quantity based mechanism into a hybrid price-quantity mechanism. Such hybrid mechanisms are not new in the literature (Roberts and Spence, 1976; Weitzman, 1978; Pizer, 2002; Newell et al., 2005); however, empirical support for such designs has been limited to date as few programs have experienced the degree of volatility observed in RIN markets in 2013.

A number of policies currently in place and being proposed in the energy sector share many features with the RFS2. Thus, our findings have important implications for how to better design these policies. In particular, our findings show that pure quantity based mechanisms leave policies susceptible to large increases in compliance costs, particularly in the presence of capacity or production constraints that are inherent in energy markets. Given the experiences with the RFS2 in 2013, anticipating and designing these policies in a way that can account for these features is imperative.

8 Conclusions

Our paper provides a comprehensive study of compliance credit prices from a relatively new class of market-based policies. We illustrate the importance of modeling the programs using a dynamic framework under uncertainty in order to rationalize observed compliance credit prices. We also illustrate the effect of both the sub-mandate structure of the RFS2 on the relationship between RINs across biofuel categories as well as the role of banking restrictions on the relationship between RIN prices across vintage years. Given the over-the-counter nature of trading in RIN markets and concerns of potential manipulation, we provide a test of market efficiency that can readily be applied to other compliance credit markets.

Studying 2013 RIN vintages, we find that policy announcements that reduced the expected future mandate levels led to large reductions in RIN prices. We estimate that the release of the 2013 Final Rule decreased the value of the subsidy (tax) the policy provides for the biofuel (fossil fuel) industry by between \$7.44 and \$8.4 billion over a two day horizon for the 2013 compliance year alone. This represents a large change in the signal the RFS2 provides for the biofuel industry. We find the firms most affected by the events were firms with significant investments in advanced biofuels, and that large corn ethanol producers were largely unaffected by the events. The finding supports the notion that compliance with the program is relatively inexpensive up to a 10% gasoline-ethanol blend, after which marginal options become costly.

Our findings illustrate the importance of designing policies such as the RFS2 in a way that can manage compliance cost expectations. Rather than following a reactionary policy and relaxing mandates when credit prices increase, policy-makers can instead create a clear, transparent rule for instances in which credit prices reach untenable levels. For example, a policy could include provisions that place a ceiling and floor on compliance credit prices (Roberts and Spence, 1976; Weitzman, 1978; Pizer, 2002; Newell et al., 2005; Lade and Lin, 2015). Such policy designs would likely increase the policy's efficiency and prevent instances like those observed in RIN markets from occurring in the future.

Quantity mechanisms using tradeable credits are an important tool used by regulators, and are especially popular for addressing climate change concerns. Future research further studying the issues highlighted above may help illuminate the discussions here regarding the relative efficiency of quantity and hybrid price-quantity mechanisms. In addition, continued research along this front, both in developing more methods to test the market efficiency of tradeable credits as well as to study the efficiency of other tradeable credit markets, is desirable.

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A Dynamic Model of Compliance: Extensions

Consider an industry composed of N firms complying with the Renewable Fuel Standard. Suppose each firm uses two types of inputs in production of fuel Q: (i) cheap and abundant conventional inputs $\mathbf{q}^c$ and (ii) costly renewable inputs $\mathbf{q}^r$. Each unit of the renewable input generates a compliance credit $\mathbf{c}$ that can be sold to other firms at time t for market clearing price $\mathbf{r}_t$. Let t denote time and T denote the compliance period that does not necessarily correspond to t. For example, time t may be measured in months or weeks while compliance is due at the end of each year in period T.

We allow uncertainty to enter firms' maximization problems through several avenues. In each period, we assume firms may experience a common price (demand) shock θ_t^p, a cost (supply) shock θ_t^j for $j = c, r$, and a policy shock θ_t^α. We denote the tuple by Θ_t, and assume all shocks are realized at the beginning of t before firms make their production decisions for the period. Thus, firms make production decisions knowing the current value and history of all shocks, but not the value of future shocks. We assume every firm knows the distribution of the parameters and is able to form consistent, rational expectations given a realized history of shocks.

We define the state variable(s) $\mathbf{B}_t$ as the amount of banked credits, where $\mathbf{B}_t$ may be a vector or single valued. Let $\Pi_{i,t}(\cdot)$ denote firm i's per period profit function. The most general formulation of our dynamic compliance problem for each firm is given by:

$$V_{i,t}(B_{i,t};\Theta_t) = \max_{\substack{\mathbf{q}_{i,t}^c, \mathbf{q}_{i,t}^r \geq 0, \\ c_t}} \Pi_{i,t}(\mathbf{q}_{i,t}^c, \mathbf{q}_{i,t}^r, \mathbf{c}_{i,t}; \mathbf{B}_{i,t}, \Theta_t) + \beta \mathbb{E}_t[V_{i,t+1}(\mathbf{B}_{i,t+1}; \Theta_{t+1})]$$

$$\begin{aligned} \text{subject to} \quad & \mathbf{B}_{i,t+1} = G_{i,t}(\mathbf{q}_{i,t}^c, \mathbf{q}_{i,t}^r, \mathbf{c}_{i,t}, \mathbf{B}_{i,t}; \Theta_t) \\ & H_{i,t}(\mathbf{B}_{it}; \Theta_t) \geq 0 \qquad t = 1, \cdots, T \\ & \mathbf{B}_{i,1} = 0. \end{aligned}$$

where $V_{i,t}(\cdot)$ is firm i's Bellman equation, β is the discount factor, $G(\cdot)$ governs the motion of the state variable(s), and $H(\cdot)$ are constraints on the state variable(s) in each period. Policy constraints are imposed through $H_{i,t}(\cdot)$, and are generally expressed as restrictions on the amount of banked credits carried into the period after T.

We consider two extensions to the model presented in Section 4. First, we allow for two compliance periods and impose banking and borrowing restrictions on the amount of RINs that can be carried between the compliance periods. For this model, we maintain the assumption that firms produce Q using only one conventional and one renewable input. Thus, the model allows us to understand the relationship between RIN vintages over time.

Second, we assume firms produce Q using a conventional and two renewable inputs, and allow for a mandate on the overall volume of the renewable inputs as well as a sub-mandate on one renewable input over a single compliance period. This allows us to understand the relationship between RIN types for the same vintage year.

For both scenarios, we posit M consumers with quasilinear, time separable preferences, with aggregate fuel demand given by:

$$D_t(P) = \sum_{m=1}^{M} x_{mt}(P), \qquad t = 1, \cdots, T_2.$$

A.1 Implication of Banking Restriction for RIN Prices

As in Section 4, we consider the case of one conventional and one renewable input, and assume every gallon of renewable fuel generates a compliance credit c_t that can be sold at market clearing price r_t. Suppose there are two compliance periods. The first compliance period occurs for $t \in [1, T_1]$ with corresponding mandate α_1, and the second compliance period occurs for $t \in [T_1 + 1, T_2]$ with mandate α_2. We write the policy constraint for each firm over both periods as:

$$\sum_{t=1}^{T_2}(q_t^r + c_t) \geq \alpha_1 \sum_{t=1}^{T_1} q_t^c + \alpha_2 \sum_{t=T_1+1}^{T_2} q_t^c.$$

where we suppress the i subscript for brevity. We allow firms to either over- or under- comply with the policy in the first compliance period, but limit the extent to which they may do so. Thus, we write the policy constraint in the first compliance period as:

$$\underline{B} \leq \sum_{t=1}^{T_1}(q_t^r + c_t) \leq \overline{B},$$

where $\underline{B}$ and $\overline{B}$ are the borrowing and banking restrictions, respectively. The constraint in T_2 is the same as in Section 4.

We rewrite the two policy constraints in terms of the amount of banked RINs as:

$$B_{T_2+1} \geq 0,$$

$$\underline{B} \leq B_{T_1+1} \leq \overline{B}.$$

Given the above setup, we write each firm's Bellman equation in each period as:

$$V_t(B_t;\Theta_t) = \max_{\substack{q_t^c, q_t^r \geq 0, \\ c_t}} P_t(q_t^c + q_t^r) - C_t^c(q_t^c) - C_t^r(q_t^r) - r_t c_t + \beta \mathbb{E}_t V_{t+1}(B_{t+1};\Theta_{t+1})$$

$$\begin{aligned} \text{subject to} \quad B_{t+1} &= B_t + q_t^r + c_t - \alpha_\tau q_t^c \\ \underline{B} &\leq B_{T_1+1} \leq \overline{B} \\ B_{T_2+1} &\geq 0 \\ B_1 &= 0. \end{aligned}$$

Given the finite time horizon, the problem is solved recursively. Let λ_{T_2} denote the firm's Lagrange multiplier on the RFS constraint. The Karush-Kuhn-Tucker (KKT) conditions for $t \in [T_1+1, T_2-1]$ are given by:

$$q_t^c \geq 0 \quad \perp \quad P_t - C_t^{c'}(q_t^c) - \beta^{(T_2-t)}\alpha_2 \mathbb{E}_t[r_{T_2}] \leq 0$$
$$q_t^r \geq 0 \quad \perp \quad P_t - C_t^{r'}(q_t^r) + \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] \leq 0$$
$$-r_t + \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] = 0.$$
$$B_{T_2+1}\lambda_{T_2} = 0.$$

In an interior solution, producing one unit of conventional fuel in t increases expected compliance costs by $\alpha \mathbb{E}_t[r_{T_2}]$, the RVO associated with conventional fuel production, while producing one unit of renewable fuel reduces the expected compliance costs by $\mathbb{E}_t[r_{T_2}]$. The third condition states that firms will purchase (sell) compliance credits until the expected future marginal compliance cost, $\mathbb{E}_t[r_{T_2}]$, equals the market clearing credit price r_t. The last condition states that if the policy constraint inds such that $B_{T_2+1} = 0$, then $\lambda_{T_2} \geq 0$.

In the first compliance period, $t \in [1, T_1]$, the firm makes it production decisions anticipating their compliance obligation in T_2 as well as the expected effect of banking and borrowing restrictions in T_1. In these periods, the KKT conditions are given by:

$$q_t^c \geq 0 \quad \perp \quad P_t - C_t^{c'}(q_t^c) - \alpha_1 \left(\beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] - \beta^{(T_1-t)} \mathbb{E}_t[\overline{\Phi}] + \beta^{(T_1-t)} \mathbb{E}_t[\underline{\Phi}]\right) \leq 0$$
$$q_t^r \geq 0 \quad \perp \quad P_t - C_t^{r'}(q_t^r) + \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] - \beta^{(T_1-t)} \mathbb{E}_t[\overline{\Phi}] + \beta^{(T_1-t)} \mathbb{E}_t[\underline{\Phi}] \leq 0$$
$$-r_t + \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] - \beta^{(T_1-t)} \mathbb{E}_t[\overline{\Phi}] + \beta^{(T_1-t)} \mathbb{E}_t[\underline{\Phi}] = 0$$

and complementary slackness conditions for the banking restriction:

$$\overline{\Phi}(\overline{B} - B_{T_1+1}) = 0 \qquad \underline{\Phi}(B_{T_1+1} - \underline{B}) = 0.$$

Given that the US fuel industry has generally over-complied with the RFS2 to date, we focus on the banking restriction. In scenarios where the banking restriction binds on the firm, the complementary slackness conditions imply $\mathbb{E}_t[\overline{\Phi}] \geq 0$ and $\mathbb{E}_t[\underline{\Phi}] = 0$. In this case, the tax-subsidy effect of the policy is muted by the expected banking restriction and the restriction acts as a barrier to arbitrage higher (lower) future expected compliance costs.

Market equilibrium is defined as in Section 4, and we can infer that the market clearing RIN prices will be given by:

$$r_t = \begin{cases} \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] - \beta^{(T_1-t)} \mathbb{E}_t[\overline{\Phi}] & \text{if } t \in [1, T_1] \\ \beta^{(T_2-t)} \mathbb{E}_t[r_{T_2}] & \text{if } t \in [T_1+1, T_2] \end{cases}$$

where $\overline{\Phi}$ is the aggregate Lagrange multiplier for the banking constraint on the fuel industry.

Thus, if the banking restriction is expected to bind in the first compliance period, RIN prices will be lower for $t \in [1, T_1]$ and discontinuously increase in period $T_1 + 1$. Thus, the banking restriction creates an option value to RIN prices in the second period, where the option value is equal to $\beta^{(T_1-t)} \mathbb{E}_t[\overline{\Phi}]$.

A.2 Implication of the Sub-mandate Structure for RIN Prices

Now assume firms use two renewable fuel inputs q_j^r where $j \in 1,2$ denotes the type of renewable fuel. Suppose each gallon of renewable fuel generates a credit, c_j, that can be sold to other firms at price r_j for $j = 1,2$. Assume there is only one compliance period over $t \in [1,T]$, and firms face no banking or borrowing restrictions over the compliance period. Suppose firms face two policy constraints: (i) a total biofuel mandate, requiring the sum of both types of biofuel be greater than a total Renewable Volume Obligation with standard α_1; and (ii) a sub-mandate that requires the total volume of q_2^r be greater than a separate RVO with standard α_2. We write the policy constraints as:

$$\sum_{t=1}^{T}\left(q_{1,t}^r + q_{2,t}^r + c_{1,t} + c_{2,t}\right) \geq \alpha_1 \sum_{t=1}^{T} q_t^c$$

$$\sum_{t=1}^{T}\left(q_{2,t}^r + c_{2,t}\right) \geq \alpha_2 \sum_{t=1}^{T} q_t^c.$$

where we suppress the i subscript for brevity. As before, we can write the constraints in compact form by defining $B_{1,t}$ and $B_{2,t}$ as:

$$B_{1,t+1}^r = B_{1,t}^r + q_{1,t}^r + q_{2,t}^r + c_{1,t} + c_{1,t} - \alpha_1 q_t^c,$$

$$B_{2,t+1}^r = B_{2,t}^r + q_{2,t}^r + c_{2,t} - \alpha_2 q_t^c,$$

and can therefore rewrite the policy constraints as:

$$B_{1,T+1} \geq 0, \quad B_{2,T+1} \geq 0.$$

Given our setup, we write each firm's maximization program as:

$$V_t(B_{1,t}, B_{2,t}; \Theta_t) = \max_{\substack{q_t^c, q_{1,t}^r, q_{2,t}^r \geq 0,\\ c_{1,t}, c_{2,t}}} P_t(q_t^c + q_{1,t}^r + q_{2,t}^r) - C_t^c(q_t^c) - \sum_j C_{j,t}^r(q_{j,t}^r) - \sum_j r_{j,t} c_{j,t} + \beta \mathbb{E}_t V_{t+1}(B_{1,t+1}, B_{2,t+1}; \Theta_{t+1})$$

$$\begin{aligned} \text{subject to} \quad B_{1,t+1}^r &= B_{1,t}^r + q_{1,t}^r + q_{2,t}^r + c_{1,t} + c_{2,t} - \alpha_1 q_t^c \\ B_{2,t+1}^r &= B_{2,t}^r + q_{2,t}^r + c_{2,t} - \alpha_2 q_t^c \\ B_{1,T_2+1} &\geq 0, B_{2,T_2+1} \geq 0 \\ B_{1,1} &= 0, B_{2,1} = 0. \end{aligned}$$

Let $\lambda_{j,T}$ denote the Lagrange Multipliers for each policy constraint. The firm's Karush-Kuhn-Tucker conditions are given by:

$$\begin{aligned} q_t^c \geq 0 \quad &\perp \quad P_t - C_t^{c'}(q_t^c) - \beta^{(T-t)}\left(\alpha_1 \mathbb{E}_t[r_{1,T}] + \alpha_2 \mathbb{E}_t[r_{2,T}]\right) \leq 0 \\ q_{1,t}^r \geq 0 \quad &\perp \quad P_t - C_{1,t}^{r'}(q_{1,t}^r) + \beta^{(T-t)} \mathbb{E}_t[r_{1,T}] \leq 0 \\ q_{2,t}^r \geq 0 \quad &\perp \quad P_t - C_{2,t}^{r'}(q_{2,t}^r) + \beta^{(T-t)}\left(\mathbb{E}_t[r_{1,T}] + \mathbb{E}_t[r_{2,T}]\right) \leq 0 \end{aligned}$$

$$-r_{1,t} + \beta^{(T-t)} \mathbb{E}_t[\lambda_{1,T}] = 0.$$

$$-r_{2,t} + \beta^{(T-t)}\left(\mathbb{E}_t[\lambda_{1,T}] + \mathbb{E}_t[\lambda_{2,T}]\right) = 0.$$

$$B_{1,T+1}\lambda_{1,T} = 0, \quad B_{2,T+1}\lambda_{2,T} = 0.$$

Market clearing prices from the optimality conditions can be inferred as previously to be equal to:

$$r_{1,t} = \beta^{(T-t)}\mathbb{E}_t[r_{1,T}] \quad \text{for } t \in [1,T]$$

$$r_{2,t} = \beta^{(T-t)}\left(\mathbb{E}_t[r_{1,T}] + \mathbb{E}_t[r_{2,T}]\right) \quad \text{for } t \in [1,T]$$

The equations reveal two important insights. First, credit prices for the sub-mandate $r_{2,t}$ can never be less valuable than credit prices for the total renewable fuel mandate $r_{1,t}$. This is intuitive because credits generated by fuels under the sub-mandate can be applied towards both the firm's sub-mandate and overall biofuel mandate. Second, if the overall renewable fuel mandate binds in expectation but the sub-mandate does not bind (i.e., $\mathbb{E}_t[r_{1,T}] > 0$ and $\mathbb{E}_t[r_{2,T}] = 0$), then credits for the total renewable fuel mandate will trade for the same price as credits for the sub-mandate.

B The Model Confidence Set Details

In this section, we study whether RIN prices have acted in manner consistent with an economically rational market in the sense of Fama (1965). The market for RINs has existed in some form since the inception of the RFS2 when parties first began holding compliance obligations under the program. Unlike cap and trade programs that typically withhold a portion of allowances and hold public auctions to create a more transparent market clearing price, RINs are generated and traded entirely outside of the control of the regulator on an over-the-counter market. In the absence of publicly available auction prices, a number of companies have emerged that survey firms and report RIN prices at various frequencies. Among the most cited industry sources of RIN prices is the Oil Price Information Service (OPIS). OPIS collects RIN data through daily phone surveys of market participants, reporting a daily high, low and mean price for each RIN type and vintage traded on the market.

Unfortunately, futures and options for RINs have only recently become available and we are unable to take advantage of futures and spot market spreads in our analysis. In April 2013, the Chicago Mercantile Exchange announced that it would begin trading RIN futures for conventional, advanced and biodiesel RINs.[29] In addition, the Intercontinental Exchange is currently offering RIN options contracts.[30] Given the recent emergence of these services, we must rely on spot market prices reported by OPIS in our main empirical analysis.

Here, we test whether reported spot prices from OPIS have acted in a manner consistent with an efficient market, using insights from our model in Section 4. A key prediction from our model is that for each RIN type and vintage, prices should satisfy the equation $r_t = \beta^{(T-t)}\mathbb{E}_t[r_T]$. Therefore, RIN prices from t to $t+1$ should satisfy:

$$r_t = \beta\mathbb{E}_t[r_{t+1}]. \tag{17}$$

Equation (17) states that RINs should follow Hotelling's rule in expectation and rise at the rate of interest. Because we observe daily RIN prices and there is presumably no cost to storing credits, it is reasonable to assume $\beta \approx 1$, i.e., the daily discount rate is essential zero. Thus, we can rewrite the growth equation as:

$$\mathbb{E}_t[r_{t+1}] - r_t = 0. \tag{18}$$

Equation (18) implies RIN prices should satisfy a rational expectations equilibrium, and current period periods should incorporate all expectations regarding expected future prices.

We test whether equation (18) holds for all observed RIN types and vintages. An important implication of (18) is that observed price changes in period $t+1$ should be uncorrelated with variables $\mathbf{x}$ observed in

[29]See CME Group (2013).

[30]See Intercontinental Exchange (2014).

period t, i.e., future RIN price movements should be unpredictable. To test whether Equation (18) holds, we test the hypothesis:

$$H_0 : \mathbb{E}_t[\mathbf{x}_t(r_{t+1} - r_t)] = 0$$

for a given set of potential predictor variables $\mathbf{x}_t$.

Unpredictability represents a necessary, though not sufficient, condition for market efficiency. Thus, our test does not necessarily address all concerns cited above, particularly those regarding manipulation of RIN markets by large financial firms. To the extent that we find significant predictability in RIN markets, however, there would be reasonable cause for concern regarding the viability of RIN markets as well as tradeable credit markets under other environmental policies. Given the available data, we believe tests of predictability of prices changes represents a reasonable test for market efficiency.

A number of methods are available to test H_0. For example, through introspection and drawing on our own knowledge of RIN markets, we could choose a vector $\mathbf{x}_t$, specify a model we believe can accurately forecast RIN prices, and test the hypothesis directly using traditional estimation techniques. In this setting, testing H_0 would amount to a joint hypothesis test of $H_0 : \beta = 0$ from the model $\Delta r_{t+1} = \mathbf{x}_t\beta + \varepsilon_{t+1}$. In the absence of an obvious superior model we could estimate a number of competing models, select the 'best' model using an information or testing criterion, and test H_0 in a similar fashion.

Given well established problems with controlling the family-wise error rate when selecting among competing models using multiple testing criterion (White, 2000), we test H_0 using a forecast exercise.[31] Specifically, given a vector of potential predictors, $\mathbf{x}_t$, we construct a large set of competing forecasts of RIN prices and compare them to the random walk model implied by equation (18). Given the set of competing forecasts, we construct a Model Confidence Set (MCS) for RIN forecasts using the methods developed by Hansen et al. (2011). The MCS is a relatively new contribution to the time series literature, and has a number of advantages over other forecast evaluation methods that are useful in the current application. Given a set of competing forecasts, the MCS identifies the best model(s), as well as all models whose performance cannot be statistically significantly distinguished from the top competing model(s).

Given the vector $\mathbf{x}'_t$, define the set M_0 as the set containing all models constructed from combinations of $\mathbf{x}'_t$, with models indexed by $i = 1, \cdots, m_0$. Each model is evaluated by its predictive ability according to a specified loss function $L_{i,t}$ for each evaluation period $t = 1, \cdots, T$. For our exercise, we use a mean squared forecast error loss function:

$$L_{i,t} = L(\Delta r_t - \Delta\hat{r}_{i,t}) = (\Delta r_t - \Delta\hat{r}_{it})^2\,,$$

where Δr_t is the realized change in RIN prices and $\Delta\hat{r}_{it}$ is the forecast change in RIN prices by model i in evaluation period t. Define $\mu_{i,j} = \mathbb{E}(d_{ij,t})$ as the expected loss differential between models i and j,

[31] Family-wise error rate is defined as the probability of rejecting at least one null hypothesis when the hypothesis is in fact true, i.e., the family-wise error rate is the probability of making at least one Type I error.

where $d_{ij,t} = L_{i,t} - L_{j,t}$. Given $\mu_{i,j}$, the MCS estimates M^*, defined as the set of all models that are indistinguishable from the best performing model, given by:

$$M^* = \{i \in M_0 : \mu_{i,j} \leq 0 \text{ for all } j \in M_0\}.$$

Hansen et al. (2011) develop methods to estimate $\hat{M}_{1-\alpha}$, which converges in probability to M^* with Type I error α. To implement the procedure, the method uses an equivalence test, δ_M, to evaluate each model in M according to their relative losses and identify the worst performing forecast model. Given δ_M, an elimination rule, e_M, eliminates the model from the set if a specified testing criterion is satisfied.

The procedure begins by setting $M = M_0$ and comparing all models based on their expected loss differentials. The equivalence test sequentially compares the 'worst' performing model, identified by δ_M, in the set and eliminates the model from the set if the elimination rule e_M is satisfied. When a model is eliminated, a new set $M = M_1$ is constructed and the procedure is repeated until the equivalence test e_M is not rejected. The output, $\hat{M}$, is thus defined as the set of all 'surviving' models from the procedure.

Hansen et al. (2011) constructs MCS p-values with the property that if $\hat{p}_i \leq \alpha$, the model is excluded from the confidence set $\hat{M}_{1-\alpha}$. This guarantees that:

$$\lim_{t\to\infty} \Pr\left(M^* \subset \hat{M}_{1-\alpha}\right) \geq 1 - \alpha.$$

Thus, the procedure guarantees that the family-wise error rate is controlled. In addition, the MCS has the advantage that the p-values can be interpreted in a similar fashion as traditional p-values for parameter inference. In this sense, a high p-value implies a low probability that the model is not contained in M^*.

Hansen et al. (2011) suggest a number of methods to construct the MCS. We construct each RIN MCS using multiple t-statistics by defining the relative sample loss statistic between model i and j as $\bar{d}_{ij} = T^{-1}\sum_{t=1}^{T} d_{ij,t}$. From this, t-test statistics are constructed as:

$$t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\hat{\text{var}}(\bar{d}_{ij})}}.$$

The test statistic is equivalent to the DM test (Diebold and Mariano, 1995) for comparing the performance of two competing forecasts. Because the test statistic depends on nuisance parameters that must be estimated, the asymptotic distribution of $\bar{d}_{ij}$ are non-standard. To correct for this, we use the bootstrap procedure developed by White (2000) to estimate $\text{var}(\bar{d}_{ij})$.

Given the t-statistics for each model, we test the hypothesis:

$$H_0 : \mu_{ij} = 0 \quad \forall i, j \in M.$$

To test H_0, we construct a test statistic and elimination rule consistent with the properties of the MCS discussed in Hansen et al. (2011). We use the test statistic $T_M \equiv \max_{i,j\in M} |t_{ij}|$. The elimination rule that identifies the model to be eliminated from the set is given by $e_M = \text{argmax}_{i \in M} \sup_{j \in M} t_{ij}$, and the model e_M is removed from the MCS whenever the absolute value of the p-value for the t-test is below the threshold α.

Given our choices above, algorithm for constructing the MCS is:

1. Define the set of all models M_0.
2. For each model, forecast RIN price changes using a moving block estimation window. Calculate $L_{i,t}$ for each model as well as $\bar{L}_i$, the average model loss.
3. Bootstrap the matrix of loss functions. Form t-statistics t_{ij} based on the relative average loss of each model. Calculate the variance based on the bootstrapped values of the loss functions.
4. Test $H_0 : \mu_{ij} = 0$ for all $i, j \in M$ using test statistic T_M. Let $P_{H_0,M} = B^{-1} \sum_b 1_{T_{\max} > T^*_{b,\max}}$ be the bootstrap p-value for the test statistic T_M. If $P_{H_0,M} < \alpha$ then $H_{0,M}$ is rejected and the model identified by e_M is eliminated from the set.
5. Repeat 5-6 until $H_{0,M}$ is not rejected and stop the procedure.

The resulting set of models is denoted $\hat{M}^*_{1-\alpha}$ and is the $(1 - \alpha)$ model confidence set. P-values each model e_{M_j} as $\hat{p}_{e_{M_j}} \equiv \max_{i \leq j} P_{H_0,M_j}$. Thus, the p-value is for each model is equal either to maximum of the bootstrap value computed in step 7 or the p-value calculated in any prior step. By construction, the p-value of the last surviving model or models is 1.[32]

We construct a MCS for each observed RIN type and vintage. To increase the power of the test, we also construct a combined forecast for each RIN type, using front year RIN prices for each type. In addition, to guard against the possibility that some daily data may be reported with a lag, we construct a Wednesday to Wednesday forecast using the combined forecast series. Table B.1 lists the variables used to construct M_0 for each RIN series. We use lag RIN price levels and differences, a number of relevant commodity futures price series, and three macroeconomic variables. We construct the initial model set M_0 using every combination of the variables in Table B.1 with up to three variables in each model, for a total of 378 forecasts.

The results from the MCS exercise are summarized in Table B.2. For each RIN series and vintage, we report the p-value associated with the random walk, its rank, as well as the size of the 90% and 75% MCS. For example, for the 2007 conventional series, the random walk forecast ranked 5th out of the 378 models, with an associated p-value of 0.866, well above conventional rejection levels. While the random walk was not the top performing model in the set M_0, it cannot be eliminated as performing statistically significantly worse than all other models for even a 20% MCS in which we are sure M^* contains the best performing

[32] Code to implement the procedure was written written by Kevin Shephard through the Oxford MFE Toolbox, and is available online at `http://www.kevinsheppard.com/` (accessed February, 2014).

Table B.1: Model Confidence Set: Description of Variables*

Variable	Description	Source
Outcome Variables		
	2007-2014 Conventional RINs	OPIS
$\Delta Y_t = Y_t - Y_{t-1}$	2011-2014 Advanced RINs	OPIS
	20010-2014 Biodiesel RINs	OPIS
Lag RIN Prices		
Y_{t-1}	Lag RIN Price Level	OPIS
ΔY_{t-1}	Lag Differenced RIN Price	OPIS
Future Data Prices*		
$X_{1,t-1}$	WTI Oil Futures Continuous Contract	NYMEX
$X_{2,t-1}$	Corn No. 2 Futures Continuous Contract	CME
$X_{3,t-1}$	Soybean Oil Futures Continuous Contract	CME
$X_{4,t-1}$	Sugar No.11 Futures Futures Continuous Contract	ICE
$X_{5,t-1}$	Henry Hub Natural Gas Futures Continuous Contract	CME
$X_{6,t-1}$	Wheat Futures Continuous Contract	CME
Macroeconomic Indicators		
$W_{1,t-1}$	3 Month US Treasury Constant Maturity Rate	FRED
$W_{2,t-1}$	Russell 3000 Index	NYSE
$W_{3,t-1}$	S&P Goldman Sachs Commodity Index	CME

*Note: For all futures price data, multiple contracts trade in any given period. We use the front month series, defined as the price for the contract with an expiration date closest to the trading day.

model in 20% of random draws of loss functions from each model. The 75% and 90% MCS sizes are 296 and 165, respectively. The large size of the MCS suggests that no single model or group of models significantly and consistently outperforms all other models.

Overall, the results from the MCS exercise are encouraging. The random walk forecast generally ranks among the top performing models, and is never rejected from the 75% or 90% MCS for any series. Some RIN series such as the 2011-2013 Advanced RIN and 2011 Biodiesel RIN series performing relatively poorly; however, Wednesday to Wednesday random walk forecasts for all series are among the top competing models, suggesting the results for those instances may be driven by report timing issues or lack of liquidity in the markets. For all forecast models, the size of the 75% and 90% MCS is large, and in many instances includes all competing forecasts. This suggests that no one model or group of models outperforms the others in a statistically significantly manner. We compared the forecasts from the top competing models for each series, and gains over a random walk forecast are minimal, and large increases in RIN prices are not captured by the forecast models.[33]

Table B.3 lists the top competing model for each RIN series and vintage. No one variable or group of variables is common across the top models for conventional RINs, though for advanced RINs, Henry Hub Futures and the lag difference of RINs appear in many of the top forecast models. The inclusion of the lag

[33]Graphs illustrating the top competing forecasts versus the random walk forecasts are available upon request.

Table B.2: Model Confidence Set Summary

	Random Walk Forecast		**Model Confidence Set**	
	P-value	Rank (of 378)	MCS-90 Size	MCS-75 Size
Conventional RINs				
2007 Series	0.866	5	296	165
2008 Series	0.865	252	378	378
2009 Series	0.806	113	378	378
2010 Series	0.917	37	114	114
2011 Series	0.883	3	244	109
2012 Series	0.631	70	378	378
2013 Series	0.818	51	378	378
2014 Series	0.711	52	331	179
Wednesday Combined Series	0.924	8	378	378
Combined Series	0.812	127	378	378
Advanced RINs				
2011 Series	0.465	196	378	275
2012 Series	0.285	101	378	203
2013 Series	0.39	80	310	228
2014 Series	0.984	43	378	378
Wednesday Combined Series	0.768	19	375	284
Combined Series	0.903	25	378	378
Biodiesel RINs				
2010 Series	0.897	6	378	378
2011 Series	0.357	192	378	340
2012 Series	0.594	93	378	350
2013 Series	0.416	95	378	378
2014 Series	0.771	41	359	249
Wednesday Combined Series	0.934	2	153	37
Combined Series	0.356	61	378	378

difference RIN price in the top performing model suggests RIN markets contain memory, and prior shocks may in part inform future shocks. Sugar futures, soybean oil futures, and the S&P-GS Commodity Index appear in many of the top competing variables. Only soybean oil futures remain in the Wednesday to Wednesday MCS, suggesting the results may be driven by either reporting timing issues or illiquidity in the biodiesel RIN market.

Given our findings that policy announcements were the main drivers of RIN prices, we also construct a number of alternative M_0 formulations and perform the MCS procedure using indicators for lagged policy announcements, where the policy announcement indicator is equal to one if a specific policy announcement occurred on the previous day and zero otherwise.[34] We consider the release of the 2013 Proposed and Final

[34]Results are not presented here, but are available upon request.

Rules, the release of the Reuters article, and the release of the 2014 Proposed Rule. The inclusion of policy indicators generally diminishes the performance of the random walk forecast, and in several instances the top performing forecast models include policy indicators. The result is consistent with our findings in section 6 that RIN prices continued to fall for a number of days following each announcement. The improvements from including the policy announcements, however, are modest. For all estimated Model Confidence Sets with policy announcement indicators, the size of the 90% and 75% sets remain large, and the random walk forecast is never excluded from the 90% MCS.

Overall, the MCS exercise suggests RIN prices as reported by OPIS appear to largely satisfy a rational expectations equilibrium. While the random walk forecast is not always the best performing forecast from the set of considered models, we find no instances in which we can reject the random walk model as statistically under-performing other models in the set. The results suggest that there may be some memory in RIN prices, particularly for advanced and biodiesel RINs. This may be driven by lagged transaction reporting or illiquid markets. In all instances, however, potential gains from using a competing forecast model are modest.

Table B.3: MCS: Top Competing Models

Series	Variables
Conventional RINs	
2007 Series	Constant, Sugar
2008 Series	Constant, Russell 3000, Treasury Bill
2009 Series	Constant, WTI Futures, Corn Futures
2010 Series	Sugar Futures, Russell 3000, S&P-GS Commodity Index
2011 Series	Corn Futures
2012 Series	Russell 3000, S&P-GS Commodity Index, Treasury Bill
2013 Series	WTI Futures, Russell 3000, S&P-GS Commodity Index
2014 Series	Russell 3000, S&P-GS Commodity Index
Wednesday Combined Series	Sugar Futures, Russell 3000
Combined Series	Lag Difference RIN, Henry Hub Futures, Treasury Bill
Advanced RINs	
2011 Series	Lag Difference RIN, Soybean Oil Futures, Henry Hub Futures
2012 Series	Corn Futures, Henry Hub Futures, S&P-GS Commodity Index
2013 Series	Henry Hub Futures, S&P-GS Commodity Index
2014 Series	Corn Futures, Soybean Oil Futures, S&P-GS Commodity Index
Wednesday Combined Series	Lag Difference RIN, Soybean Oil Futures
Combined Series	Corn Futures, Henry Hub Futures
Biodiesel RINs	
2010 Series	Constant, Lag RIN, Sugar Futures
2011 Series	Lag RIN, Sugar Futures, Henry Hub Futures
2012 Series	Soybean Oil Futures, Russell 3000, S&P-GS Commodity Index
2013 Series	Soybean Oil Futures, Sugar Futures, S&P-GS Commodity Index
2014 Series	Sugar Futures, Russell 3000, S&P-GS Commodity Index
Wednesday Combined Series	Soybean Oil Futures
Combined Series	Sugar Futures, Russell 3000, S&P-GS Commodity Index

C Robustness Checks

C.1 RIN Abnormal Returns

In Section 6 we specify normal returns for RINs as a function of log price changes of WTI, ethanol and soybean oil futures contracts. Here, we consider specifications allowing for alternative specifications of normal returns, using commodity price series that more directly influence ethanol and biodiesel production costs. For conventional and advanced RINs, we specify normal returns as a function of reformulated gasoline (RBOB), yellow number 2 corn, number 11 sugar, soybean oil, and Henry Hub natural gas futures prices. For biodiesel RINs we use New York Harbor ultra low sulfur diesel (ULSD) futures prices instead of gasoline futures prices. All futures prices are for July 2014 contracts, and are collected from the Commodity Futures Exchange. We estimate equation (15) separately for each RIN series using the alternative normal returns specifications, and estimate specifications using flexible time controls.

Results for the alternative specifications are presented in Table C.1. As in Table 3, all normal return estimates are insignificant, but have the expected signs suggested by our theoretical model. Increases in RBOB and ULSD futures decreases the respective RIN prices, and magnitudes are similar to those observed for increases in WTI futures prices. Increases in biofuel input prices increases RIN prices with corn, sugar, soybean oil and natural gas price increases leading to moderate increases in RIN prices.

Abnormal return estimates around the three event dates are nearly identical to those estimated in Table 3. As previously, the largest abnormal returns occur for all RIN series around the release of the 2013 Final Rule. Abnormal return estimates are more heterogeneous across RIN types following the release of the Reuters article and 2014 Proposed Rule. Prices for conventional RINs decreases most on the day the Reuters article was released, but recover over the subsequent two days. Advanced RINs did not experience abnormal returns on the publication date of the Reuters article, but experienced abnormal positive returns on the day following the release, while biodiesel RINs did not experience any statistically significant abnormal returns around the event dates. All series experienced small, negative abnormal returns on the date the 2014 Proposed Rule was published, and much larger abnormal returns on the following day.

Overall, the exercise confirms our findings from Section 6. Specifically, movements in commodity markets and input prices for biofuel production are unable to explain the variation observed in RIN markets over the sample period.

Table C.1: Regression Results - Dependent Variable: Log 2013 RIN Price Changes*

		Conventional RINs		Advanced RINs		Biodiesel RINs	
		(1)	(2)	(1)	(2)	(1)	(2)
Normal Returns							
RBOB Futures		-0.261	-0.249	-0.469	-0.380	–	–
		(0.340)	(0.338)	(0.354)	(0.369)	–	–
ULSD Futures		–	–	–	–	-0.360	-0.338
		–	–	–	–	(0.427)	(0.422)
Corn Futures		0.159	0.154	0.226	0.193	0.166	0.113
		(0.193)	(0.181)	(0.243)	(0.237)	(0.227)	(0.230)
Sugar Futures		0.241	0.202	0.289	0.193	0.408	0.404
		(0.312)	(0.317)	(0.295)	(0.318)	(0.278)	(0.298)
Soybean Oil Futures		0.557	0.535	0.184	0.216	0.715	0.729
		(0.362)	(0.365)	(0.441)	(0.449)	(0.449)	(0.464)
Natural Gas Futures		0.043	0.069	0.162	0.173	0.034	0.026
		(0.213)	(0.220)	(0.213)	(0.227)	(0.195)	(0.202)
Constant		0.006	0.069	0.001	-0.025	-0.000	-0.000
		(0.004)	(0.044)	(0.003)	(0.041)	(0.003)	(0.039)
Abnormal Returns	Day						
2013 Final Rule	0	-0.134**	-0.120**	-0.134*	-0.120*	-0.061	-0.059
	1	-0.148**	-0.138**	-0.137*	-0.126*	-0.142**	-0.143**
	2	-0.197**	-0.179**	-0.158**	-0.138**	-0.181**	-0.168**
	3	0.022	0.037	0.041	0.051	0.049	0.052
	4	0.045	0.053	0.041	0.043	0.025	0.029
	5	0.032	0.051	0.052	0.065	0.040	0.041
Reuters Article	0	-0.149**	-0.135**	-0.025	0.009	-0.054	-0.035
	1	0.087*	0.094*	0.146**	0.171**	0.048	0.067
	2	0.052	0.069	-0.000	0.034	-0.010	0.008
	3	0.000	0.013	-0.021	0.010	-0.030	-0.016
	4	-0.059	-0.039	-0.059	-0.016	-0.047	-0.019
	5	-0.086*	-0.069	-0.005	0.027	-0.032	-0.013
2014 Proposed Rule	0	-0.042	-0.030	-0.036	-0.031	-0.045	-0.046
	1	-0.188**	-0.183**	-0.120*	-0.122*	-0.215**	-0.217**
	2	0.059	0.075	-0.025	-0.016	-0.001	-0.002
	3	-0.009	-0.001	-0.002	-0.000	0.039	0.033
	4	0.019	0.036	-0.023	-0.012	-0.059	-0.050
	5	0.083*	0.095*	0.150**	0.153**	0.112*	0.111*
Flexible Time Controls		No	Yes	No	Yes	No	Yes
N		422	422	422	422	422	422
SQ 95% Critical Values		-0.0786	-0.0804	-0.0997	-0.0935	-0.0682	-0.0722
SQ 99% Critical Values		-0.1001	-0.0999	-0.1412	-0.1374	-0.1309	-0.124

*Note: Standard errors in parentheses are Newey-West errors with 5 lags. Inference for abnormal returns are based on SQ critical values. The lower tail SQ critical values are given at the bottom of the table. Stars denote significance with * $p<0.05$ and ** $p<0.01$.

C.2 Commodity Market Abnormal Returns

We first consider the robustness of the losses observed in soybean oil futures contracts following the release of the Reuters article. Figure C.1 plots the empirical densities of the residuals from the event study estimates for soybean oil futures contracts for all non-event days. To do this, we regress the log daily soybean oil future price changes on the log differences in the S&P-GS Commodity Index and a mean daily return and estimate a kernel density function of the residuals for all non-event days. The left graph is the empirical density of the residuals for specification (1) of Table 5, and the right graph is the residual empirical density from specification (2) including flexible time controls. The vertical line in each figure represents the observed abnormal return on the day the Reuters article was released leaking an early version of the proposed cuts to the 2014 RFS2 standards. As can be seen, the return on the event day lie far in the left tail of both distributions, suggesting soybean markets experienced a statistically significant, large abnormal return on the day of interest.

To ensure the results are not driven by our selection of July 2014 future contracts, we run similar regressions as in section 6.3 for March, May, July, September, and December futures contracts for all commodity prices for 2014 and 2015.[35] Tables C.2 and C.3 present the abnormal return estimates for the event day and day after each even for each contract. Significance values are determined using empirical SQ critical values. As can be seen, no significant abnormal returns are observed for any event for WTI crude oil, ethanol, No. 11 sugar, or No. 2 yellow corn futures contracts. The only significant abnormal returns are observed for soybean oil futures contracts on the day the Reuters article was released. Abnormal return point estimates range from -1.48% to -2.05% across the contracts, and all but three contracts experience statistically significant negative returns. The results confirm our main findings.

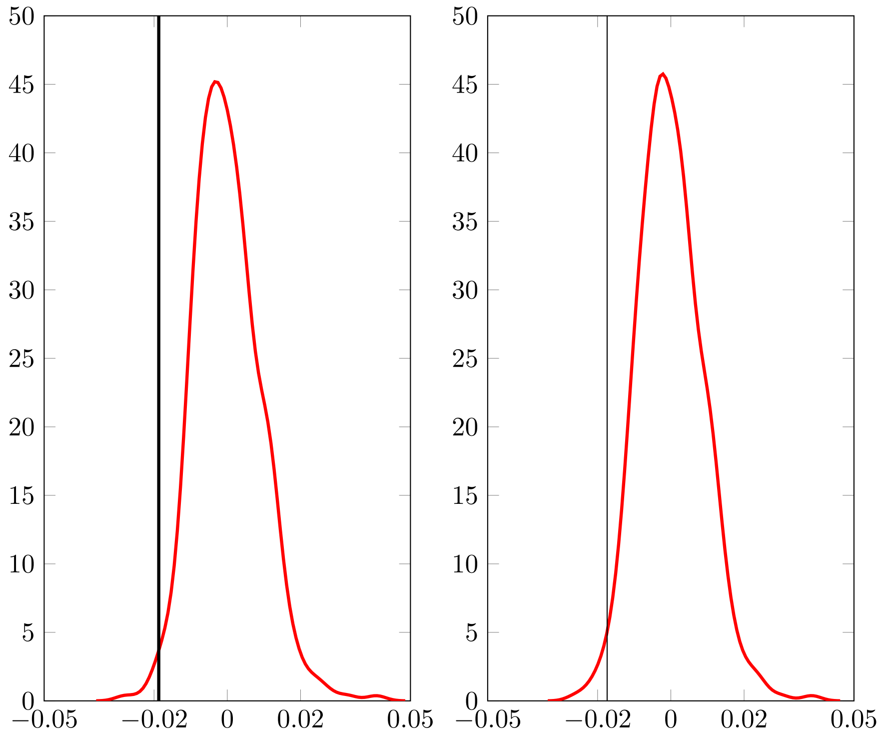
C.3 Biofuel Firm Abnormal Returns

Figure C.2 graphs the cumulative abnormal returns (CARS) over a five day horizon for each biofuel firm. The graphs are meant to provide further insight into which firms drive the results presented in Table 7, and abnormal return estimates should not be interpreted as causal nor attributable losses or gains due to the events of interest. Causal attribution would require a more exhaustive study of each series to ensure no other events occurred around the event window of interest. This is beyond the scope of the current paper.

Cumulative abnormal returns were estimated by regressing the log daily stock price change on an aggregate market index, a mean daily return, and flexible time controls for each individual stock. All estimates use a 90 day estimation window, though using a longer window size does not affect our results. The left column graphs CARs for large biofuel producers with varied exposure to advanced and biodiesel production.

[35] Futures contracts are only observed for March, May, July and October for No. 11 sugar futures contracts.

Figure C.1: Soybean Oil Normal Return Density*



*Note: The left figure graphs the empirical normal return density using specification (1) and the right figure graphs the empirical normal return density using specification (2) from Table 7. The vertical line represents the estimated abnormal return on the date of the publication date of the Reuters Article.

The right column graphs CARs for smaller biofuel producers, each of which is either a biodiesel producer or advanced ethanol producer. The first, second and third rows correspond to cumulative abnormal returns following the 2013 Final Rule, Reuters article, and 2014 Proposed Rule release dates. Note the different scale for each axis.

Following the release of the 2013 Final Rule, the largest abnormal returns are observed among smaller advanced and biodiesel firms (e.g., Gevo and Methes Energies International). In addition, larger biofuel producers with investments in advanced biofuels (e.g., Pacific Ethanol and Cosan) experience small negative returns. Interestingly, Valero appears to have experienced a sustained positive abnormal return. Given that Valero is both a major oil refiner as well as is among the largest biofuel producers in the US, the result is consistent with a costly biofuel policy binding on the firm.

Little movement is observed among large biofuel producers following the Reuters article; however, large losses were observed for a few small biodiesel producers, consistent with our findings in commodity markets. Large losses and gains are observed for larger biofuel producers following the release of the 2014 Proposed rule; however, estimates are noisy, consistent with the findings that losses were not statistically significant in Table 7.

Table C.2: Fuel Market Abnormal Returns by Contract

	Contract	2013 Final Rule Day 0	2013 Final Rule Day 1	Reuters Article Day 0	Reuters Article Day 1	2014 Proposed Rule Day 0	2014 Proposed Rule Day 1
Ethanol	December-13	0.0104	-0.0077	-0.0093	0.007	-0.0009	0.016
	March-14	0.0057	-0.0079	-0.0083	0.0061	-0.0067	-0.0121
	May-14	0.0052	-0.008	-0.0084	0.0006	-0.0066	-0.0122
	July-14	0.0057	-0.0075	-0.0078	0.0008	-0.0063	0.004
	September-14	0.0058	-0.0074	-0.0077	0.0009	-0.0062	0.0041
	December-14	0.006	-0.0073	-0.0076	0.0012	-0.006	0.0043
	March-15	0.0061	-0.0072	-0.0075	0.0013	-0.0059	0.0044
	May-15	0.0061	-0.0072	-0.0075	0.0013	-0.0059	0.0044
	July-15	0.0061	-0.0072	-0.0075	0.0013	-0.0059	0.0044
	September-15	0.0061	-0.0071	-0.0074	0.0013	-0.0058	0.0044
	December-15	0.0059	-0.0074	-0.0076	0.0013	-0.0059	0.0043
WTI Crude	December-13	-0.0045	-0.0028	-0.0124	0.0018	-0.0017	-0.0048
	March-14	-0.0045	-0.0015	-0.0079	0.0003	-0.0024	-0.0053
	May-14	-0.0057	-0.0019	-0.0073	0.0004	-0.003	-0.0064
	July-14	-0.0061	-0.0021	-0.0065	0.0003	-0.0034	-0.0069
	September-14	-0.0058	-0.0013	-0.0052	0.0004	-0.0035	-0.0066
	December-14	-0.0055	-0.0005	-0.0035	0.0005	-0.0031	-0.0062
	March-15	-0.0055	0	-0.0024	0.0003	-0.0022	-0.0057
	May-15	-0.0055	0.0005	-0.0022	-0.0003	-0.0017	-0.0053
	July-15	-0.0052	0.001	-0.002	-0.0005	-0.0013	-0.0049
	September-15	-0.0046	0.0015	-0.0016	-0.0004	-0.0007	-0.0046
	December-15	-0.0041	0.0018	-0.0011	-0.0007	-0.0003	-0.0044

Note: SQ test critical values for each contract is given in Table 5. Abnormal returns represent those returns that cannot be explained bo corresponding movements in the S&P-GS Commodity Index, or in the case of WTI crude, the Russell 3000 Index, and a daily mean return. Specification (2) includes flexible time controls. * denotes the hypothesis is rejected at the 5% empirical critical value and ** denotes the hypothesis is rejected at the 1% empirical critical value.

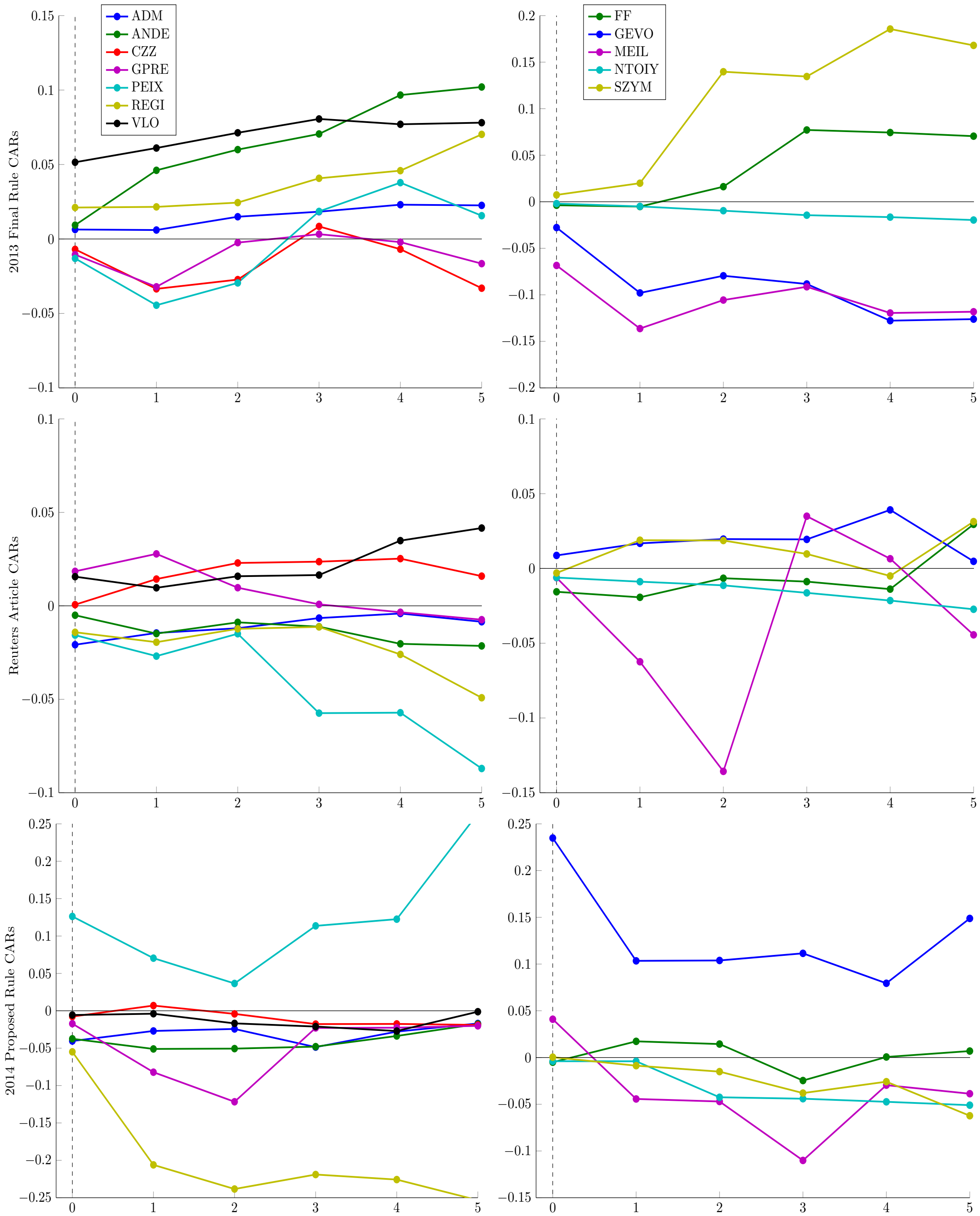
Table C.3: Fuel Market Abnormal Returns by Contract

		2013 Final Rule		Reuters Article		2014 Proposed Rule	
	Contract	Day 0	Day 1	Day 0	Day 1	Day 0	Day 1
Soybean Oil	December-13	-0.0111	-0.0086	-0.0205*	0.0025	-0.0118	-0.0077
	March-14	-0.01	-0.008	-0.0196*	0.0017	-0.0122	-0.0076
	May-14	-0.0092	-0.0067	-0.0191*	0.0026	-0.0128	-0.007
	July-14	-0.008	-0.0066	-0.0187*	0.003	-0.0131	-0.0067
	September-14	-0.0077	-0.0061	-0.0177*	0.0035	-0.0135	-0.0064
	December-14	-0.008	-0.0068	-0.0152	0.0053	-0.0153	-0.0052
	March-15	-0.0076	-0.0036	-0.0148	0.0055	-0.0151	-0.0048
	May-15	-0.0078	-0.0007	-0.0148	0.0053	-0.015	-0.0034
	July-15	-0.008	-0.0002	-0.0162*	0.0078	-0.015	-0.0037
	September-15	-0.0078	0.0043	-0.0161*	0.0051	-0.0159	-0.0015
	December-15	-0.0079	0.0042	-0.0162*	0.0003	-0.009	-0.0076
No. 11 Sugar	March-14	0.003	0.0189	0.0133	0.0058	-0.0042	0.0124
	May-14	0.0012	0.0172	0.0129	0.0061	-0.0018	0.0111
	July-14	0.0007	0.0167	0.0114	0.0055	0.0003	0.01
	October-14	0.0005	0.0154	0.0105	0.0051	0.0032	0.0096
	March-15	0.0003	0.0141	0.0097	0.0046	0.0042	0.0089
	May-15	0.0009	0.0141	0.0086	0.0041	0.004	0.0082
	July-15	0.001	0.0148	0.0064	0.0041	0.0045	0.0069
	October-15	0.0029	0.0162	0.0049	0.0037	0.0052	0.007
No. 2 Yellow Corn	December-13	0.0003	0.0005	-0.0091	0.0089	-0.0098	-0.0226
	March-14	0.0004	0.0001	-0.0087	0.0077	-0.0134	-0.0214
	May-14	0.001	0.0007	-0.009	0.0079	-0.0145	-0.0205
	July-14	-0.0001	-0.0004	-0.0089	0.0067	-0.0143	-0.0196
	September-14	0.0007	-0.0011	-0.0084	0.0059	-0.0142	-0.0189
	December-14	0.0023	-0.0005	-0.0086	0.0064	-0.0146	-0.0182
	March-15	0.0029	0.0016	-0.0079	0.0052	-0.0147	-0.017
	May-15	0.003	0.0017	-0.0067	0.0041	-0.015	-0.0157
	July-15	0.0021	0.0009	-0.0064	0.0041	-0.0156	-0.016
	September-15	0.0028	0.0025	-0.0029	0.0021	-0.0141	-0.0159
	December-15	0.0075	0.0006	-0.0042	0.0086	-0.0146	-0.0143

Note: SQ test critical values for each contract is given in Table 5. Abnormal returns represent those returns that cannot be explained bo corresponding movements in the S&P-GS Commodity Index, or in the case of WTI crude, the Russell 3000 Index, and a daily mean return. Specification (2) includes flexible time controls. * denotes the hypothesis is rejected at the 5% empirical critical value and ** denotes the hypothesis is rejected at the 1% empirical critical value.

Figure C.2: Biofuel Firm Cumulative Abnormal Returns*

(a) Large Biofuel Producers (b) Small Biofuel Producers



*Note: The figure graphs cumulative abnormal returns (CARs) by firm for each policy event of interest. The left column graphs CARs for large biofuel producers, and the right column graphs CARs for biofuel producers with smaller production capacities.