The Pass-Through of RIN Prices to Wholesale and Retail Fuels under the Renewable Fuel Standard

Christopher R. Knittel, Ben S. Meiselman, James H. Stock

Abstract: The US Renewable Fuel Standard (RFS) requires blending increasing quantities of biofuels into the surface vehicle fuel supply. The RFS requirements are met through a system of tradable permits called Renewable (fuel) Identification Numbers, or RINs. We exploit the large fluctuations in RIN prices during 2013–15 to estimate the pass-through of RIN prices to US wholesale and retail fuel prices. We control for common factors by examining spreads of physically similar fuels with different RIN obligations. Pooling six different wholesale petroleum fuel spreads, we estimate a pooled long-run or equilibrium pass-through coefficient of 1.00 with a standard error of 0.11. This pass-through occurs within two business days. The only fuel for which we find economically and statistically significant failure of pass-through is retail E85, which contains up to 83% ethanol; the pass-through of RIN prices to the retail E85–E10 spread is precisely estimated to be close to zero.

JEL Codes: C32, Q42

Keywords: E85, Energy prices, Fuels markets, RBOB, Retail fuel spreads, Wholesale fuel spreads

THE US RENEWABLE FUEL STANDARD (RFS) requires the blending of increasing quantities of biofuels into the US surface vehicle transportation fuel supply. Developed initially in 2005 and expanded in the Energy Independence and Security Act (EISA) of 2007, the goals of the RFS program are to reduce both greenhouse gas emissions and US dependence on oil imports.

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The RFS requirements are met through a system of tradable compliance permits called Renewable (fuel) Identification Numbers, or RINs. RINs are generated when a renewable fuel is produced or imported and are detached when the renewable fuel is blended with petroleum fuel for retail sale, at which point RINs can be traded. Refiners and refined-petroleum product importers ("obligated parties") must hand in ("retire") RINs annually to the US Environmental Protection Agency (EPA) in proportion to the number of gallons of nonrenewable fuels they sell into the surface transportation fuel market. The sale of a RIN by a biofuel owner to an obligated party serves as a tax on petroleum fuels and a corrective subsidy to renewable fuels and is revenue neutral across the fuel market as a whole.

This paper examines the extent to which RIN prices are passed through to wholesale and retail fuel prices. This question is of interest for several reasons. First, the market mechanism whereby the RFS increases consumption of renewable fuels is by RIN prices reducing pump prices for fuels with high renewable content and increasing pump prices for fuels with low renewable content. Thus a central question for RFS policy is whether this pass-through of RIN prices occurs at the retail level. Second, if RIN prices are less than fully passed through to wholesale fuel prices, then an obligated party with a net RIN obligation is left with net RIN price exposure, so that an increase in RIN prices creates a financial burden on the obligated party that is not recouped by higher refined product prices. Third, a more general question on which there is a large literature concerns the pass-through of costs to wholesale and retail fuel prices. The costs studied here, RIN prices, fluctuate substantially on a daily basis, providing an opportunity to estimate dynamic pass-through relations at the daily level.

Through 2012, the cost of meeting RFS obligations through RINs was low, and the RIN market received little public attention. Starting in the winter of 2013, however, the price of conventional renewable fuel RINs (D6 RINs) rose sharply in response to an enhanced understanding that the RFS volumetric standards were approaching the capacity of the fuel supply to absorb additional ethanol. The predominant gasoline blend during this period was E10, which is up to 10% ethanol, and as system-wide ethanol approached 10% this pool became saturated, a situation referred to in the industry as the "E10 blend wall." Throughout 2013–15, RIN prices fluctuated through a wide range. These fluctuations have been widely and convincingly attributed by market observers and academics as stemming from the E10 blend wall combined with policy developments concerning the direction of the RFS (Irwin 2013a, 2013b, 2014; Lade, Lin, and Smith 2015). As a result, these RIN price fluctuations serve as a source of variation that allows us to identify RIN price pass-through.

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The question of RIN price pass-through to retail fuels has been addressed recently by the EPA in the context of its proposed rule for the 2014, 2015, and 2016 standards under the RFS (Burkholder 2015). That work examines the link between RIN prices and refined fuels by comparing price spreads on physically comparable fuels with different RIN obligations to the value of the net RIN obligation of that spread. For example, diesel fuel and jet fuel have similar chemical compositions, but diesel fuel is obligated under the RFS whereas jet fuel is not. Thus the spread between the spot prices of diesel and jet fuel, both in the US Gulf, provides a comparison that in theory should reflect the price of the RIN obligation of diesel fuel under the RFS while controlling for factors that affect the overall price of oil, local supply disruptions, and evolving features of the petroleum market that might affect the diesel-gasoline spread or the crack spread. In the retail market, Burkholder (2015) also examines the spread between E85, a fuel with between 51% and 83% ethanol, and E10, the dominant fuel during this period, which contains up to 10% ethanol. As is explained in the next section, during this period the net RIN obligation from blending E10 was essentially zero, so we expect Burkholder to find no effect of daily RIN price fluctuations on E10 prices.

This paper complements the analysis in Burkholder (2015). Burkholder's analysis is based on inspection of time series plots. The main contribution of this paper is to use econometric methods to estimate the extent of pass-through, to estimate pass-through dynamics, and to quantify the sampling uncertainty of these estimates. Like Burkholder, we examine the link between fuel price spreads and the value of the net RIN obligation of those fuels. We also use a longer data set and examine some wholesale spreads between obligated and nonobligated fuels, and spreads including biofuels, that are not examined by Burkholder.

The empirical analysis in this paper examines both the long-run, or equilibrium, pass-through coefficient and short-run pass-through dynamics. We estimate long-run pass-through using levels regressions. Because many of these prices fluctuate seasonally, our base specifications control for seasonality. We estimate the speed of this pass-through using both vector autoregressions and distributed lag regressions estimated on daily data for wholesale prices and on weekly data for retail prices.

This paper also relates to the substantial literature estimating the pass-through of changes in crude oil prices to retail prices, as well as whether this pass-through depends on the direction of the change in crude prices; see, for example, Borenstein, Cameron, and Gilbert (1997), Bachmeier and Griffin (2003), Lewis (2011), and Stolper (2016). Relative to this literature, the contribution of this paper is to examine the pass-through of this specific cost which is central to the design and operation of the RFS, and to provide additional evidence on price pass-through dynamics at the daily level. In a contribution postdating the working paper version of this paper, Burkhardt (2016) examines RIN pass-through at the refinery level using crude prices paid and refinery sales prices. His pooled estimates for gasoline and diesel indicate more-than-complete pass-through, although the estimated pass-through coefficient is not significantly different from 1.

Section 1 provides additional background on RINs, the RFS program, and RIN obligations. Section 2 describes the economic theory of pass-through and relates theory to our empirical strategy. Section 3 describes the data. Section 4 estimates long-run pass-through of RIN prices to wholesale and retail fuels. Section 5 analyzes the short-run dynamics of RIN price pass-through, and section 6 concludes.

1. RINS AND THE RFS PROGRAM

The RFS program divides renewable fuels into four nested categories: total renewable, advanced, biomass-based diesel (BBD), and cellulosic. These categories, which are shown in figure 1, are defined by the reduction in life-cycle emissions of greenhouse gases (GHGs) relative to petroleum, by feedstock and by fuel characteristics. Under the EISA, each of these four categories has its own volumetric requirements, which the EPA translates into four corresponding fractional standards through annual rule makings.

There are four types of RINs corresponding to the different fuel categories: cellulosic fuels generate D3 RINs, BBD generates D4 RINs, advanced noncellulosic non-BBD fuels generate D5 RINs, and conventional fuels (renewable fuels that meet the

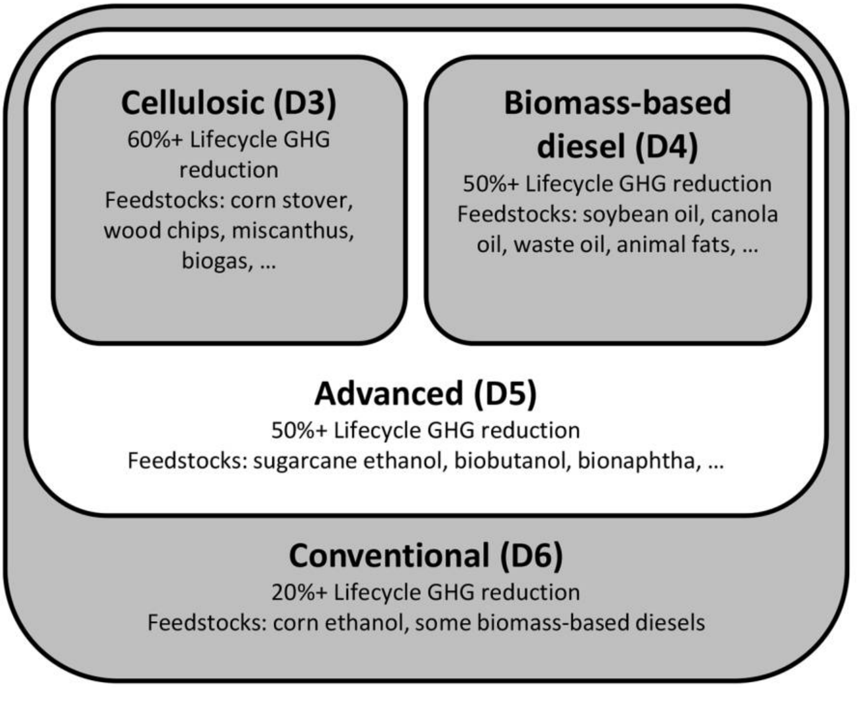

Figure 1. The RFS nested fuel structure

80% lifecycle GHG emissions reduction requirement but do not qualify as advanced biofuels) generate D6 RINs. The units of RINs are ethanol-equivalent RIN gallons: one gallon of corn ethanol generates 1 D6 RIN, but because of the higher energy content, one wet gallon of biomass-based diesel generates 1.5 D4 RINs.[1] Under the nested compliance system, a D4 RIN can be used to demonstrate compliance with the BBD mandate, the Total Advanced mandate, or the Total Renewable mandate. Similarly, a D5 RIN can be used to demonstrate compliance with the Total Advanced or Total Renewable mandate. A D6 RIN can only be used to demonstrate compliance with the Total Renewable mandate.

Figure 2 depicts a simplified version of the flow of RINs for corn ethanol. RINs are generated when the distiller produces ethanol. The distiller sells the physical ethanol, and with it the "attached" RIN, to an entity that blends the ethanol into petroleum gasoline to sell as a finished fuel (E10 or a higher blend). The RIN detaches when the physical gallon of ethanol is blended, at which point the RIN can be sold to an obligated refiner or importer or, if the owner of the detached RIN is an obligated party, the owner can retain the RIN. The obligated party then submits the RIN to the EPA to demonstrate compliance.

During 2013, there were 13,351 million D6 RINs generated, almost entirely from corn ethanol. There were 558 million D5 RINs generated, slightly over 80% of which were produced by advanced noncellulosic ethanol (mainly Brazilian cane ethanol). There were 2,739 million D4 RINs generated, corresponding to 1,765 million wet gallons of biomass-based diesel, and there were 0.4 million D3 RINs generated. Because the volume of D3 RINs is negligible during our sample period, we ignore D3 RINs and cellulosic biofuels henceforth.

Figure 3 shows RIN prices for the period of our data, January 1, 2013–March 9, 2015. This was a period of high RIN price volatility, primarily in 2013 but also, to a lesser extent, in 2014–15, and the research in this paper exploits this variation in RIN prices to estimate pass-through. In the winter of 2013, D6 RIN prices rose from under \$0.10 to much higher prices, hitting \$1.40 in the summer of 2013 before falling back below \$0.30 in the late fall of 2013. Prices were more stable during 2014, although they rose in the winter of 2014–15.

As discussed in Burkholder (2015), the initial rise in RIN prices in the winter of 2013 stemmed from increasing market awareness that the RFS volume requirements

1. There are additional nuances. Different biofuels have different energy contents and their RIN generation is adjusted accordingly. The biomass-based diesel product with the largest volume during this period is mono-alkyl ester biodiesel, which generates 1.5 ethanol-equivalent D4 RINs per physical gallon of BBD. Non-ester renewable diesel generates 1.7 D4 RINS per physical gallon. Some biomass-based diesel is produced by pathways that do not qualify for a D4 RIN but generate D6 RINs ("conventional biodiesel" or "conventional renewable diesel"). These nuances do not matter for the empirical analysis in this paper.

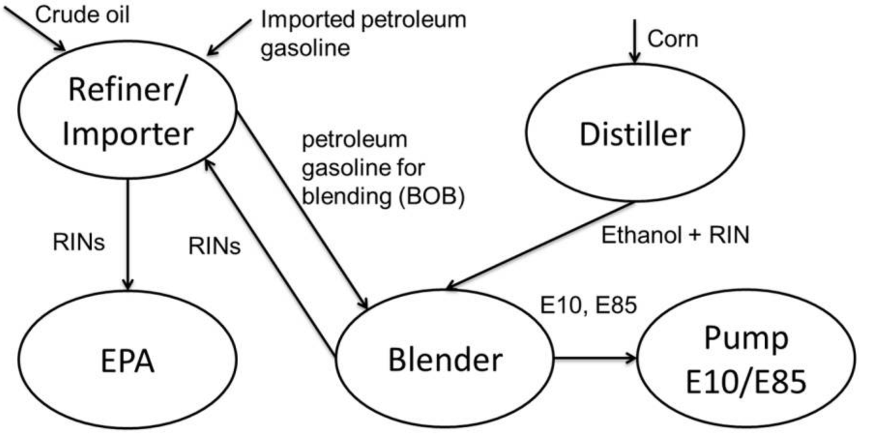

Figure 2. Simplified RIN generation and obligation on the gasoline supply chain (ethanol only). RINs are generated when the renewable fuel is produced or imported, are separated from the fuel upon blending into the fuel supply, and are retired by obligated parties (refiners or importers of nonrenewable fuels).

were approaching or exceeding the so-called E10 blend wall, the amount of ethanol that can be blended into E10, the dominant blend of gasoline which is up to 10% ethanol. As is suggested by the event markers in figure 3 and as is discussed in detail by Irwin (2013a, 2013b, 2014) and Lade et al. (2015), the subsequent variations in RIN prices arose in large part because of changing expectations about future RFS policy. Events that influenced these expectations included a leaked proposal for 2014 volumes, a 2014 proposal that was never finalized, EPA public statements indicating evolving policy, and repeated delays of proposed standards for 2015. More generally, the movements in RIN prices over this period were not linked to economic growth, shifts in diesel versus gasoline demand, or other features that might affect price spreads between obligated and nonobligated fuels other than through RIN prices themselves.

Because of the nested compliance system, the RIN prices satisfy the inequalities, $P_{D4} \geq P_{D5} \geq P_{D6}$, where P_t^{D4}, P_t^{D5}, and P_t^{D6} respectively are the price of a D4, D5, and D6 RIN. During most of this period, the three RIN prices were within a few cents of each other. When all three RIN prices were essentially equal, higher-value RINs (such as D4) were being used to satisfy obligations lower in the nesting hierarchy (such as the conventional renewable fuel obligation), so the higher-value RINs were trading at the price of the D6 RIN.

In 2013, EPA required that, for each gallon of petroleum gasoline or diesel sold into the surface fuels market, an obligated party must retire 0.0113 D4 RINs to meet the BBD standard, 0.0162 D4 or D5 RINs to meet the Total Advanced standard, and 0.0974 D4, D5, or D6 RINs to meet the Total Renewable standard. Because of the RFS nesting structure, a D4 RIN retired to meet the BBD standard also counts toward

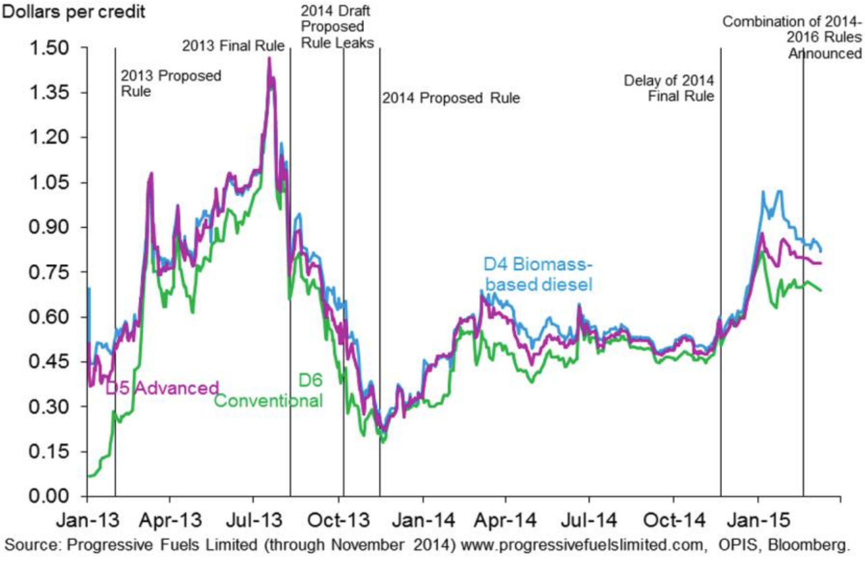

Figure 3. Daily RIN prices, January 1, 2013–March 9, 2015

the Total Advanced and Total Renewable standard. For the moment, suppose that the nested mandates are binding, so an obligated party met the per gallon requirement by retiring 0.0113 D4 RINs, 0.0162 – 0.0113 = 0.0049 D5 RINs, and 0.0974 – 0.0162 = 0.0812 D6 RINs. Then the cost of this bundle of RINs retired per gallon of obligated nonrenewable fuels is:

$$B_t = 0.0113P_t^{D4} + 0.0049P_t^{D5} + 0.0812P_t^{D6} \quad \text{(price of per gallon RIN obligation).} \tag{1}$$

In fact, equation (1) holds whether or not each of the individual mandates are individually binding: under the nesting structure, if a higher-value RIN is used to satisfy a lower-value obligation, then the two RIN prices equate and equation (1) still holds.[2] Because RIN prices change daily, the price of the RIN bundle changes daily even though the per gallon RIN obligation (the coefficients in [1]) remains constant.

In principle, the per gallon RIN obligations change annually as the EPA ramps ups the renewable requirement in the RFS. However, EPA's initial 2014 proposed standard was never finalized, and it was not until June 2015 that EPA re-proposed the

2. For example, suppose that D4 RINs are being used to satisfy the D6 requirement, as was the case during much of this sample period. Then the price of the D4, D5, and D6 RINS will be equal, so that any "excess" D4 RINs used to satisfy the D6 (conventional) requirement can be valued equivalently at the D4 or D6 price.

2014 standard and proposed a 2015 standard. Because there was no new standard in place for 2014 or 2015, the industry operated under the 2013 obligation during our full sample period of January 1, 2013–March 9, 2015. We therefore use equation (1) to compute the price of a RIN bundle obligation per gallon of petroleum fuel for our full sample period.

2. THE ECONOMICS OF PASS-THROUGH AND EMPIRICAL STRATEGY

The market prices of RINs provide the economic incentives whereby sufficient volumes of renewable fuels are produced and sold into the fuel supply to achieve the fractional RFS compliance standards. In effect, the RIN obligation of an obligated party imposes a tax of amount B_t, given by equation (1), on each gallon of nonrenewable fuel. Similarly, blending a gallon of renewable fuel produces a RIN that can be sold to generate an additional source of revenue in addition to that obtained for its energy, so this RIN provides a subsidy for the production and use of the renewable fuel.

The basic economics of this tax-and-subsidy mechanism are shown in figure 4. The subsidy value is determined by the economic fundamentals of the cost of the biofuels, the cost of the petroleum fuels, and the demand for biofuels. Figure 4*A* illustrates the situation for biodiesel. During our sample period, the blend fractions for biodiesel were sufficiently low that in effect biodiesel and petroleum diesel were perfect substitutes so that the demand for biodiesel is perfectly elastic at the price of petroleum diesel. Because biodiesel is more expensive to produce, the RIN value is determined by the marginal cost of production at the biodiesel mandate, which is the difference between the supply and demand curves at the obligated volume. In this case, the RIN subsidy accrues to the biodiesel producers to offset their higher costs.

Figure 4*B* illustrates a different configuration, in which the driver of the RIN value is low demand for the biofuel. This reflects the situation during our sample period for ethanol, where the fact that the vast majority of fuel sold is E10 (the so-called E10 blend wall) makes it difficult to blend more than 10% ethanol into the fuel supply. The main conduit for this additional ethanol is E85, which can contain between 51% and 83% ethanol, and which is available at a very small fraction of gas stations. Figure 4*B* depicts how, in this circumstance, blending more ethanol requires deep discounts to ethanol to stimulate additional consumption of E85. In this case, the RIN subsidy accrues mainly to purchasers of E85, not to producers.

The effectiveness and efficiency of the RFS depend on the RIN price tax and subsidy passing through to producers and to ultimate consumers. This pass-through could be less or more than one to one if there are market failures. For example, recall that the RIN is separated at the point of blending, which typically occurs at a wholesale terminal upstream of the ultimate consumer at the pump. If there is monopoly power at the point of blending, then the owner of the fuel might not pass on the full RIN value to the retail outlet purchasing the blended product. Similarly, if there were

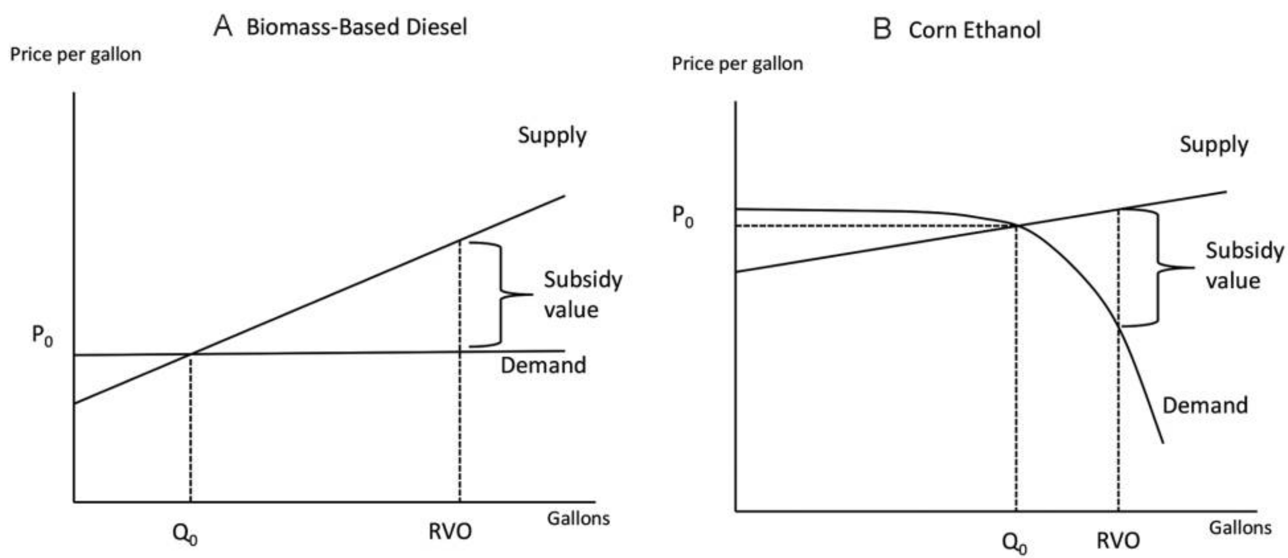

Figure 4. RIN price determination in terms of market fundamentals

monopoly power among the few gas stations that sell E85, then some of the RIN value could be retained by the retail outlet and not passed on to the consumer. Stolper (2016) provides a model of partial pass-through at retail outlets based on retail monopoly power, and Burkhardt (2016) provides a model of how refineries might not fully pass through RIN obligation values if they have monopoly power. In all these cases, the market failure can be a local one induced by a combination of the large fixed infrastructure costs in the fuel distribution system and lack of local competition.

The foregoing discussion suggests that, under perfect competition, the price of the RIN obligation should pass through one for one to the price of an obligated fuel, whether that price is wholesale or retail. In theory, one might try to measure pass-through by estimating the relationship between the price of an obligated fuel—for example, the spot price of bulk diesel fuel—and the price of its RIN obligation. In practice, however, this approach is not promising because the price of obligated fuels fluctuates for many reasons other than RIN prices, including the price of crude oil, seasonal factors in demand and supply, and supply chain interruptions. For example, in our sample the wholesale spot price of low-sulfur diesel in the Gulf has a standard deviation of 42.1¢/gal whereas its RIN obligation B_t has a standard deviation of 2.3¢/gal. An econometric attempt to disentangle this small signal from the large noise is not promising.

Instead, the approach used in this paper is to control for many sources of fluctuations in fuel prices by examining not fuel prices themselves, but spreads between the prices of fuels that are physically similar but have different RIN obligations. For example, ultra-low sulfur number 2 diesel and jet fuel are physically close products, but diesel (a surface transportation fuel) is an obligated fuel under the RFS whereas jet fuel is not. In equilibrium a refiner would be indifferent between producing for the diesel or jet fuel market, as long as the price received by the refiner, net of the RIN obligation, is the same. That is, in equilibrium we would expect that the spread between the price of Gulf diesel and Gulf jet fuel would equal the value B_t of the RIN obligation on a gallon of diesel. (Here, we abstract from other factors that could affect the spread, such as other taxes, transportation, seasonal fluctuations, and physical differences.) More generally, if refiners and importers fully pass through the cost of the bundle of RINs to the wholesale price of obligated fuels, then we would expect the spread between the price of the obligated fuel and the price of the comparable nonobligated fuel to equal the cost of the bundle of RINs. Because the main drivers of the price of these fuels, such as the price of oil, are the same, the fluctuations in the spread between these two prices is much smaller than in either of the individual fuels: in our sample, the standard deviation of the Gulf diesel–Gulf jet fuel spread is 4.5¢/gal. Thus econometric analysis of movements in this spread and how they relate to RIN prices is more promising than for the individual obligated fuel prices directly.

The RFS imposes RIN obligations on surface transportation fuels but not air transportation fuels, and it imposes RIN obligation on American fuels but not European fuels. The wholesale petroleum gasoline sold in the United States that can be blended with ethanol to make E10 or E85 (reformulated blendstock for oxygenated blending, RBOB) is similar physically to wholesale petroleum gasoline sold in Europe (European blendstock for oxygenated blending, EBOB). Thus there is an arbitrage relationship for the spread between wholesale petroleum gasoline in New York Harbor and Rotterdam. An importer could sell EBOB in Rotterdam, which would not incur a RIN obligation, or sell RBOB in New York, which would incur a RIN obligation. If the importer fully passes through the cost of the bundle of RINs to the wholesale price of the fuels, then we would expect the difference between the price of EBOB in Rotterdam and the price of RBOB in New York to equal the additional cost of the RIN obligation that the importer incurs on the New York sale, net of transaction costs.

This logic extends to other spreads. Let P_t^i and P_t^j be the price of fuels i and j on day t, and let S_t^{ij} denote the spread between these two prices. The equilibrium relation we study is the relation between the spread $S_t^{ij} \equiv P_t^i - P_t^j$ and its net RIN obligation:

$$S_t^{ij} = \alpha_{ij} + \theta_{ij} R_t^{ij} + u_t^{ij}, \tag{2}$$

where R_t^{ij} is the price of the net RIN obligation on the spread, which is the difference between the RIN obligation on fuel i and the RIN obligation on fuel j, and where u_t^{ij} represents the other factors that influence the spread. For the Gulf diesel–Gulf jet fuel spread example, Gulf diesel has a RIN obligation of B_t and Gulf jet fuel has no RIN obligation, so the net RIN obligation is $R_t^{\text{gulfdiesel,gulfjet}} = B_t$. In fact, for the six wholesale petroleum spreads we study, the first fuel has a RIN obligation of B_t and second fuel does not have an obligation, so B_t is the net RIN obligation for all six wholesale petroleum spreads.

The coefficient of interest is θ_{ij}, the pass-through coefficient for spread (i, j). Because the units are all \$/gallon, a pass-through coefficient $\theta_{ij} = 1$ corresponds to complete pass-through. The relationship in equation (2) between the spread and the net RIN obligation represents an equilibrium relationship, which we will also refer to as a long-run relationship because it is specified in levels of the variables.

We also examine spreads between two retail fuel prices, E10 and E85. We define the net RIN obligation on a blended retail fuel as the weighted sum of the RIN obligations on its component wholesale fuels. For example, the net RIN obligation on E10 is equal to the fraction of petroleum gasoline in E10 times the RIN obligation on petroleum gasoline, plus the fraction of ethanol in E10 times the RIN obligation on ethanol. Note that the RIN obligation on a gallon of ethanol is negative, equal to the revenue generated by selling a D6 RIN. During our sample period, E10 contained approximately 10% ethanol, the vast majority of which was corn ethanol, and 90% petroleum gasoline. Blending a gallon of E10 thus typically generated 0.1 D6 RINs from the ethanol but entailed an obligation (to the upstream obligated party) of 0.9 RIN bundles from the petroleum gasoline. Thus the net RIN obligation X_t^{E10} from blending a gallon of E10 is the sum of the obligation on the 0.9 gallons of petroleum gasoline and the (negative) obligation on the 0.1 gallons of ethanol:

$$X_t^{E10} = -0.1P_t^{D6} + 0.9B_t. \tag{3}$$

Similarly, over this sample period E85 averaged 74% ethanol, so its net RIN obligation is:

$$X_t^{E85} = -0.74P_t^{D6} + 0.26B_t. \tag{4}$$

The net RIN obligation for the E85–E10 spread therefore is $R_t^{E85-E10} = X_t^{E85} - X_t^{E10}$.[3]

An implication of equation (3) is that the effect of a change in the price of D6 RINs on the net E10 RIN obligation is a very small net subsidy: at the 2013 fractional standards, the RIN revenue from blending 0.1 gallons of ethanol essentially offsets the RIN obligation on the 0.9 gallons of petroleum fuel. For example, if all RIN prices were \$1, then blending 0.1 gallons of ethanol would generate 10.0¢ while the RIN obligation on the petroleum content would be $0.9 \times 0.0974 \times \$1.00 = 8.8$ ¢, for a net subsidy of 1.2¢/gallon.

In practice, the relationship (2) might hold only with a lag. Even in informationally efficient markets for petroleum fuels, we might observe lags in pass-through because of details such as when RFS news is announced or potentially thin trading days in some RIN markets. At the retail level, the literature on retail gasoline pass-through (discussed above) documents lags of several weeks in passing through product costs to retail prices. In section 5, we therefore also consider dynamic versions of (2) that allow for lagged responses, and we defer further discussion of those specifications to that section.

3. THE DATA AND DESCRIPTIVE STATISTICS

The data consist of daily fuel prices and the prices of D4, D5, and D6 RINs from January 1, 2013, to March 9, 2015. Prices on D4, D5, and D6 RINs are primarily from Progressive Fuels Limited.[4] Domestic wholesale prices were obtained from the Energy

3. Equations (3) and (4) assume that all the ethanol blended into E10 and E85 is conventional (corn) ethanol. In reality, a small amount of cane ethanol, which generates a D5 RIN, is also used. However cane ethanol is less than 3% of total ethanol and in any event during our sample the prices D5 and D6 RINs were essentially equal (see fig. 2), so for the purpose of computing the E10 and E85 RIN obligation a negligible error is made by assuming that all the ethanol generates a D6 RIN.

4. RIN price data from Progressive Fuels Limited are proprietary. Progressive Fuels Limited can be reached online at http://www.progressivefuelslimited.com and by phone at 239-390-2885. Our Progressive Fuels Limited data end November 30, 2014, and were filled in using OPIS data. These RIN prices are traded prices and do not necessarily reflect prices embedded in long-term contracts for RINs.

Information Administration:[5] New York Mercantile Exchange prompt-month futures prices for reformulated blendstock for oxygenated blending (RBOB) New York Harbor, and spot prices for Brent oil, RBOB Los Angeles, Ultra-low sulfur No. 2 diesel New York Harbor and US Gulf Coast, and Kerosene-type jet fuel US Gulf Coast. Two wholesale European prices, obtained from Argus, were used: the Rotterdam barge German diesel (10 parts per million [ppm] sulfur) price, and the price of European blendstock for oxygenated blending (EBOB) free on board Rotterdam (both quoted in dollars per tonne, converted to dollars per gallon).[6] Biofuel prices were obtained from Bloomberg: prompt-month spot prices for ethanol (E100) free on board Chicago, New York Mercantile Exchange prompt-month futures prices for European domestic ethanol free on board Rotterdam (quoted in euros per cubic meter and converted to dollars per gallon), and spot prices for soy methyl esters biodiesel (B100) US Gulf Coast. Retail fuels prices for diesel, E10, and E85 are national average pump prices produced by the American Automobile Association and reported by (and downloaded from) Bloomberg.[7] The data are for US business days (defined as days the NYMEX is open), typically close of business local time. Additional data details are available in the online appendix.

We constructed various spreads from these data. Recall that obligated fuels are those sold for use in the surface transportation sector in the United States; nonobligated fuels are fuels used in Europe and fuels used domestically for purposes other than surface transportation.

We analyze four RIN-obligated fuels: New York RBOB, LA RBOB, New York diesel, and Gulf of Mexico diesel. A number of candidate “control” nonobligated fuels exist for each of these fuels. We considered four different control fuels: Gulf of Mexico jet fuel, Rotterdam diesel, European reformulated gasoline, and Brent crude. The product of both the RIN-obligated and control fuels yields 16 potential spreads one could analyze. The ideal control fuel will have similar supply and demand shocks; therefore, the difference between changes in the RIN-obligated fuel and the control fuel will be due to changes in RIN prices. The control fuels can deviate from this ideal scenario because of differences in the physical product and market differences stemming from geography.

5. Spot prices were downloaded from http://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm, and futures prices were downloaded from http://www.eia.gov/dnav/pet/pet_pri_fut_s1_d.htm.

6. Rotterdam diesel and EBOB data from Argus are proprietary. Our Argus data begin January 3, 2012. Bloomberg data were used for missing values in the main sample and for seasonal adjustment using earlier dates.

7. The only adjustment for outliers was for the E85 price, which has five episodes of large measured price changes that are reversed within one to four days and appear to be measurement errors; these observations were omitted from the regressions.

We reduce the number of spreads we analyze by first determining whether there is a control fuel that dominates all of the other control fuels across both dimensions. When this is the case, we use only one control fuel. For example, in the case of New York Harbor diesel, Rotterdam diesel is both closest in product and has the lowest transportation costs of the candidate control fuels. When a single control fuel does not dominate on both dimensions, we choose a fuel that is closest in product space and another that is closest in terms of transportations costs, which we discuss below.[8]

The wholesale spreads are the price differences, in dollars per gallon, between a fuel that is obligated under the RFS and a similar fuel that is not obligated:

Diesel spreads: Gulf diesel–Gulf jet fuel spread = Ultra-low sulfur No. 2 diesel spot, US Gulf–Jet fuel, US Gulf
NYH diesel–Rotterdam diesel spread = Ultra-low sulfur No. 2 diesel spot, New York Harbor–Barge diesel, Rotterdam
Gulf diesel–Rotterdam diesel spread = Ultra-low sulfur No. 2 diesel spot, US Gulf–Barge diesel, Rotterdam

Gasoline spreads (wholesale): NYH RBOB–EBOB spread = RBOB prompt-month futures, New York Harbor–EBOB, Rotterdam
NYH RBOB–Brent spread = RBOB prompt-month futures, New York Harbor–Brent spot
LA RBOB–Brent spread = RBOB spot, Los Angeles–Brent spot

We also consider two wholesale price spreads involving biofuels. The first is the spread between the Chicago ethanol price and the Rotterdam ethanol price; the second is the spread between the spot price of biodiesel in the Gulf and the Gulf ultra-low sulfur No. 2 diesel price. These spreads are discussed in more detail in section 5.

8. This discussion on the choice of spreads has focused on the fuel characteristics. The spread choice can also be approached from an econometric perspective. The reason to use a spread, rather than just an individual fuel, is to control for the many non-RIN reasons, such as supply and demand shocks, that fuel prices move. From an econometric perspective, a good control spread is one for which the RIN "signal" is large, relative to the non-RIN reasons for the spread moving: if so, the regression error will be large and, given the variation in RIN prices, the pass-through coefficient will be estimated more precisely. Although one could use these obligated and nonobligated fuels to construct alternative spreads, the econometric value of doing so is limited because those spreads would be linear combinations of one another. In standard OLS notation, let X be the regressor matrix and let $Y1$ and $Y2$ be two spreads. Then $(X'X)^{-1}X'(Y1 + Y2) = (X'X)^{-1}X'Y1 + (X'X)^{-1}X'Y2$, that is, the OLS pass-through coefficient on a spread that is the sum of two other spreads is the sum of those pass-through coefficients. The standard errors in our pooled regressions account for the correlations among the innovations in the spreads so those standard errors would not be reduced by including spreads that are linear combinations of the already-included spreads.

On the retail side, we examine the retail fuel E85–E10 spread (= E85 price – E10 price).[9] We also examine changes in the E10 price directly, without a spread for a control, to examine the prediction of a negligible effect of changes in RIN prices on the E10 price.

3.1. Time Series Plots and Summary Statistics

Figures 5–7 plot the time series data on the wholesale diesel spreads, the wholesale gasoline spreads, and the E85–E10 spread. Each plot includes the spread and the cost of the net RIN obligation, shifted to have mean zero over the full sample to facilitate visual comparison. Table 1 reports summary statistics for all the spreads considered in the paper, along with the net RIN obligations.

The standard deviations of the six wholesale refined product spreads over the estimation sample are less than $0.22. The value of the net RIN bundle for these wholesale fuels averaged $0.056 over this period, with a standard deviation which is one-tenth to one-half that of the refined product spreads. Of the series we consider, the largest fluctuations were in the E10 price, driven by the sharp drop in the price of oil starting in July 2014. The net RIN obligation on the E85–E10 spread is large and negative, averaging $0.392/gallon over this period. Notably, the standard deviation of the E85–E10 net RIN obligation exceeds the standard deviation of the E85–E10 spread by one-fourth, suggesting incomplete pass-through.

Several of the series have substantial high-frequency noise. This is particularly true for the NYH diesel–Rotterdam diesel and Gulf diesel–Rotterdam diesel spreads (fig. 5*B*, 5*C*), but also for the NYH RBOB–EBOB spread and the E85–E10 spread (figs. 6*A*, 7). While the range of variation of the diesel spreads is roughly the same as the RIN price obligation, the gasoline and retail spreads vary over much larger ranges than the RIN price obligation, as indicated by the standard deviations in table 1.

Consistent with the analysis in Burkholder (2015), the wholesale spreads in figures 5 and 6 broadly move with the RIN obligation price; however, variation in the RIN obligation price is just one of many reasons for movements in these spreads. Some of these non-RIN movements are idiosyncratic to certain spreads, for example, the spikes in the NYH diesel–Rotterdam diesel spread (fig. 5*B*) during the late winters of 2014 and 2015, indicating temporarily tight markets for diesel and heating oil in the northeast United States. Other non-RIN movements are more persistent, such as

9. Another spread of potential interest is the retail E10–Pump diesel spread. Pump diesel has a lower renewable content than E10 so entails a net RIN obligation. However, these fuels have different seasonals and different physical characteristics, and the standard deviation of the E10–Pump diesel net RIN obligation is 0.9¢ over the sample, which is dwarfed by the 17.5¢ standard deviation of the E10–Pump diesel spread. It is therefore not surprising that preliminary econometric estimates using this spread had very large standard errors, making that analysis uninformative, and we do not pursue this spread here.

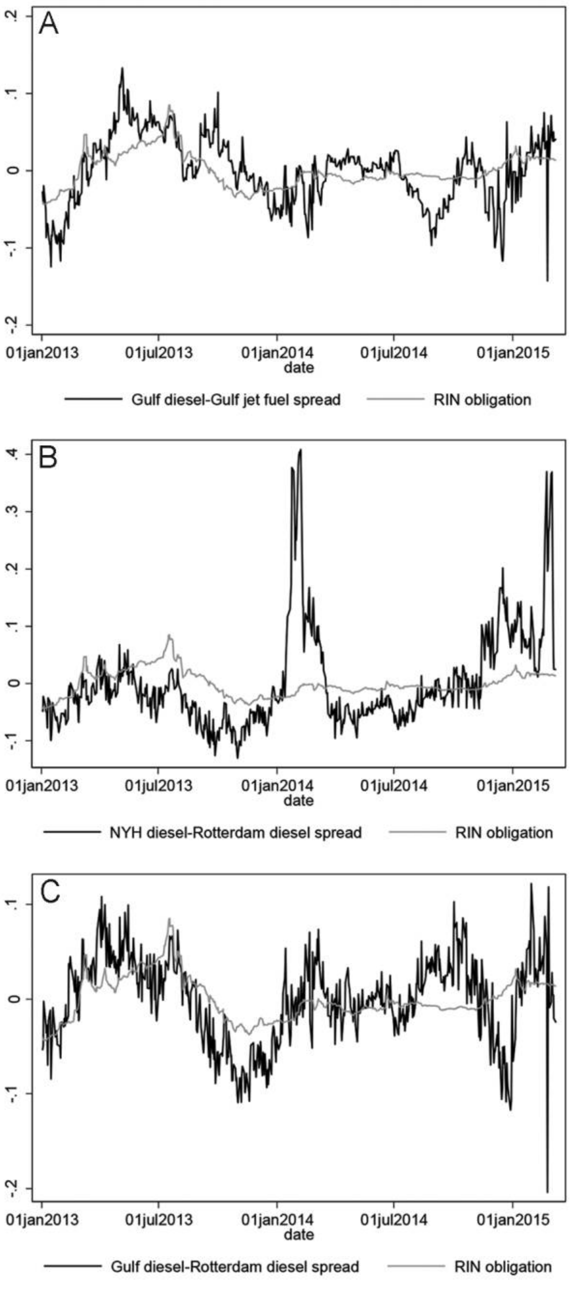

Figure 5. Wholesale diesel fuel spreads and net RIN obligation. Series shifted to have mean zero. Color version available as an online enhancement.

the decline in the NYH RBOB–EBOB spread (fig. 6*A*) during the summer of 2014 at a time that the value of the RIN obligation was slowly increasing.

Figure 7 presents mixed evidence on the co-movements of the E85–E10 spread and its net RIN obligation price. E85 prices fell relative to E10 during the spring and summer of 2013 as RIN prices initially rose. The movement in early 2013 was consistent with retail pass-through because rising RIN prices correspond to a falling net E85–E10 RIN obligation price as E85 is a renewables-heavy fuel. However, E85 prices rose only slightly as RIN prices fell in the fall of 2013, and through 2014 and 2015 fluctuations in the RIN obligation price appear less connected to the spread.

3.2. Seasonality

Fuel prices fluctuate seasonally. A standard method for allowing for seasonality in regressions with monthly data is to include 11 monthly indicator variables. However, monthly indicators are not appropriate for daily data because they jump from the end of one month to the start of the next. Instead, we estimate the seasonal component using sines and cosines evaluated on calendar days at the first four seasonal harmonic frequencies (shown in eq. [5]). The eight seasonal variables (four sine and four cosine) flexibly allow for seasonal patterns while imposing smoothness from day to day. Henceforth, we refer to these eight variables as our base set of seasonal control variables.[10]

The final two columns of table 1 report the results of estimating a regression of the row variable onto the eight seasonal control variables:

$$S_t^{ij} = \mu_{ij} + \sum_{k=1}^{4} \gamma_{c,k}^{ij} \cos(2\pi tk/366) + \sum_{k=1}^{4} \gamma_{s,k}^{ij} \sin(2\pi tk/366) + \nu_t. \quad (5)$$

For table 1, this regression was estimated using all available data prior to 2013; the period of our analysis was excluded from this regression to avoid confounding RIN price fluctuations with normal seasonal patterns. Five of the six wholesale petroleum spreads have seasonals that are significant at the 5% level, and for several of the spreads the seasonals explain a large fraction of the overall variation. In contrast, RIN prices do not exhibit seasonal variation in the pre-2013 data.

3.3. Persistence

Over a sufficiently long time period, we would expect the spreads and RIN prices to be stationary. However, over our short sample the assumption of stationarity might not be a good statistical description of these series. Figures 3 and 5–7 show low frequency

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10. Including the first six seasonal harmonics would be equivalent, with monthly data, to including 12 monthly indicators. Preliminary investigation indicated that the full six harmonics were not necessary so for parsimony the first four harmonics were used, and the results are robust to this choice.

Table 1. Daily Spreads and Prices: Summary Statistics

		Summary Statistics and Unit Root Tests: Jan. 1, 2013–March 9, 2015						Seasonal Regressions[a]	
	Series Start Date	Mean	SD	Min	Max	DF-GLS	ADF	p-Value	R^2
Fuels and fuel spreads:									
Gulf diesel–Gulf jet fuel	6/14/2006	.032	.045	–.111	.165	–2.012**	–2.454	.001	.119
NYH diesel–Rotterdam diesel	6/14/2006	.056	.086	–.074	.464	–2.893***	–3.396**	.238	.060
Gulf diesel–Rotterdam diesel	6/14/2006	–.022	.046	–.225	.100	–1.758*	–2.880**	.033	.122
NYH RBOB–EBOB	1/6/2010	.109	.099	–.171	.484	–3.694***	–3.985***	.000	.462
NYH RBOB–Brent	10/3/2005	.263	.146	–.013	.611	–1.488	–2.497	.000	.457
LA RBOB–Brent	10/3/2005	.330	.212	–.123	1.095	–2.071**	–2.995**	.000	.282
Chicago ethanol–Rotterdam ethanol	2/1/2010	.191	.378	–.453	1.944	–2.384**	–3.437***	.867	.079
Gulf biodiesel–Gulf diesel	1/28/2013	1.152	.589	.345	2.271	. . .	. . .	. . .	. . .
E85–E10	8/27/2012	–.503	.131	–.759	–.195	–1.144	–3.022**	. . .	. . .
E10	10/3/2005	3.317	.428	2.037	3.786	–.258	–.155	.049	.143

RINs and net RIN obligations:									
D6 RIN	3/16/2009	.557	.235	.069	1.445	−.617	−2.565	.869	.054
D5 RIN	7/8/2011	.638	.228	.220	1.465	−1.316	−1.632	. . .	. . .
D4 RIN	3/20/2009	.665	.227	.215	1.450	−1.912*	−1.868	.994	.024
RIN bundle (obligation on wholesale petroleum fuels)	3/20/2009[b]	.056	.023	.012	.141	−.727	−2.416	.612	.084
Gulf biodiesel–Gulf diesel net RIN obligation	7/8/2011	.942	.318	.304	2.035	. . .	. . .	. . .	. . .
E85–E10 net RIN obligation	7/8/2011	−.392	.165	−1.015	−.052	−.629	−2.555	. . .	. . .

Note. Units for the first four columns are dollars per gallon for fuels, and dollars per RIN-gallon for RINs. The last two columns report the *p*-value on the *F*-statistic testing the joint significance of the seasonal variables in a regression of the row variable on a constant and the seasonals (Newey-West standard errors, 30 lags), and the R^2 of the seasonals. The DF-GLS and ADF statistics test the null hypothesis that the row variable has a unit root, against the alternative that it is stationary (intercept, no time trend, maximum of six lags, lag determined by AIC); DF-GLS uses asymptotic critical values, ADF uses MacKinnon critical values. The summary statistics in the first four numeric columns, and the two unit root tests, are computed over January 1, 2013–March 9, 2015 (the full estimation sample). Entries with "…" indicate too few observations or too many missing observations to compute the relevant time series regressions.

[a] The seasonal regressions were estimated using all available data through December 31, 2012, for those series with at least one year of pre-2013 data.

[b] RIN bundle obligation begins to include D5 RINs starting 2011 so the RIN bundle obligation has missing values from January 2, 2011, to July 7, 2011.

* The unit root tests reject the unit root null at the 10% significance level.

** The unit root tests reject the unit root null at the 5% significance level.

*** The unit root tests reject the unit root null at the 1% significance level.

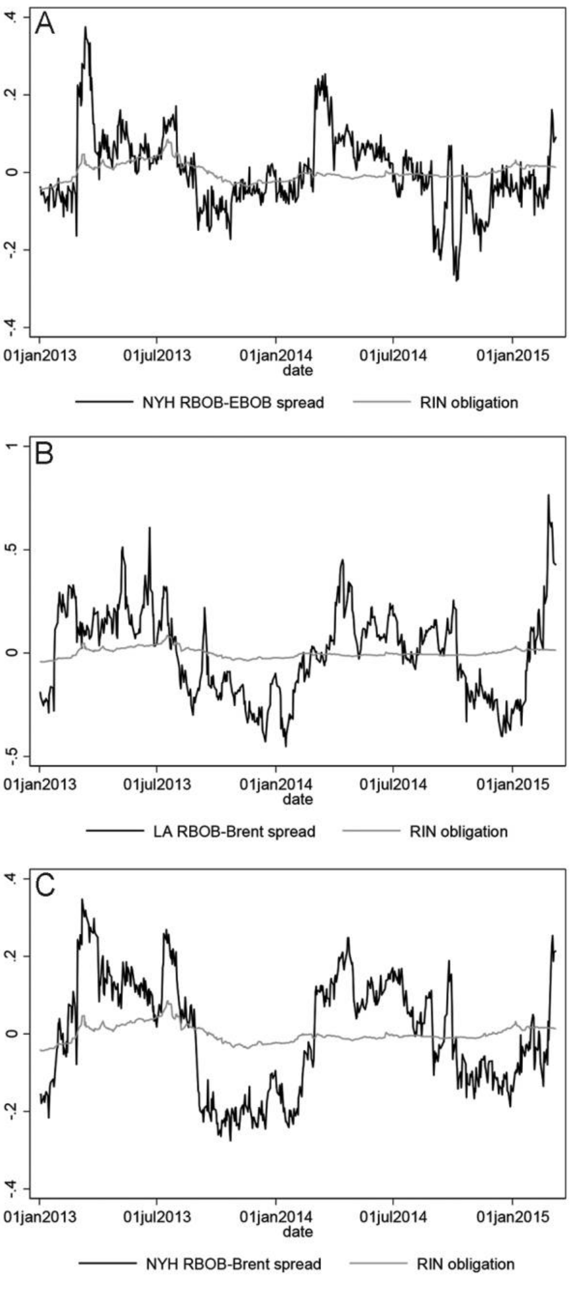

Figure 6. Wholesale gasoline fuel spreads and net RIN obligation. Series shifted to have mean zero. Color version available as an online enhancement.

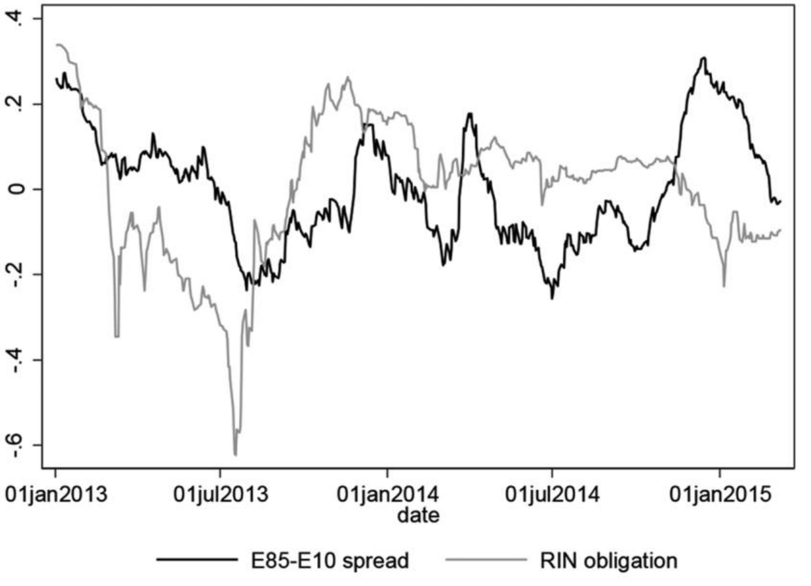

Figure 7. Retail E85–E10 spread and net RIN obligation. Series shifted to have mean zero. Color version available as an online enhancement.

movement, or persistence, in both the spreads and RIN prices in our sample. A large body of econometric methods and practice has developed around handling time series data with low frequency movements. The efficient estimator for the pass-through coefficient θ depends on whether the two series—for example, a wholesale fuel spread S_t^{ij} and its associated net RIN obligation R_t^{ij}—are integrated of order zero or one, and, if they are integrated of order one, whether the series are cointegrated.

To guide the specification of the time series regressions, the fifth and sixth numeric columns of table 1 report two unit root test statistics, the DF-GLS statistic and the augmented Dickey-Fuller statistic, both computed using data-dependent lag length selection as described in the table note. Looking across the unit root tests, nine of the 12 unit root tests for wholesale petroleum spreads reported in table 2 reject the unit root null at the 10% level, while only one of the six unit root tests for RIN prices, and none of the unit root tests for the composite RIN obligations, reject the unit root null at the 10% level.[11] The strong rejections for the spreads, the low power of unit root tests in general, and the theoretical notion that the spreads should be mean reverting

11. DF-GLS and augmented Dickey-Fuller unit root tests, applied to the D4, D5, and D6 RIN price series with a constant (no drift, AIC lag selection), fail to reject the null hypothesis of a unit root at the 10% level in five of the six cases, and in the sixth case rejects the unit root at the 10% but not 5% level.

over a sufficiently long time period, together suggest to us that the preferred model for these variables is that they are integrated of order zero. However, the evidence is mixed so for robustness we also use methods that are appropriate if the series are integrated of order one.

4. TIME SERIES ANALYSIS: LONG-RUN PASS-THROUGH

We now turn to time series regression analysis of the relation between fuel prices and the cost of net RIN obligations. We begin by examining long-run (or equilibrium) pass-through by estimating equation (2) and variations which include seasonal and other control variables. The next section examines pass-through dynamics.

4.1. Methods

The largest swing in RIN prices in figure 3 was the price increase in the spring and early summer of 2013, with a subsequent decline in the late summer and fall, followed by a smaller rise in the spring of 2014. These swings are associated with the revelation of news about future RFS policy over this period. While the large magnitude of these swings provides variation that we can usefully exploit for our pass-through analysis, their timing coincides with seasonal patterns in fuel prices as gasoline shifts from winter to summer blends and vice versa. We therefore take two approaches to handling this potentially confounding seasonality. Our primary approach is to augment the estimating equations to include the eight seasonal control variables in equation (5). As a secondary approach, we use seasonally adjusted spreads, where the seasonal adjustment is performed by estimating equation (5) for each spread using all available pre-2013 data for each spread, then subtracting off the part predicted by the seasonals. This latter approach is appealing because it mimics the standard practice of using seasonally adjusted data and because the seasonal adjustment predates the estimation period of interest. However, several of our series start only shortly before 2013, which introduces considerable estimation error into this pre-2013 seasonal adjustment procedure. We therefore use pre-2013 seasonal adjustment as a sensitivity check.

We use two different approaches to estimating the long-run, or equilibrium, levels relation between the fuel spreads and their RIN obligations. Section 2 reported mixed evidence concerning whether the variables are integrated of order one or zero. Because the preponderance of unit root tests for the spreads point to stationarity, our base approach is to estimate (2) by OLS, including seasonal controls, using Newey-West heteroskedasticity- and autocorrelation-consistent standard errors. As a secondary approach, we use the dynamic OLS (DOLS) efficient cointegration estimator (Stock and Watson 1993), implemented using five leads and lags of the first differences of the RIN obligation as additional regressors and also using Newey-West standard errors. This latter estimator is efficient if the variables in (2) have unit roots and are cointegrated.

4.2. Results

Table 2 presents the long-run, or equilibrium, pass-through estimates for the individual wholesale petroleum fuel spreads (first six columns) and for the E85–E10 retail spread (final column). The regressions vary in their treatment of seasonals, estimation method, and sample period. In all cases, the rows for regressions (1) through (6) report the coefficient and Newey-West standard error on the net RIN obligation. For the wholesale petroleum fuel spreads, the net RIN obligation is the price of the RIN bundle B_t defined in equation (1). For the E85–E10 spread, the net RIN obligation is $R_t^{E85-E10}$ as defined in the text after equation (4). Coefficients on control variables are not reported.

The results in table 2 suggest four conclusions. First, there is consistent evidence of full long-run (equilibrium) pass-through of RIN prices to wholesale fuels. In our preferred specification (1), the estimated coefficients are between 0.68 and 1.57. These estimates have a wide range of precision, from a tight standard error of 0.14 for the Gulf diesel–Rotterdam diesel spread to 0.70 for the LA RBOB–Brent spread. This lower level of precision is consistent with the large non-RIN variation in several of these series evident in figures 5 and 6.

Second, this evidence of full pass-through in wholesale fuels is robust to estimating the pass-through coefficient by DOLS instead of OLS (regression [2]), using two additional seasonal harmonics (regression [3]), using data seasonally adjusted by pre-2013 seasonal factors (regression [4]), and extending the sample back to 2010 (or the earliest date the spread is available, whichever is later; regression [5]), and to using either 20 or 40 lags to compute the Newey-West standard errors (not shown) instead of the 30 lags used in table 2. Of these five different specifications and the six wholesale spreads, only two of the 30 pass-through coefficients are different from 1 at the 10% level, and none are at the 5% level.[12] This said, many of the coefficients are imprecisely estimated.

Third, the results for wholesale fuels change if one ignores the seasonality in the spreads (regression [6]). The evidence in table 1 indicates that, before 2013, the fuel spreads have seasonal variation but the RIN prices do not, and the discussion above describes how RIN prices in 2013 and 2014 happened to move concurrently with

12. A natural instinct is to use the longest available data span, that is, regression (5), as the base case. Prior to 2013, there was very little variation in the price of D6 RINs, and the fractional obligations of D4 and D5 RINs were so low that the implied cost of RINs for obligated fuels varied by less than 2 cents. Moreover, because the RIN system was relatively new and RIN values were so low, before 2013 there was limited understanding of the RIN system so the pass-through coefficients post-2013 could be different than before 2013. For these reasons, and because our spreads start at different dates, we focus henceforth on regressions estimated using the 2013–15 sample.

Table 2. Fuel Spreads Levels Regressions and Cointegration Statistics

	Wholesale Spreads						Retail
Regression Coefficients (SEs)	Gulf Diesel–Gulf Jet Fuel	NYH Diesel–Rotterdam Diesel	Gulf Diesel–Rotterdam Diesel	NYH RBOB–EBOB	NYH RBOB–Brent	LA RBOB–Brent	E85–E10 (3-Week Lag of Net RIN Obligation)
(1) OLS, full sample, seasonals	1.159	1.565	.818	.682	1.086	.711	–.075^^^
	(.154)	(.424)	(.142)	(.332)	(.310)	(.701)	(.102)
(2) DOLS, full sample, seasonals	1.199	1.650	.836	.579	1.031	.744	–.085^^^
	(.156)	(.454)	(.159)	(.311)	(.326)	(.725)	(.107)
(3) OLS, full sample, augmented seasonals	1.150	1.543	.844	.618	1.066	.670	–.071^^^
	(.151)	(.411)	(.135)	(.265)	(.304)	(.609)	(.099)
(4) OLS, full sample, seasonally adjusted data	1.059	.628	.603^^	.954	1.436	1.906	–.079^^^
	(.225)	(.469)	(.185)	(.354)	(.477)	(.749)	(.118)

(5) OLS, extended 2010–15 sample, seasonals	.777^	1.303	.799	.802	.921	.445	.167^^^
	(.127)	(.235)	(.143)	(.187)	(.261)	(.498)	(.097)
(6) OLS, full sample, no seasonals	1.157	.770	.985	1.805^	3.519^^^	3.527^^	.235^^^
	(.225)	(.520)	(.247)	(.416)	(.713)	(1.263)	(.118)
Engle-Granger ADF cointegration test	−3.268*	−3.420**	−3.232*	−4.350***	−2.613	−3.354**	−3.070*

Note. The data are daily and the full sample is January 1, 2013–March 10, 2015. In the OLS regressions, the dependent variable is the spread and the regressors are its net RIN obligation and, if indicated, the set of four sine and four cosine seasonal variables described in the text. The reported coefficient and standard error are on the level of the net RIN obligation. DOLS regressions additionally include five leads and five lags of the first difference of the net RIN obligation (coefficients not shown). The augmented seasonals add sines and cosines evaluated at the fifth and sixth seasonal frequencies, for four additional regressors. All standard errors are Newey-West with 30 lags.

* The Engle-Granger ADF statistic tests the null of no cointegration against the alternative of cointegration, using asymptotic critical values; these cointegration tests reject non-cointegration at the 10% significance level.

** Cointegration tests reject non-cointegration at the 5% significance level.

*** Cointegration tests reject non-cointegration at the 1% significance level.

^ Reported regression coefficients are significantly different from 1 at the 10% significance level.

^^ Reported regression coefficients are significantly different from 1 at the 5% significance level.

^^^ Reported regression coefficients are significantly different from 1 at the 1% significance level.

standard seasonal shifts in fuels. Ignoring seasonality in fuel prices evidently results in omitted variable bias.

Fourth, the results for the retail E85–E10 spread are entirely different than those for the wholesale petroleum spreads. Whereas the evidence supports full pass-through to wholesale spreads, the pass-through coefficient for the E85–E10 spread is estimated to be close to zero in all six specifications. In table 2, the net RIN obligation enters with a 3-week lag; this specification is used because of the lagged pass-through of wholesale gasoline prices to retail fuel prices discussed above. These coefficients are somewhat sensitive to the lag choice, indicating somewhat larger (smaller) pass-through as the lag increases (decreases) (unreported results). We defer further analysis of retail pass-through dynamics until the next section. In any event, the levels regressions for the E85–E10 spread indicate very little pass-through, typically with confidence intervals of ± 0.2 that include zero. In short, the regression results for the E85–E10 retail spread in table 2 provide at best weak evidence of partial long-run RIN price pass-through to the retail E85 price.

4.3. Pooled Wholesale Spread Regressions

Many of the standard errors in table 2 are large, so we also use regressions that pool across the wholesale petroleum spreads. Table 3 reports results for pooled regressions, which impose the cross-equation restriction that the pass-through coefficient θ is the same for each spread. Each spread, however, is allowed to have different seasonals and, for the DOLS estimator, different coefficients on leads and lags of the net RIN obligation. The justification for this pooling is that the theory of pass-through does not distinguish between any of these different wholesale markets, so that the long-run coefficient should be the same even if the spreads have different seasonal patterns. As in table 2, standard errors are Newey-West with 30 lags. The regressions are pooled over three groups: the three diesel spreads, the three gasoline spreads, and the six combined wholesale petroleum spreads.

Pooling improves the precision of the estimators, especially for the gasoline spreads. The estimated pass-through coefficient is within one standard deviation of unity for pooled gasoline spreads and within two standard deviations of unity for pooled diesel spreads. When all six wholesale spreads are pooled, the long-run pass-through coefficient is estimated to be 1.00 using OLS or 1.01 using DOLS with the base set of seasonal variables, with a standard error of 0.11 (OLS) or 0.12 (DOLS).

5. TIME SERIES ANALYSIS: PASS-THROUGH DYNAMICS

We now turn to the short-run dynamics of RIN price pass-through.

5.1. Methods

Our primary method for estimating the dynamic response of the fuel spreads to unexpected changes in the value of the net RIN obligation is to estimate impulse response

Table 3. Pooled Levels Regressions for Wholesale Spreads

Regression Coefficients (SEs)	Diesel	Gasoline	Diesel and Gasoline
(1) OLS, full sample, seasonals	1.181	.826	1.003
	(.154)	(.269)	(.115)
(2) DOLS, full sample, seasonals	1.228	.785	1.007
	(.164)	(.284)	(.122)
(3) OLS, full sample, augmented seasonals	1.179	.785	.982
	(.147)	(.260)	(.109)
(4) OLS, full sample, seasonally adjusted data	.764	1.432	1.098
	(.211)	(.306)	(.159)

Note. All regressions are of the form of the spread in levels against its net RIN obligation in levels, with additional regressors. The diesel regressions pool three diesel spreads, the gasoline regressions pool three gasoline spreads, and the diesel and gasoline regressions pool all six spreads. The coefficient on the levels is constrained to be the same for the pooled spreads, but the other coefficients are allowed to differ across spreads. Standard errors are Newey-West with 30 lags and allow both for own- and cross-serial correlation in the errors. See the notes to table 1.

^ Reported regression coefficients are significantly different from 1 at the 10% significance level.

^^ Reported regression coefficients are significantly different from 1 at the 5% significance level.

^^^ Reported regression coefficients are significantly different from 1 at the 1% significance level.

functions using vector autoregressions (VARs). First consider the case of an individual spread (not pooled). In this case, the VAR has two variables: the spread and its net RIN obligation. As is discussed below, we order the net RIN obligation first, so the vector of time series variables in the bivariate VAR is $Y_t = (R_t^{ij}, S_t^{ij})$. The VARs are specified in levels of Y_t and have the form:

$$Y_t = \Psi_0 + \sum_{k=1}^{p} \Psi_k Y_{t-k} + \Gamma W_t + \eta_t, \tag{6}$$

where W_t is a vector of control variables and η_t is the VAR innovation (the one-step ahead population forecast error). In our base specification, W_t consists of the eight seasonal controls. The coefficient matrix Ψ_k is a matrix of autoregressive coefficients on the kth lag of Y. The coefficients in the matrices $\{\Psi_k\}$ and Γ are unrestricted.

The dynamic response of interest is the response of the fuel spread to an unexpected change in the RIN price obligation. In the VAR, this unexpected change in the RIN price obligation is the forecast error in the RIN obligation ("RIN price innovation"), which is the first element of η_t in (6). Thus the dynamic response of interest is the impulse response function of the fuel spread (Y_{2t}) with respect to η_{1t}. This is computed as the impulse response function from a structural vector autoregression using a Cholesky factorization, with the RIN obligation ordered first.

We also estimate pooled VARs, in which we impose the restriction that the dynamic response to a RIN price innovation is the same for each of the spreads. This is accomplished by imposing restrictions on the $\{\Psi_k\}$ matrices. Specifically, for a group of n pooled spreads, the restrictions are that the matrices $\{\Psi_k\}$ of the n bivariate VARs are identical across each spread. The matrices Γ are not restricted across spreads so that different spreads can have their own seasonals. As in the individual VARs, the pooled VARs are specified in levels.[13]

For our base specification, the bivariate weekly VAR with the set of eight seasonal controls, the Bayes information criterion selected a VAR lag length $p = 2$ for five of the six spreads and a lag length of three for the remaining spread; the Akaike information criterion selected a lag length of two for four of the six spreads. We therefore use a lag length of two as the base specification. Using longer lag specifications does not change any of the main results, although some of the impulse responses for the first few days are more jagged. Results for longer lag lengths (four and six) are reported in the appendix.

We also estimated bivariate VARs for the E85–E10 fuel spread and its net RIN price obligation. Because of the slower pass-through to retail prices documented in the literature, this VAR is estimated on weekly data—weeks ending Tuesday to minimize holidays and to maintain the calendar gap between observations. Preliminary lag length analysis pointed to one or two lags (Bayesian information criterion or Akaike information criterion, respectively), so we used two lags.

Our alternative method for estimating pass-through dynamics is to use unrestricted distributed lag regressions. Because these regressions do not include lagged values of the spread, they are estimated in first differences to avoid spurious correlation in levels. The regressions thus are of changes in the fuel spread against current and lagged values of changes in the RIN obligation, plus seasonal controls, and the dynamic multipliers are cumulated so that they are on the same basis as the VAR impulse response functions.[14] If RIN price movements are exogenous, for example, if they are determined solely by expectations of future policy, then these distributed lag regressions provide an alternative way to estimate impulse response functions without imposing the parametric VAR restrictions.

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13. These restrictions are implemented as restrictions on a $(n + 1)$-variable Cholesky-factorization VAR where $Y_t = (R_t, S_{1t}, \ldots, S_{nt})$. In this VAR, the restrictions are that, in the equation for S_{jt}: (i) the coefficients on lags of S_{it}, $i \neq j$, are zero; (ii) the coefficients on S_{jt-k} are equal to the corresponding kth own-lag coefficients for all spreads; and (iii) the coefficients on R_{t-k} are equal (for a given k) across all spread equations. In addition, in the equation for R_t, the coefficients on S_{jt-k} are imposed to be equal for a given lag k.

14. Specifically, the distributed lag regressions are of the form $\Delta S_t^{ij} = \mu_{ij} + \beta^{ij}(L)\Delta R_t^{ij} + \gamma^{ij} W_t + u_t^{ij}$, where ΔS_t^{ij} is the change in the spread between fuel i and fuel j, $\beta^{ij}(L)$ is a lag polynomial, ΔR_t^{ij} is the change in the net RIN obligation between fuel i and fuel j, and W_t is a vector of controls. The cumulative effect on the spread of a change in the net RIN obligation price after k days is the sum of the first k coefficients in the distributed lag polynomial $\beta^{ij}(L)$.

5.2. Results

Impulse response functions for the bivariate wholesale spread VARs are presented in figure 8, and the impulse responses for the pooled VARs are presented in figure 9. Figure 10 presents the impulse response functions for the E85–E10 spread and, in the lower panel, the alternative estimate of these dynamics from a distributed lag regression. Numerical values of the pooled impulse responses for wholesale fuels, for the first 10 business days, are presented in table 4.

The results in figures 8–10 and table 4 suggest two conclusions. First, the pass-through of RIN prices to wholesale fuel prices is large and fast, but not immediate. In the VAR that pools all six spreads (final panel in fig. 9 and final two columns in table 4), more than 70% of the RIN price innovation is passed through to the spread in the same day as the RIN price innovation, and after two days the pass-through coefficient is 0.99. A similar pattern is found in the bivariate VARs estimated using the individual spreads: across all these VARs, the lowest same-day pass-through is 0.46 (the Gulf diesel–Gulf jet fuel spread), and all VARs have dynamic pass-through coefficients within one standard deviation of 1.00 after two days.

Second, the weekly impulse responses in figure 10 suggest no, or at most a small, pass-through of RIN prices to E85 prices. This finding is consistent with the levels regressions reported in the previous section. The estimated dynamic pass-through differs depending on whether it is estimated using the VAR or the distributed lag method, with the VAR indicating a negative pass-through and the distributed lag estimating a small positive pass-through that reaches approximately 0.2 after 5 weeks. In both methods, however, the dynamic pass-through coefficient from one week onward is within a standard error of zero.

These findings are robust to increasing the VAR lag length to four or to six, to using seasonally adjusted data (with seasonals fit pre-2013) instead of using seasonal controls, and to including the spot price of Brent crude as controls. With the exception discussed above for the E85–E10 spread, these results are also robust to estimating the dynamics using distributed lag regressions instead of VARs. These sensitivity checks are reported in the appendix.

5.3. E10 Prices

Critics of the RFS claim that the RFS raises the price of gasoline, while advocates of biofuels claim that the mandate lowers the price of gasoline. There are (at least) two channels for this assertion. The first channel is that the production cost of biofuels—in the case of US retail gasoline, this effectively means corn kernel ethanol—are higher (critics) or lower (advocates) than the price of petroleum gasoline. Knittel and Smith (2015) examined these claims and concluded that, from 2003 to 2010, blending corn ethanol into gasoline modestly lowered the retail cost of E10, but by less than 10¢/gallon. The second alleged channel is that RIN prices get passed along into blended gasoline so that fluctuations in RIN prices drive up the price of blended gasoline. As was

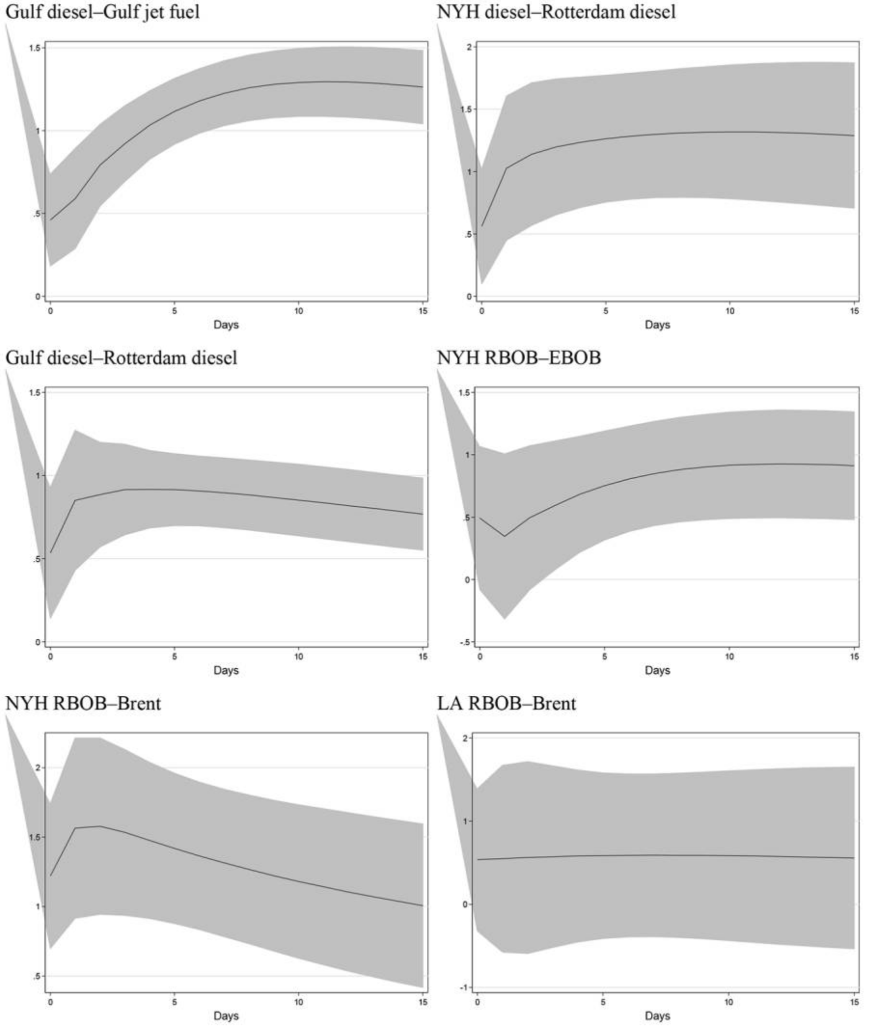

Figure 8. Impulse response functions of fuel prices to RIN obligation innovation: bivariate VARs for wholesale fuels. Graphs depict structural impulse response of the indicated spread to a RIN price innovation along with a 67% confidence interval. The VAR is estimated over the full sample, including the eight sine and cosine seasonal control variables. The impulse response functions are computed using a Cholesky factorization with the RIN obligation ordered first.

discussed in section 2, the net RIN obligation on E10 is very nearly zero: at the 2013 RFS standard, blending petroleum gasoline into E10 entails a RIN obligation on the petroleum that is almost entirely offset by the D6 RIN generated when blended with corn ethanol.

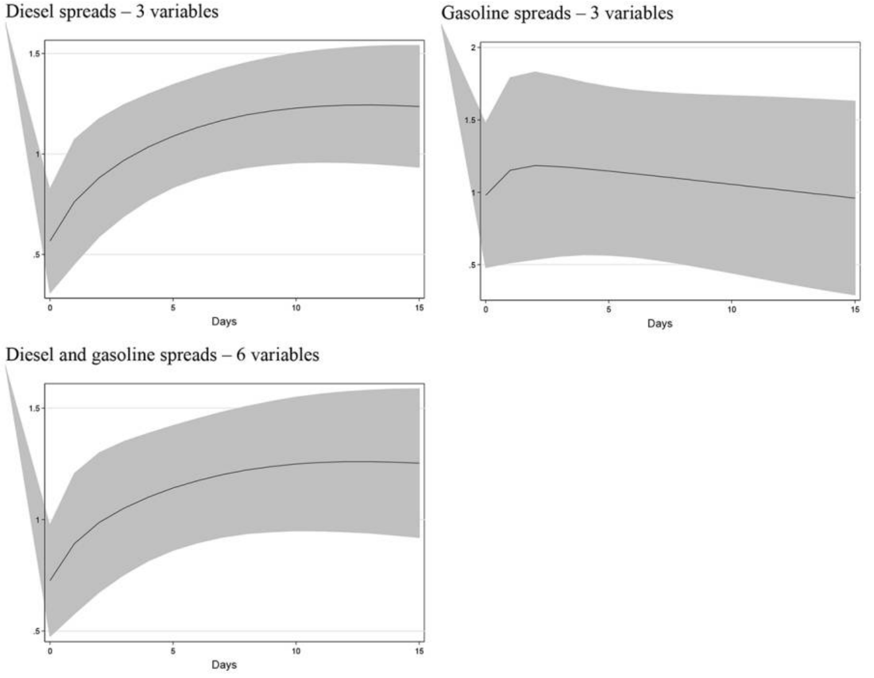

Figure 9. Impulse response functions of fuel prices to RIN obligation innovation: pooled VARs for wholesale fuels. The impulse response functions are for pooled VARs with the indicated fuel spreads, where the VAR is restricted so that the impulse response function with respect to a RIN price innovation is the same for all spreads. See the notes to figure 8.

We empirically examine the theoretical prediction that D6 RIN price fluctuations should have essentially no effect on E10 retail prices. Table 5 presents distributed lag regressions of the first difference of E10 retail prices on current and lagged first differences of the price of the D6 RIN. The regressions include seasonal factors and use weekly data because of the expected slower pass-through to retail than to wholesale prices. The dynamic pass-through coefficients fluctuate around zero, and although in a few cases they are statistically significantly different from zero, most of the coefficients are not. Taken literally, the regressions indicate that a $1 D6 RIN would reduce E10 retail prices by $0.065 after 6 weeks. This estimate is not statistically significantly different from the theoretical prediction of 1.2¢/gal (see the calculation in the text following eq. [4]), but neither is it significantly different from zero, nor is its sign robust to including changes in the price of Brent as a control variable. The results in table 5 provide empirical support for the theoretical prediction that RIN price fluctuations have a negligible effect on E10 pump prices.

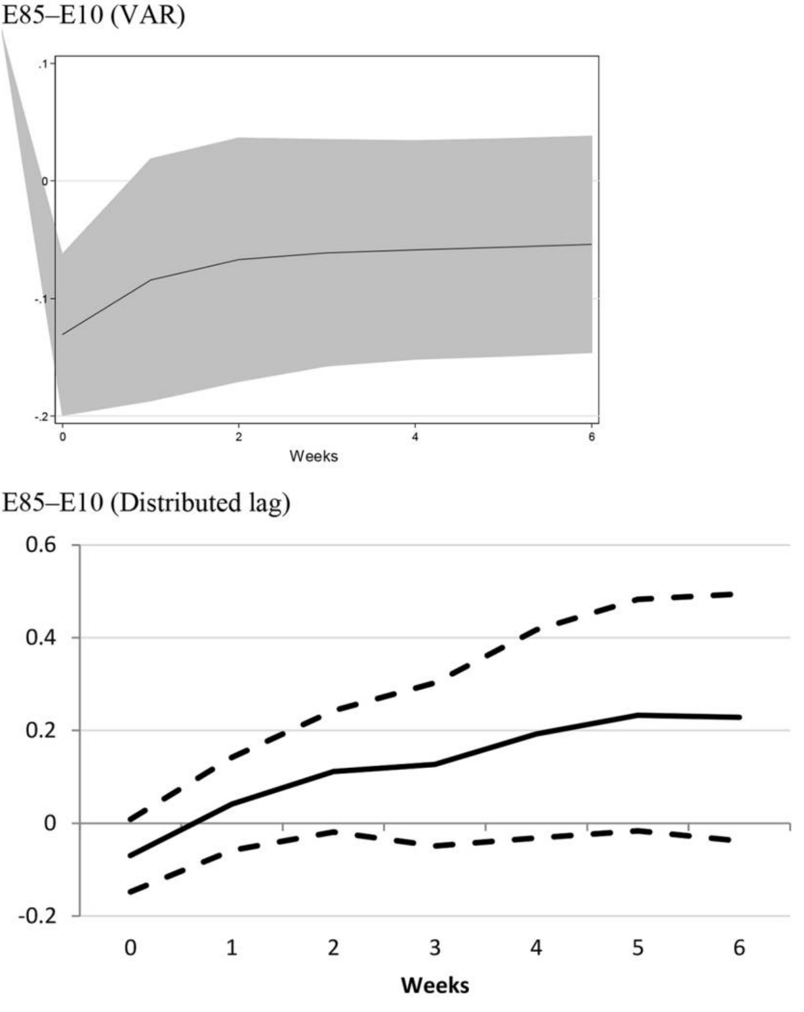

Figure 10. Impulse response functions of fuel prices to RIN obligation innovation for the E85–E10 spread (weekly): bivariate VAR impulse response functions (*top panel*) and distributed lag cumulative dynamic multipliers (*lower panel*) The VAR in the top panel is specified as in figure 8, except that it is estimated on weekly data. The cumulative dynamic multipliers in the bottom panel are computed using a distributed lag regression of weekly changes in the E85–E10 spread on current and lagged weekly changes in the E85–E10 net RIN obligation, including the eight seasonal control variables. Standard errors in the second panel are Newey-West (eight weekly lags).

Table 4. Pooled VARs: Cumulative Structural Impulse Response Functions, Wholesale Spreads

	Diesel		Gasoline		Diesel and Gasoline	
Lag	Coefficient	SE	Coefficient	SE	Coefficient	SE
0	.567	(.266)	.980	(.513)	.725	(.257)
1	.762	(.319)	1.152	(.657)	.892	(.323)
2	.882	(.302)	1.184	(.665)	.987	(.321)
3	.967	(.286)	1.178	(.637)	1.051	(.307)
4	1.034	(.271)	1.164	(.611)	1.101	(.294)
5	1.089	(.263)	1.147	(.597)	1.142	(.287)
6	1.133	(.261)	1.129	(.592)	1.175	(.286)
7	1.167	(.264)	1.111	(.595)	1.201	(.289)
8	1.194	(.268)	1.092	(.604)	1.222	(.294)
9	1.214	(.274)	1.074	(.616)	1.238	(.300)
10	1.228	(.280)	1.055	(.629)	1.249	(.308)
Seasonals?	Y		Y		Y	

Note. Entries are impulse responses, with standard errors in parentheses. Sample period is January 1, 2013–March 9, 2015. The diesel VARs pool three diesel spreads, the gasoline VARs pool three gasoline spreads, and the diesel and gasoline VARs pool all six spreads. VARs for all indicated spreads are constrained to have the same coefficients, including the same impact coefficient. All VARs have two daily lags and exogenous seasonal controls, and they are estimated in levels. All spreads have the same net RIN obligation. The impulse response functions are identified by ordering the RIN obligation ordered first in a Cholesky factorization.

^ Coefficients are statistically different from 1 at the 10% level.

^^ Coefficients are statistically different from 1 at the 5% level.

^^^ Coefficients are statistically different from 1 at the 1% level.

5.4. Wholesale Biofuel Spreads

Another strategy for estimating pass-through of RIN prices is to examine spreads involving biofuels. First consider ethanol. During 2013 and 2014, the United States exported approximately 36 million gallons of ethanol to the Netherlands, the main entry point for US biofuels into the European market.[15] Arbitrage across the United States and European markets suggests that the price received by the seller should be the same in the two markets, net of transportation and other transaction costs. Because the RIN on a gallon of ethanol sold at wholesale in the United States is not detached until further downstream, the seller does not receive any extra value from the RIN beyond the price received for the wholesale gallon. Thus transatlantic arbitrage leads to the prediction

15. US fuel ethanol exports by destination are reported by the Energy Information Administration at http://www.eia.gov/dnav/pet/pet_move_expc_a_epooxe_eex_mbbl_m.htm.

Table 5. Dynamic Pass-Through of D6 RIN Prices to the E85–E10 Spread, E10 Prices, and the Chicago Ethanol–Rotterdam Ethanol Spread

	E85–E10		E85–E10		ΔE10		ΔE10		Chicago Ethanol–Rotterdam Ethanol Spread	
Lag	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
0	–.131*	(.070)	–.070	(.078)	.035	(.104)	.042	(.072)	.161	(.157)
1	–.084	(.106)	.041	(.100)	–.064	(.046)	–.013	(.034)	.148*	(.071)
2	–.067	(.106)	.112	(.131)	–.044	(.054)	.088*	(.039)	–.025	(.100)
3	–.061	(.099)	.127	(.176)	–.087	(.049)	.050	(.052)	–.195	(.130)
4	–.059	(.095)	.193	(.224)	–.158***	(.037)	–.079	(.041)	.013	(.086)
5	–.057	(.095)	.233	(.250)	–.139**	(.043)	–.059	(.049)	.049	(.116)
6	–.054	(.094)	.228	(.266)	–.065	(.058)	.005	(.047)	.007	(.073)
7									–.046	(.099)
8									.033	(.093)
9									–.046	(.090)

10					−.155	(.118)
11					−.056	(.066)
12					.194	(.105)
13					.111	(.088)
14					−.170*	(.072)
15					−.124	(.081)
Regressor	E85–E10 net RIN obligation	E85–E10 net RIN obligation	D6 price	D6 price	D6 price	
Method	VAR	Distributed lag	Distributed lag	Distributed lag	Distributed lag	
Frequency	Weekly	Weekly	Weekly	Weekly	Daily	
Seasonals?	Y	Y	Y	Y	Y	
Brent?	N	N	N	Y	N	

Note. Entries are cumulative dynamic multipliers estimated by distributed lag regressions. The first and second columns regress the change in the E85–E10 spread on the net RIN obligation of E85 relative to E10. The third and fourth columns regress the change in the E10 retail price on the change in the D6 RIN price and its lags. The fifth column regresses the change in the Chicago ethanol–Rotterdam ethanol spread on the change in the D6 RIN price and its lags. All five regressions are estimated in first differences with seasonal controls. Sample period is January 1, 2013, to March 9, 2015. The first four regressions are estimated using weekly data (weeks ending Tuesday), and the ethanol spread regression is estimated using daily data. The regression in column 4 also includes current and two lags of weekly changes of the Brent spot price as additional controls. Standard errors are Newey-West (eight weekly lags, 30 daily lags).

* Coefficients are statistically different from 0 at the 10% level.

** Coefficients are statistically different from 0 at the 5% level.

*** Coefficients are statistically different from 0 at the 1% level.

that the spread between US wholesale ethanol and European ethanol should not depend on RIN prices.

The final column of table 5 presents evidence that supports this theoretical prediction. We report cumulative dynamic multipliers from a distributed lag regression of the first difference of the Chicago ethanol–Rotterdam ethanol spread on current and lagged first differences of the D6 RIN price, at the daily level with three business weeks of lags and seasonal controls. The signs of the estimated coefficients fluctuate around zero, and only two of the 15 are significant at the 5% level. The coefficients are in all cases very small: after 5 days, the estimated pass-through of a $0.10 increase in the RIN price is $.005, not statistically significantly different from zero.

Next consider biodiesel. The spread between the spot price of Gulf biodiesel and the spot price of Gulf (petroleum) diesel has a large net RIN obligation: a gallon of Gulf biodiesel generates 1.5 D4 RINs when blended, while a gallon of petroleum diesel incurs the much smaller RIN bundle obligation B_t. When biodiesel is a small fraction of blended diesel, as it was during our sample, these two fuels are nearly perfect substitutes, although biodiesel has a lower smaller energy value. The Gulf biodiesel–Gulf diesel spread is plotted in figure 11, along with its net RIN obligation. There is strikingly close comovement between the Gulf biodiesel–Gulf diesel spread and its net RIN obligation during 2013. However, this relationship shifted in 2014, when the biodiesel blender's tax credit (which was in effect all of 2013) expired. Starting the winter of 2014, political discussions were under way to reinstate the biodiesel tax credit, possibly as a producers' tax credit instead of a blenders' tax credit, and the blenders' tax credit was reinstated retroactively at the end of 2014 without an extension into 2015.[16] This uncertainty contributed to large shifts in the spread at unknown dates. Moreover, there are many missing observations in the Gulf biodiesel price, and the early prices are rounded to the nearest $0.05. In short, the 2013 data in figure 11 strongly suggest full or very substantial pass-through of RIN prices in this market. Unfortunately, many daily observations are missing from the Gulf biodiesel data. Because of the missing data and the confounding movements induced by the blenders' tax credit, we do not undertake econometric analysis of this spread.

6. DISCUSSION AND CONCLUSIONS

Taken together, these results support the view that RIN prices are passed through quickly, but not immediately, into the wholesale prices of obligated fuels. Based on the pooled, six-fuel VAR, 73% of an unexpected change in the price of the RIN obligation is passed through in the same day, rising to 98% after two business days (standard error of 32 percentage points). The pooled long-run pass-through estimate is 1.00 with a standard error of 0.11. This rapid and complete pass-through is consistent

16. See Irwin (2015) for details on the biodiesel tax credit.

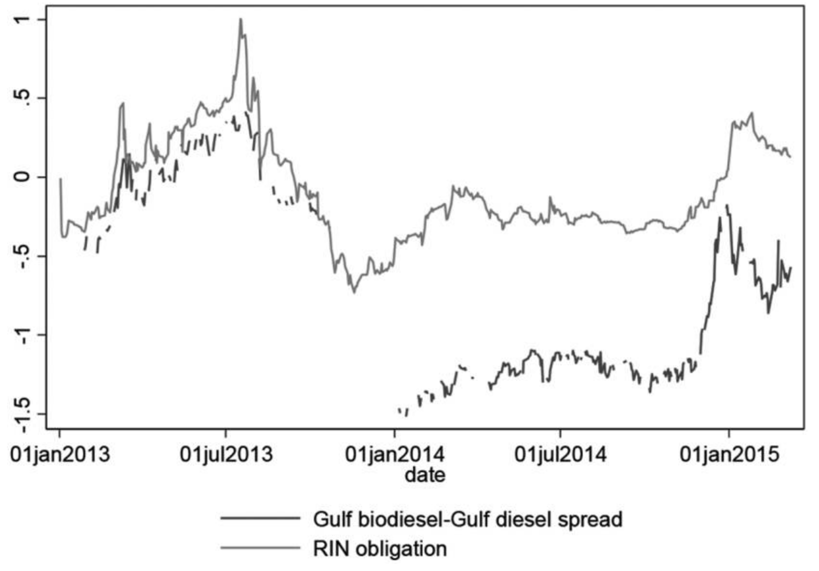

Figure 11. Gulf biodiesel–Gulf diesel spread and net RIN obligation Color version available as an online enhancement.

with economic theory and with efficiently operating wholesale fuels markets. Although there is less data on wholesale biofuels prices, the data we analyzed is also consistent with complete pass-through in wholesale biofuels markets. We take our estimates of full pass-through at the wholesale level as evidence supporting the conventional wisdom that derived demand for petroleum inputs into transportation fuel is very inelastic relative to domestic supply, at least in the short run. The results for national average retail E10 prices are also consistent with economic theory: the net RIN obligation of E10 is negligible, and there is no statistically discernible movement of E10 prices with RIN prices.

In contrast to these results, there appears to be little or no pass-through of RIN prices to national average E85 retail prices. Because the variation in the price of the E85–E10 net RIN obligation is very large during this sample, this absence of pass-through is striking. Whether the estimated pass-through is zero or slightly positive depends on the estimation method, but even so our largest pass-through estimate of the specifications including seasonals is only 0.23 after 6 weeks.

This analysis has caveats. Despite the large fluctuations in RIN prices, the fluctuations in the net RIN obligations are sufficiently small that for many spreads the pass-through coefficients and dynamics are imprecisely estimated. Because there are strong seasonal patterns in many fuel prices and because some of the largest RIN price movements coincide with seasonal fuel price swings, it is important to control for seasonality when studying these relationships. However, the short span of the data for which there are large seasonal fluctuations means that controlling for seasonals also introduces imprecision.

The finding of full pass-through to wholesale prices provides evidence against a recurring narrative about the incidence of the RFS. In particular, concerns that petroleum refiners bear the burden of the RFS appear to be unjustified, as our finding of full wholesale pass-through indicates that petroleum refiners recoup the cost of RINs. As discussed in detail in Burkholder (2015), an obligated party with a net RIN obligation, such as a merchant refiner, is able to recoup their RIN costs on average through the prices they receive in the wholesale market, even though this mechanism would not be apparent on the balance sheet of the obligated party because there is no explicit revenue line item offsetting the explicit cost of purchasing RINs. Even with full pass-through, however, an obligated party could face RIN price risk because of timing differences between when the RIN obligation is incurred and when RINs are acquired.

To us, our most intriguing and challenging finding is the near absence of pass-through of RIN prices to national average retail E85 prices. This finding raises questions about a major market mechanism by which the RFS is designed to influence behavior. By subsidizing renewable fuel and taxing nonrenewable fuel, the RFS should reduce the relative price of renewable-intensive retail fuels, thereby raising consumption of those retail fuels. A few years ago, when the ethanol content of E10 was still below 10%, the RFS could also operate by raising the blend fraction of ethanol in E10, even without pass-through to retail prices. However, now that E10 contains 10% ethanol, inducing more ethanol consumption requires increasing the sales of higher blends, which in turn requires providing consumers a price incentive to purchase those blends. Open questions for future research include where in the supply chain this failure of pass-through occurs, whether this failure arises from local market power at one or more points in the supply chain downstream from the wholesale fuels market, and whether this failure can be addressed by policy interventions within or outside of the RFS.

REFERENCES

Bachmeier, Lance J., and James M. Griffin. 2003. New evidence on asymmetric gasoline price responses. *Review of Economics and Statistics* 85 (3): 772–76.

Borenstein, Severin, A. Colin Cameron, and Richard Gilbert. 1997. Do gasoline prices respond asymmetrically to crude oil price changes? *Quarterly Journal of Economics* 112 (1): 305–39.

Burkhardt, Jesse. 2016. Incomplete regulation in an imperfectly competitive market: The impact of the renewable fuel standard on U.S. oil refineries. Unpublished manuscript, Yale University, School of Forestry and Environmental Studies.

Burkholder, Dallas. 2015. A preliminary assessment of RIN market dynamics, RIN prices, and their effects. http://www.regulations.gov/#!documentDetail;D=EPA-HQ-OAR-2015-0111-0062.

Irwin, Scott. 2013a. What's behind the plunge in RIN prices? *farmdoc daily*, no. 3, 193.

———. 2013b. More on ethanol RINs pricing. *farmdoc daily*, no. 3, 208.

———. 2014. Rolling back the write down of the renewable mandate for 2014: The RINs market rings the bell again. *farmdoc daily*, no. 4, 148.

———. 2015. Implications of changing the biodiesel tax credit from a blender to a producer credit. *farmdoc daily*, no. 5, 142.

Knittel, Christopher R., and Aaron Smith. 2015. Ethanol production and gasoline prices: A spurious correlation. *Energy Journal* 36 (1): 73–113.

Lade, Gabriel E., C.-Y. Cynthia Lin, and Aaron Smith. 2015. The effect of policy uncertainty on market-based regulations: Evidence from the Renewable Fuel Standard. Unpublished manuscript, University of California, Davis, Department of Agricultural and Resource Economics.

Lewis, Matthew S. 2011. Asymmetric price adjustment and consumer search: An examination of the retail gasoline market. *Journal of Economics and Management Strategy* 20 (2): 409–49.

Stock, James H., and Mark W. Watson. 1993. A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica* 61 (4): 783–820.

Stolper, Samuel. 2016. Who bears the burden of energy taxes? The critical role of pass-through. Unpublished manuscript, Harvard University, Harvard Kennedy School.