Essays on Environmental Economics

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Dedication

This dissertation is dedicated to my family, for their support and love.

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I would like to express my gratitude to my wife and children for always being there to support me and encourage me to succeed.

Abstract

This dissertation consists of two chapters. Chapter 1 examines the effect of transportation costs of shipping ethanol on retail gasoline prices over space. The Renewable Fuel Standard (RFS) of 2007 legislated a new market into existence in the U.S. by mandating that ethanol be blended with petroleum in retail gasoline markets. Using a quantile difference-in-differences econometric approach to analyze weekly retail gasoline price data for over 200 cities from 2007 to 2014, we find evidence that the mandate differentially impacted gasoline prices across the U.S. Specifically, we find that cities farther from ethanol production centers paid higher retail gasoline prices than cities close to ethanol production centers. We argue that the observed retail price differences are driven by market frictions associated with transportation costs for ethanol which, unlike petroleum, cannot be shipped via pipeline. This effect has been exacerbated due to the run-up in ethanol RIN (renewable identification numbers) prices starting in 2013. Importantly, the effect of this market friction on retail gasoline prices varies with the relative prices of ethanol and petroleum blendstock. Our results highlight the spatial incidence associated with the mandated ethanol market. While unanticipated, we argue that these market frictions are not surprising.

In Chapter 2 we investigate the forecasting performance of a variety of individual models found in empirical literature and their linear combinations in the context of carbon dioxide (CO_2) emissions. We conduct out-of-sample forecasting exercise by using state-level data for CO_2 emissions in the U.S. Forecast error and tests of predictive accuracy are compared both for individual models and their linear combinations.

Consistent with reported results on the application of forecast combinations, we show that the forecast combination technique generally improves forecast accuracy. The best performing combination outperforms all the individual models as the forecast horizon increases. More importantly, forecast accuracy from the best performing individual model is not significantly better than that of the best combination forecast. Among the class of forecast combinations considered in this paper, bias-corrected average forecast performs relatively well.

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Chapter 1

New Markets and New Market Frictions: Evidence from Ethanol and Retail Gasoline Prices

1.1 Introduction

Whenever policymakers pass a new regulation which either directly or indirectly creates a market, there are often both intended and unintended consequences. The unintended consequences of laws have received significant attention in the economics literature recently (Goulder et al. (2012) and Bento et al. (2015)). However, one class of unintended consequences due to new regulations that has received little attention occurs when new regulation creates new market frictions.

Most generally, market frictions are transaction costs. For example, gravity models in the trade literature show that increased distance between trade partners decrease the volume of trade due to market frictions of increased transportation costs (Shepherd (2012)). If new regulations create asymmetric transaction costs, then, new regulations can create market frictions which differentially affect newly regulated agents. We argue that the passage of the Renewable Fuel Standard (RFS) in 2007 in the United States is one example.

RFS created a mandate that makes blenders of retail gasoline mix ethanol with refined petroleum such that total ethanol consumed in the U.S. in a given year exceeds some minimum level. The thousands of blenders have long existed and are distributed widely throughout the U.S. serving to blend various additives to retail gasoline. The mandate effectively forced them to blend ethanol into gasoline as well under penalty of fine. This together with the concentration of ethanol production in the Midwest created a market for transportation of ethanol to demand centers across the U.S. Pipelines provide the cost-effective way to transport refined petroleum to and from landlocked parts of the U.S. and transportation by rail and truck generally used only for short distances (Borenstein and Kellogg (2014)). Due to lack of ethanol pipelines, though, ethanol must be shipped via rail and truck throughout the U.S. Relative to pipelines used for petroleum, then, shipping ethanol via these channels is more costly than shipping petroleum due to higher transportation costs.[1]

To meet the RFS mandate, an obligated party can either purchase minimum required volume of ethanol for blending into gasoline or buy Renewable Identification Numbers (RINs) in the market.[2] The RFS was likely not binding for most of the initial period of the mandate; more ethanol was produced than mandated. Before 2013 the price of corn ethanol RINs had been close to zero and, therefore, the RFS was likely not binding during this period. In 2013 corn ethanol based RIN prices started to increase, reaching about $1.00 per gallon in March 2013. Among the reasons cited

[1] Though we do not study them here there is evidence that railroads exercise market power in the transportation of ethanol by price discriminating based on environmental regulations at the route destinations (Hughes (2011)). While we focus on the direct shipping aspect of transportation cost, we note that transportation costs can come in many forms. As a result, our study is complementary to this earlier work.

[2] Once ethanol is produced, a serial number is assigned to a batch of ethanol to identify the type of fuel and gallons of ethanol. Known as RINs, these unique numbers allow Environmental Protection Agency to monitor compliance with the RFS. RINs are separated after they are initially sold and can be traded in the open market. Obligated parties (refiners, blenders, and importers) fulfill the mandate requirement by mixing at least the minimum required volume of biofuel, or, alternatively, by purchasing enough RINs from the third parties.

for the run-up in RIN prices for corn ethanol are rising RFS-mandated volumes and the E10 (10% ethanol and 90% refined petroleum) ethanol blend wall.[3]

In this paper, we present evidence that the RFS created a market friction through the transportation cost channel. We show that when RIN prices started to increase the RFS mandate asymmetrically affected the retail price of gasoline throughout the U.S. as a function of shipping distances. To do so, we constructed a comprehensive weekly panel dataset of retail gasoline prices in over 200 U.S. cities. We combine that data with weekly oil and ethanol price data. Importantly, the dataset includes different measures of the distance between demand and supply centers of ethanol. We calculate the shortest distances between cities and ethanol refineries as well as between cities and ethanol production centers (i.e. Midwest). This allows us to explicitly control for transportation costs associated with shipping ethanol by rail and truck to blending stations in and around cities where retail gasoline is sold. In addition, there is a debate whether positive ethanol RIN prices since 2013 contributed to rising gasoline prices.[4] We control for the higher RIN prices after 2013 in studying the distance effect of ethanol shipping on retail gasoline prices.

We use quantile difference-in-differences estimator to test for the effect of the distance market friction created by RFS on retail gasoline prices. There are three main reasons for using a quantile regression rather than OLS technique. First, the incentive to blend varies by wholesale petroleum price. As the relative price for wholesale petroleum increases, the incentive for blenders to substitute ethanol for petroleum increases. Since wholesale petroleum blendstock is the main input in finished gasoline, the incentive to blend ethanol varies over the distribution of gasoline prices. Specifically, blenders want to use higher ethanol blends when gasoline prices are high. Therefore, conditional quantiles of retail gasoline price distribution can be thought of representing the variation in blending decisions. Unlike the mean effect

[3]See `http://www.eia.gov/todayinenergy/detail.cfm?id=11671`. Last accessed: May 10, 2015.

[4]See `http://ethanolrfa.org/page/-/rfa-association-site/studies/informa_gasoline_price_analysis.pdf?nocdn=1`. Last accessed: May 10, 2015.

from OLS, quantile regression method accounts for this substitution effect across the retail gasoline price distribution. Second, we are interested in how the market frictions created by the ethanol standard differentially affect gasoline prices over space. In our quantile regressions, we allow for these frictions to vary differentially across both different ethanol shipping distances and different retail gasoline prices. Third, refiner profits (often proxied by the crack spread) vary with demand for gasoline. Ethanol can have a differential effect on gasoline prices as demand rises and falls through the refiner profits channel as ethanol reduces the market power of refiners during high demand periods (Knittel and Smith (2015)). Quantile techniques account for this asymmetric effect throughout the distribution of gasoline prices explicitly, while OLS can only identify the mean effect.

We find that when RIN prices started to increase in 2013, cities farther from ethanol production centers paid significantly higher retail gasoline prices relative to cities nearer to production centers when relative oil and ethanol prices made blending more profitable. This result follows from intuition expected from the incentives to blend under a binding mandate: the mandate binds at the year level. However, within a year blenders can choose to blend ethanol and petroleum only when it is profitable to do so. It is profitable to blend ethanol in place of refined petroleum when the price of petroleum is relatively higher than ethanol. The influence of this blending decision on retail gasoline price is exacerbated when the ethanol must be shipped at high cost far from production centers.[5] Subject to standard difference-in-differences identification assumptions, we take our results as causal evidence that the ethanol regulation exacerbated the effect of market friction after 2013 which asymmetrically affected retail gasoline prices in the U.S.

There is an important policy implication of our results. Regulation that creates new markets should also account for the market frictions which emerge from setting up that market in order to mitigate those effects. With RFS, our evidence suggests

[5]When blending ethanol is expensive, blenders may purchase RINs in the open market or use their own RINs banked in the previous year. We discuss the implications of this alternative compliance avenue below.

that the cost of accommodating this regulation to blenders varied over space. As a result, the mandate's stringency could have varied over space with the cost of the market friction. Generally, this falls into a framework of accounting for the incidence associated with creating a new market or regulatory framework (Bovenberg et al. (2008)).

Our results contribute to two different areas in the economics literature. First, there is a healthy debate in the literature about the effect of the ethanol mandate on gasoline prices.[6] These studies tend to use PADD (Petroleum Administration of Defense Districts) level data (Du and Hayes (2009), Du and Hayes (2011) and Knittel and Smith (2015)). Knittel and Smith (2015) makes the convincing claim that, overall, the ethanol mandate has had little to no effect on average gasoline prices ($\sim$ -10 cents). While we do not claim to identify the total effect of the ethanol mandate, our quantile difference-in-differences design allows us to address the incidence of the mandate across the U.S. at different levels of gasoline prices.[7]

Second, we contribute to the literature on how new regulations affect economic activity in unintended ways (Dinardo and Lemieux (2001), Goulder et al. (2012) and Bento et al. (2015)). We show that even in cases like RFS where there is a relatively well-functioning market for satisfying the regulation, there can still be market frictions created by a regulation which affect the incidence of the regulation.[8] These market frictions, in this case created by the lack of transportation infrastructure in ethanol industry, affect the incidence of the policy. Policy makers should consider mitigating those effects when new regulations create new markets.[9]

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[6]There is an additional question as to how substitutable ethanol and gasoline are for consumers (Anderson (2012)). We are not able to address this question whatsoever. Although there is evidence that ethanol and petroleum are imperfect substitutes, as long as consumer preferences within a city are fixed over time our results are robust to this issue since we use city fixed effects in our econometric model.

[7]There is an additional question as to the non-market CO_2 effects of the ethanol mandate due to the interaction between land and fuel markets created by policy toward ethanol (Bento et al. (2015)). We do not address this important policy question in this paper.

[8]This is distinct from regulatory rents more generally Rose (1985).

[9]There is new literature which discusses this in the context of spatial variation in the damages from pollution by source (Fowlie and Muller (2013) and Carson and LaRiviere (2014)).

The rest of the paper is organized as follows. Section 1.2 discusses the economics of ethanol blending and gives a background on ethanol mandate and transportation. Section 1.3 describes data and the variables used in the paper. We present the econometric specification in section 1.4. In section 1.5 we discuss the estimation results. Then, we conduct robustness analysis of our empirical results in section 1.6. Section 1.7 summarizes and concludes.

1.2 Ethanol Blending Economics and Background

This section provides a background for the ethanol industry in order to develop the design of the empirical method. We describe the industry and the law first generally. We then introduce how distance between ethanol refineries and demand centers can act as a market friction due to relatively large transportation costs of shipping ethanol.

Renewable Fuel Standard

Initially, used as an octane booster and to meet air quality requirements, ethanol is now an important input in transportation fuel.[10] The Energy Policy Act of 2005 required increased use of ethanol by introducing Renewable Fuel Standard. It mandated use of 4 billion gallons of ethanol in 2006 and further increasing by 0.7 billion gallons each year until 2012.

Energy Independence and Security Act (EISA) of 2007 supplanted the 2005 RFS and set mandated volumes through 2022 for total renewable fuels and various biofuel subcategories from non-corn sources, including advanced biofuels, cellulosic biofuels, and biomass-based diesel.[11] While the updated RFS does not specify corn ethanol mandate explicitly, ethanol derived from corn starch counts toward the non-advanced

[10]The Clean Air Act Amendments of 1990 lead local regulators to require use of oxygenated fuels in all areas with the worst vehicle emissions that exceed the federal carbon monoxide air quality standard.

[11]EISA defines advanced biofuel as renewable fuel, other than ethanol derived from corn starch, that would reduce lifecycle greenhouse gas emissions by 50%.

biofuel portion of the total renewable fuel mandate. It mandates consumption of 9 billion gallons of renewable fuels in 2008, 20.5 billion gallons in 2015, and 36 billion gallons by 2022. The implied volume of corn ethanol mandate is set at 9 billion gallons in 2008 and is capped at 15 billion gallons in 2015 and thereafter. In this paper we focus on corn ethanol because it makes up the vast majority of the RFS mandate and the actual use of total renewable fuels in 2007-2014 sample period. To encourage the use of renewable fuels, federal and state governments provide biofuel tax incentives in addition to the mandate which penalizes lack of compliance. Federal blenders tax credit, also known as volumetric ethanol excise tax credit (VEET), provided a \$0.51 credit (\$0.45 since 2009) for every gallon of pure ethanol mixed with gasoline to blenders of ethanol until 2012 when VEET was allowed to expire.

Figure 1.1 plots the production, consumption, and mandated levels of fuel ethanol in the U.S. The 2005 RFS was not binding as the actual production and consumption of ethanol was greater than the mandated quantity. This corresponds to a period when the use of MTBE (methyl tertiary-butyl ether), an oxygen additive, was banned nationwide, effectively leading to an increased demand for ethanol to be used as an oxygenate. Even when more stringent RFS of 2007 replaced the 2005 RFS, the fuel ethanol production and consumption levels have generally been above the new RFS-target levels until 2012-2013. Coupled with a RIN price of zero, we take this as evidence that the RFS did not bind until 2013.

The price of a RIN is a better indicator of a binding mandate and its value is determined by the difference between the supply and demand prices for ethanol. The RIN prices will be zero if the equilibrium quantity of ethanol exceeds the mandate and positive if the equilibrium quantity falls below the mandate. Before 2013 corn ethanol RIN prices did not significantly deviate from zero.[12] As the Figure 1.2 shows, the situation was much different starting in 2013 when RIN prices increased sharply

[12]See Figure 1 at `http://farmdocdaily.illinois.edu/2013/07/rins-gone-wild.html`. Last accessed: May 10, 2015.

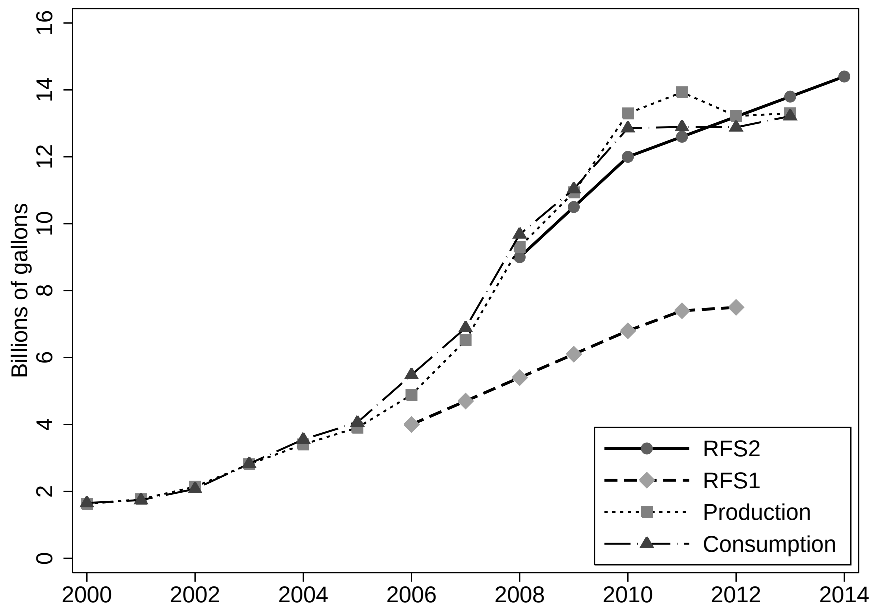

Figure 1.1: Fuel Ethanol Mandate, Production, and Consumption

Source: U.S. Energy Information Administration, *Monthly Energy Review*, October 2014; Energy Independence and Security Act of 2007; Energy Policy Act of 2005.

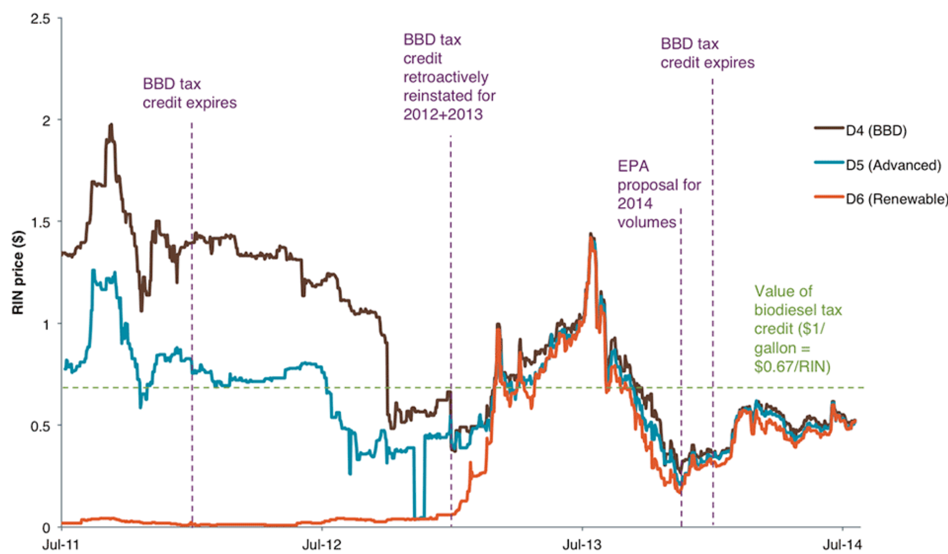

Figure 1.2: Prices of Renewable Identification Numbers

Notes: D4, D5, and D6 represent historical RIN prices for biomass-based diesel (BBD or biodiesel), advanced biofuel, and corn ethanol, respectively.
Source: The International Council on Clean Transportation.

and have since stayed positive. The higher the RIN prices, the more costly it is to meet the RFS mandate.[13]

There are at least three reasons why RIN prices increased in 2013. First, gasoline consumption in the U.S. decreased relative to 2007 levels. When the RFS was enacted into law, the mandated volumes of renewable fuels were based on projected gasoline consumption in the U.S. Actual gasoline consumption was 135.5 billion gallons in 2013, while in 2007 it was equal to 142.4 billion gallons.[14] Second, as the RFS target levels increased each year while gasoline consumption declined, certain PADD (Petroleum Administration for Defense Districts) regions have reached ethanol saturation point. Because of E10 blend wall, increasing the use of ethanol may require purchasing RINs in the open market. Third, continued increase in ethanol consumption under the RFS coupled with lower gasoline consumption and E10 blend wall will eventually require investment in infrastructure that can handle higher ethanol blends. As a result, blending ethanol has become more expensive in the sense that blenders must still need to meet their renewable obligations under the RFS. In the past obligated parties had generally used more ethanol and banked the excess RINs when blending ethanol was profitable.[15] However, as the mandated volumes of fuel ethanol increased and more and more blenders reached E10 blend wall, they started drawing down their stocks of RINs.[16] This together with the anticipation of continued future decline in RIN inventories contributed to rising RIN prices in 2013.

Introduction of gasoline with greater than 10% ethanol content in the market has generally been slow due to lack of infrastructure. Even though in 2011 EPA allowed E15 (gasoline with up to 15% ethanol content) for use in light-duty motor vehicle models of 2001 and later, it is not widely available and is mainly sold in some of the

[13] EPA announced in November, 2013 that it expected to cut the ethanol consumption obligations to 13 billion gallons for 2014, a reduction of 1.4 billion gallons from the mandated level. The EPA's proposal is aimed to keep the ethanol blend share close to 10%.

[14] U.S. EIA Short Term Energy Outlook, November 12, 2014.

[15] The RFS regulations allow the obligated parties to use banked RINs toward up to 20% of the their current year obligations.

[16] See `http://farmdocdaily.illinois.edu/2014/04/rin-stocks-part-1-valuation.html`. Last accessed: May 10, 2015.

Midwestern states. Similarly, market penetration of flex-fuel vehicles capable of using E85 (gasoline with up to 85% ethanol content) has been lower than expected.[17]

Positive RIN prices might also be due to transaction costs and speculative components. The anecdotal evidence suggests that some market participants in the RIN market are purchasing RINs when the prices are low and selling RINs for a premium when the prices are high. Given the opacity of RIN market, we are not able to assess how much of the ethanol RIN price spikes might be due to the speculative activity (if any) in the RIN market.

Transportation of Ethanol

Distance plays a significant role in explaining price differentials across locations where markets are not completely integrated (Engel and Rogers (1996)). With respect to the ethanol mandate, distance between ethanol refineries and blending terminals could act as a market friction due to lack of infrastructure in the ethanol industry. Infrastructure for efficient movement of ethanol from the production centers in the Midwest to population centers on the coasts is lacking, and spatial variation in infrastructure development and ethanol plant location will have a significant effect on ethanol shipping costs (Das et al. (2010)).

Ethanol production is concentrated mainly in the Midwest, closer to corn growing counties in the Corn Belt. This is not surprising given that corn is the main feedstock in corn ethanol and hauling corn is more expensive. Nevertheless, ethanol is shipped throughout the U.S. Figure 1.3 shows the distribution of ethanol plants, blending terminals, and corn production by county in the United States as of 2011.[18] Blending terminals are distributed across the U.S. closer to demand centers. Consequently, as the Figure 1.4 shows, there is a geographical variation in how quickly ethanol

[17] Consumption of E85 fuels was equivalent to 137.2 million gasoline gallon equivalent for 2011, which is only 1% of total ethanol consumed in the U.S. in 2011. See `http://www.eia.gov/renewable/afv/index.cfm`. Last accessed: May 10, 2015.

[18] Ethanol plant locations are taken from the Renewable Fuels Association, corn data - from the U.S. Department of Agriculture 2009 yields data, and active fuel terminal locations - from the Internal Revenue Service.

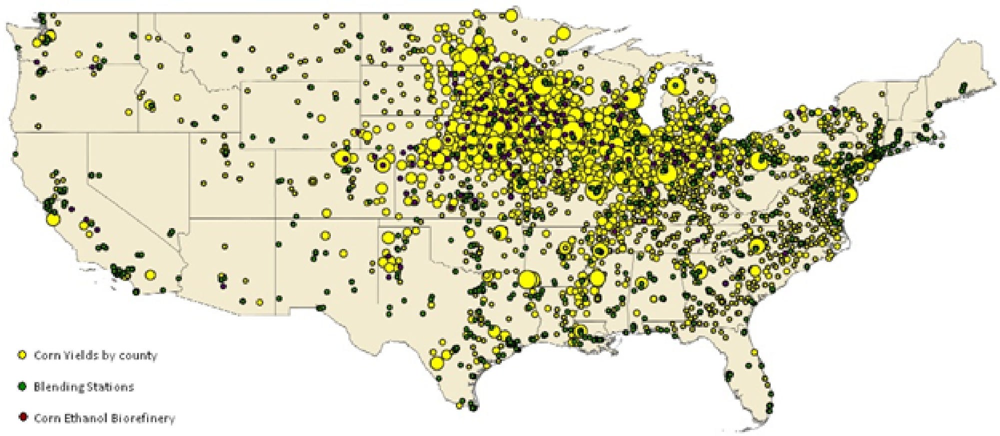

Figure 1.3: Location of Corn Growing Counties, Biorefineries, and Gasoline Terminals

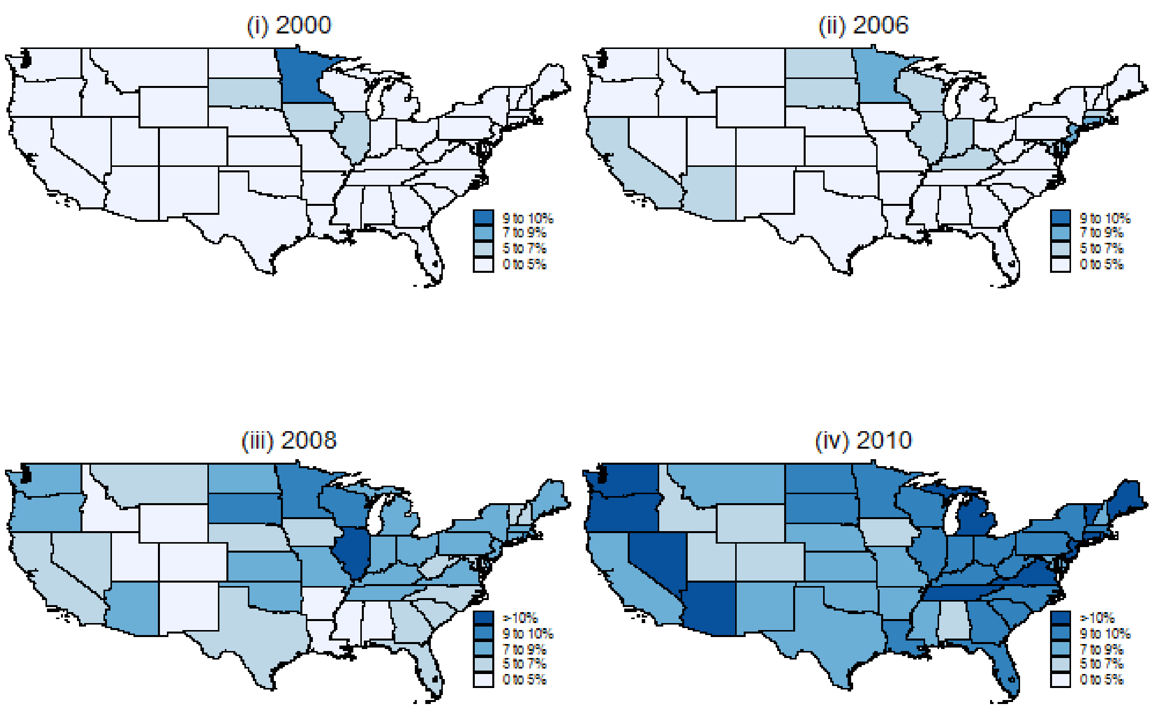

Figure 1.4: Ethanol Blend Share for Selected Years (%)

Source: U.S. Energy Information Administration.

penetrated different markets. Before the RFS was made into law, ethanol was the main oxygenate additive in finished gasoline in the Midwest (panel i). However, when the use of MTBE was phased out nationwide by 2006, ethanol emerged as a primary fuel oxygenate component in other states as well (panel ii). With the more stringent 2007 RFS, ethanol usage increased throughout the U.S., although for the first few years most of the additional ethanol had been absorbed in the Midwest (panel iii). This is as expected as most ethanol refineries are located close to the Corn Belt. In addition, Midwestern states could utilize more ethanol because they already had necessary infrastructure in place before the federal mandate became a law. However, as the RFS requires greater ethanol consumption in the subsequent years, additional ethanol has to be absorbed elsewhere, specifically East and West Coasts where the gasoline consumption is much higher than the other regions in the U.S. (panel iv). Because more ethanol has to be shipped to other regions that are farther from the Midwest, this likely implied greater cost to blenders there due to higher ethanol transport costs. As ethanol consumption increased, certain PADD regions have reached the 10% ethanol blend share. For example, ethanol blend share in PADD 1 and PADD 2 regions has been around 10% since 2009 (see Figure 1.5), which likely meant that additional ethanol had to be shipped to other PADD regions.[19]

In addition to the ethanol shipping distance, per gallon transportation costs are greater for ethanol than for petroleum due to the mode of transportation (Morrow et al. (2006)). Ethanol produced in the Midwest is transported via barges (5%), trucks (29%), and rail (66%) to wholesale terminals near population centers (USDOE (2010).) While barges are the cost effective way to transport ethanol, ethanol is shipped by more expensive means, mainly by rail for longer distances and by trucks for shorter distances. Shipping ethanol by pipelines is virtually nonexistent. A 2010 study by the U.S. Department of Energy found construction of separate ethanol pipelines from the Midwest to the East Coast to be economically not viable at current

[19] The share of ethanol in total finished gasoline can be above 10% without actually reaching the blend wall if consumption of E15 and E85 fuels is present in the market. However, the consumption of E85 is more prevalent only in upper Midwest due to the availability of E85 infrastructure there.

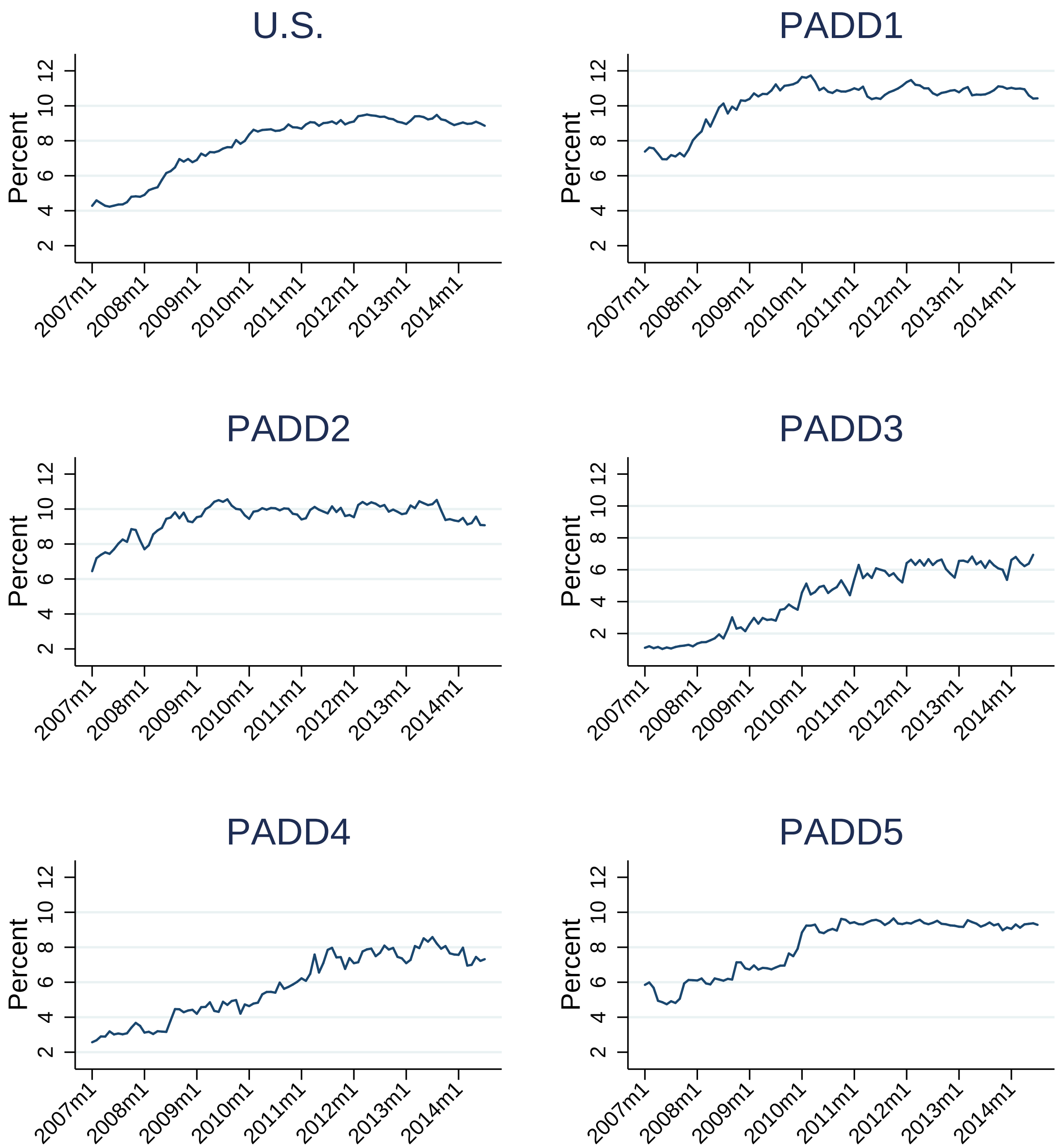

Figure 1.5: Ethanol Blend Share by PADD Regions

Notes: Ethanol blend share in PADD 1 and PADD 2 regions has been around 10% since 2009. As the RFS mandated volumes are expected to increase further, other PADD regions are likely to see increased ethanol consumption soon.
Source: U.S. Energy Information Administration.

ethanol consumption projections.[20] Furthermore, existing petroleum pipelines used to transport petroleum products cannot be used in shipping ethanol because the water found in low level pipelines causes ethanol to separate from gasoline and mix with water. Therefore, unlike other petroleum additives, ethanol cannot be mixed into gasoline at refineries to be shipped via existing pipelines. Consequently, because of these factors and infrastructure bottlenecks in the ethanol industry, shipping ethanol can be relatively more expensive. Physically transporting ethanol to the East and West Coasts costs at least $0.13 per gallon and to regional markets it costs about $0.07 per gallon (Coltrain (2001)). These numbers are in 2001 prices and are likely a lower bound. Hughes (2011) found that railroads have market power in the ethanol shipment and price discriminate based on environmental regulations at destination points (e.g. carbon monoxide non-attainment areas). In addition, shipping via rails sometimes proved problematic due to rail transportation constraints. In the past, cold weather and increased crude oil shipments were blamed for causing rail traffic to back up in the Midwest, leading to an increase in premium for ethanol in New York relative to the price in Chicago from $0.25 (January, 2014) to $1.0 a gallon (February, 2014).[21]

While at blending terminals, ethanol is kept in separate tanks underground and then splash blended with motor gasoline to the desired level before being delivered to retail gasoline stations. The minimum quantity of ethanol required to be blended is a yearly volume regulated by RFS.[22] The maximum amount of ethanol to be blended is 10% in volume. Blenders make decisions to blend ethanol that must meet or exceed the mandated amount. The exact amount of ethanol content depends on several

[20] There are a few places where ethanol is shipped by pipelines (for example, in Florida). These are typically short pipelines and the volumes of ethanol shipments are small. See `http://www.afdc.energy.gov/pdfs/km_cfpl_ethanol_pipeline_fact_sheet.pdf`. Last accessed: May 10, 2015.

[21] See, for example, The Wall Street Journal articles available here `http://online.wsj.com/articles/SB10001424052702303546204579439740561525518` and here `http://online.wsj.com/articles/SB10001424052702303847804579479643372241358`. Last accessed: May 10, 2015.

[22] This is a unique feature of the regulatory structure for ethanol: the mandated level of ethanol to be blended is an absolute yearly volume rather than a percent of total retail gasoline consumed. This is a useful aspect of the policy for our study: a volumetric mandate permits blenders to have more flexibility to choosing their blending strategy within a year as opposed to a percentage requirement. A percentage requirement implies that as the quantity demanded of gasoline fluctuates within a year, blenders would have to respond more quickly.

factors, such as the mandate, local and state regulations, relative prices of ethanol and petroleum blendstock, seasonal oxygenation regulations, and reid-vapor pressure (RVP).[23] Some studies found blending at 10% ethanol and 90% gasoline blendstock, known as E10, to be more prevalent in the corn-growing locations than places far from such feedstocks (Walls et al. (2011)). Underdeveloped ethanol infrastructure and the cost of transporting ethanol from geographically remote ethanol refineries in the Midwest to blending terminals across the U.S. limit the ability of blenders at far away places to take advantage of low cost ethanol during high oil price periods. For these reasons, we hypothesize that the cost of frictions in this newly created market (e.g. ethanol delivery and logistics) heterogeneously affects retail gasoline prices over space.

Our primary goal in this study is to estimate how the ethanol mandate affects retail gasoline prices across space due to market frictions (e.g. transportation costs).[24] The wholesale price of refined petroleum is in large part driven by oil prices and refiners' ability to exercise market power. The price of ethanol is largely driven by the price of corn and how mandated levels of ethanol interact with capacity constraints of refiners. However, as noted below we are concerned with blenders' decisions. As a result, our identifying assumption is that the capacity of gasoline supply is constant over the 2007-2014 sample period considered in this paper. This implies that changes in the gasoline price are totally driven by demand shifts and that retail gasoline blenders are price takers.

[23] For example, because ethanol increases RVP, petroleum blendstock may be optimized so that after mixing with ethanol RVP does not exceed the established standards.

[24] As noted before, a related question is how the ethanol mandate affected average gasoline prices across the United States. Proponents of biofuel policy argue that ethanol blending reduces energy prices. For example, recently Agriculture Secretary Tom Vilsack wrote that "use of ethanol ... suppresses gas costs by as much as $1.37 a gallon." (See `http://www.ethanolproducer.com/articles/8922/vilsack-biofuels-can-continue-to-lower-consumer-gas-prices`. Last accessed: May 10, 2015). These estimates are based on a study by Du and Hayes (2009) and their subsequent studies in 2011 and 2012. Du and Hayes estimate the relationship between ethanol production and the profit margin for oil refiners. These studies found that ethanol production lowered gasoline prices by 89 cents in 2010 and $1.09 in 2011. Knittel and Smith (2015) show that these results are likely driven by spurious correlations. Knittel and Smith (2015) find that the effects of ethanol production on gasoline prices are near zero and statistically insignificant.

1.3 Data

Our objective in this paper is to present evidence that the RFS asymmetrically affected the retail price of gasoline throughout the U.S. as a function of shipping distances. We use a panel dataset of weekly prices from January, 2007 to July, 2014 that spans pre- and post-U.S. binding ethanol mandate. All price data are converted to July, 2014 U.S. dollars using the U.S. Bureau of Labor Statistics consumer price index (CPI) for urban consumers. We focus on contiguous U.S. by excluding observations for states Alaska and Hawaii. The dataset includes data for 208 cities from 35 states that are widely distributed throughout the U.S.

This paper analyzes data collected from a variety of sources. For retail gasoline prices, we use wholesale rack prices of unbranded gasoline with up to 10% ethanol paid by retailers. Retail gasoline prices are given by cities across the U.S. and are taken from Bloomberg databases. Corn ethanol prices are weekly average prices at Iowa ethanol plants and are obtained from Agricultural Marketing Resource Center at Iowa State University. By using ethanol prices at Iowa plants we assume that the production price of ethanol is set in the Midwest ethanol market.[25]

The price of crude oil is used as a proxy for petroleum blendstock. We use PADD-level crude oil spot prices with delivery points within those PADD regions.[26] We use PADD-level prices because of substantial divergence between Brent and WTI (West Texas Intermediate) crude oil prices beginning in 2011. For PADD 2 region, we use WTI crude oil spot price for Cushing, Oklahoma, for PADD 3 - Light Louisiana sweet crude oil price with delivery point in St.James, Louisiana. However, we lack PADD-level prices for PADD 1 and PADD 5 regions. Instead, for PADD 1 region we use weekly Brent oil prices because PADD 1 region refines oil imported mainly

[25] USEPA (2010) uses ethanol spot price on Chicago Board of Trade and adjusts for transportation costs to deliver ethanol from the Midwest to end use terminals. Because Iowa is the the largest ethanol producing state, and ethanol produced in Iowa is no different from ethanol produced in other Midwestern states, it is reasonable to use Iowa ethanol prices.

[26] By using the oil price directly we assume that there is no variation in refinery profits. However, as long as variations in oil refinery profits are uniformly distributed across the United States to all blenders this problem amounts to measurement error in the price of oil variable.

from abroad as well as domestically produced oil. Though, in recent years, East Coast refiners have been reducing imported crude oil and increasing domestic crude oil thanks to increased domestic crude oil production and its lower cost.[27] As for PADD 5 region, we use Alaska North Slope crude oil spot price because the region refines oil imported from Alaska, in addition to oil produced in California. Additional regression results without PADD 1 and PADD 5 regions are presented as well. We matched the PADD-level oil prices with states and cities located within those PADD regions. A barrel of oil is equivalent to 42 gallons and we divide the oil price by 42 to get per gallon price. Crude oil price data are taken from Bloomberg databases.

Since ethanol prices vary across regional markets due to transportation costs, we use distance from ethanol plants to destination points to proxy for ethanol shipping costs. Ethanol is first delivered to blending terminals, there blended with petroleum, and then delivered to gasoline stations. Since blending terminals are located in and around cities, we use distance from ethanol plants to cities, instead of from ethanol plants to blending terminals to cities. Importantly, we use different measures of distances between demand and supply centers of ethanol. This allows us to explicitly control for transportation costs associated with shipping ethanol via rail and truck to blending terminals in and around cities where retail gasoline is sold. We find the shortest distances between cities and ethanol refineries as well as between cities and ethanol production center in the Midwest. We define the ethanol production center as the geometric center of six Midwestern states where the vast majority of ethanol is produced. The largest ethanol producing states are Iowa, Nebraska, Illinois, Minnesota, Indiana, and South Dakota. These states accounted for about 75 percent of the domestic ethanol production over the sample period.[28] The next largest ethanol producing states, Ohio and Wisconsin, each expected to produce one-half the amount of the smallest of the six largest ethanol producing states in 2014. The centroid of these six states, which we define as the ethanol production center in the Midwest,

[27] See EIA article at `http://www.eia.gov/todayinenergy/detail.cfm?id=21092`. Last accessed: May 10, 2015.

[28] Renewable Fuels Association: Ethanol Industry Outlook for 2007 through 2014.

falls within the boundaries of the state of Iowa, the largest ethanol producing state. We find the shortest distance (in thousands of miles) from each city to the ethanol production center in the Midwest using great-circle distance.

For the shortest distance from each city to ethanol refineries, we use weighted average distance from each city to the nearest ethanol refineries. Because most ethanol plants are small-scale producers, using distance to the single nearest ethanol plant would likely underestimate the distance effect on gasoline prices. However, since ethanol can still come from these smaller ethanol producing plants, we experimented with alternative measures of distance, such as the weighted average distances from cities to the closest four to eight ethanol refineries. We discuss these measures of distance in the robustness checks below.

Table 1.1 presents the summary statistics for the sample period that is the basis of this study. The distance from cities to the ethanol production center in the Midwest ranges from 26 miles up to around 1,450 miles. For the sample period, PADD-level oil prices ranged from low \$30 to a high of \$162 per barrel. In per gallon terms, PADD-level oil prices ranged from \$0.72 to \$3.85 with a standard deviation of \$0.47. Per gallon cost of corn ethanol at Iowa plants ranged from \$1.56 to \$3.15 with a standard deviation of \$0.38. The blender's decision to mix ethanol into finished gasoline depends on the relative prices of ethanol and petroleum blendstock. The existence of market friction in ethanol transportation may change the competitiveness of ethanol to blenders, especially for those that are farther away from the Midwest. The price spike in the delivery price of ethanol in early 2014 due to back up in rail traffic is one example of the existence of market friction in the ethanol market.

Several states have their own renewable fuel programs. Some of these programs predate federal ethanol mandates. Table 1.2 presents a list of six states that have statewide oxygenate mandates. For example, in Minnesota all gasoline must contain at least 10% ethanol, but blends with at least 9.2% of pure ethanol (e.g. excluding denaturants and other permitted components) by volume are considered to be in

Table 1.1: Summary Statistics

Variable	Unit	Mean	Std.Dev.	Min	Max
Distance	1,000 miles	0.68	0.34	0.03	1.45
Retail gasoline price	U.S.$ per gal.	2.70	0.50	0.95	5.31
PADD-level oil price	U.S.$ per gallon	2.35	0.47	0.72	3.85
WTI oil price	U.S.$ per gallon	2.24	0.41	0.87	3.75
Ethanol price	U.S.$ per gal.	2.27	0.38	1.56	3.15

Notes: The data is for 208 U.S. cities covering January, 2007-July, 2014. *Distance* is the great circle distance from cities to ethanol production center in the Midwest. Retail gasoline price is the wholesale rack price of unbranded gasoline with up to 10% ethanol paid by retailers. All price data are deflated into July, 2014 U.S. dollars.

Table 1.2: State Ethanol Mandates

State	Ethanol in Gasoline (%)	Effective Date
Florida	9 to 10	Dec 21, 2010
Hawaii	10	1994
Minnesota	9.2 to 10	2003
Missouri	10	Jan 1, 2008
Oregon	10	Nov 1, 2009
Washington	2 to 10	Dec 1, 2008

Source: Weaver et al. (2010); U.S. Department of Energy, Energy Efficiency and Renewable Energy, Alternative Fuels Data Center.

compliance.[29] Hawaii, Minnesota, Missouri, and Oregon require that gasoline contain at least 10% ethanol in volume. Because we are also interested in potential impacts of blending ethanol above the required standard on gasoline prices, we experiment by excluding the cities within those states.

1.4 Econometric Model

The geographically remote locations of biorefineries coupled with the underdeveloped ethanol infrastructure created a market for ethanol transport. Due to the mode of transportation and underdeveloped infrastructure, shipping ethanol is more expensive. When the RIN prices started to increase in 2013, blending ethanol at farther away places from the Corn Belt have likely occurred at greater costs. We investigate the effects of higher transportation costs of ethanol on retail gasoline prices over space after the RFS policy started binding in 2013. To do so we use a research design which is a very specific form of difference-in-differences design. Similar to Kiel and McClain (1995), we consider a continuous treatment, which is distance from a city to the ethanol production center in the Midwest. Kiel and McClain (1995) used direct distance from the house to a new garbage incinerator to study the effect an incinerator had on housing values. In our model we consider a similar framework where transportation costs of shipping ethanol increases with distance from a city to ethanol sources. We control for when the policy started binding, not when the policy was passed in 2007. If the corn ethanol RIN prices before 2013 were essentially zero, they sharply increased starting in 2013. As the Figure 1.2 shows, the value of ethanol RINs skyrocketed from about 5 cents at the end of 2012 to approximately $1.50 by July of 2013. While the price of RINs since came down, it is nowhere close to pre-2013 levels. The value of RINs affects blender's choice of compliance method. For example, when the RIN price increases it encourage blending ethanol because purchasing RINs

[29] See `https://www.revisor.mn.gov/statutes/?id=239.791`. Last accessed: May 10, 2015.

increase the cost of gasoline production.[30] This explains why we are using 2013 as a reference year rather than 2007.

Our identification relies on the assumption that changes in gasoline prices are driven by demand shifts and, therefore, supply capacity is assumed to be constant during the study period. We estimate difference-in-differences quantile regression specification with continuous distance treatment effect discussed above. This modeling is identical to a standard difference-in-differences strategy with the only difference that the treatment is continuous. There is a great deal of variability in distance measure as our dataset includes cities distributed throughout the U.S. while ethanol production is concentrated in the Midwest. We control for when the mandate started binding nationally. The dataset covering 2007-2014 includes period when the policy was binding (2013-2014) and when the policy was not binding (2007-2012).

The literature on quantile regression shows that it has been applied in various settings. For instance, the technique has been used in studying the impact of welfare reform on earnings (Bitler and Hoynes, 2006), returns to education (Arias et al., 2001), birthweight determinants (Abrevaya and Dahl, 2008). Our quantile difference-in-differences method applies the difference-in-differences approach to each quantile of the data instead of mean. There are three main reasons for using a quantile regression rather than OLS technique. First, the incentive to blend varies by the relative prices of wholesale petroleum and ethanol. Since finished gasoline is at least 90% petroleum, the incentive to blend ethanol varies over the distribution of gasoline prices. Therefore, conditional quantiles of retail gasoline price distribution can be thought of representing the substitution effect in blending decisions. In contrast, OLS estimates the mean effect and cannot account for this substitution effect arising from dynamic market incentives. Second, in our quantile regressions we allow for the market frictions to vary differentially across both different ethanol shipping distances and different retail gasoline prices. Third, refiner profits (often proxied by the crack spread) vary with

[30] Reuters article reported that higher RIN prices cost refiners at least $1.35 billion in 2013. See `http://www.reuters.com/article/2014/03/31/us-rins-spike-costs-analysis-idUSBREA2U0PT20140331`. Last accessed: May 10, 2015.

demand for gasoline. Ethanol can have a differential effect on gasoline prices as demand rises and falls through the refiner profits channel as ethanol reduces the market power of refiners during high demand periods (Knittel and Smith (2015)). Quantile techniques account for this asymmetric effect throughout the distribution of gasoline prices explicitly, while OLS can only identify the mean effect.

The main empirical specification regresses the retail gasoline price on the relative prices of oil and corn ethanol, and distance variables:

$$\begin{aligned}
P_{g_{it}} = {} & \gamma_{0,\tau} + \gamma_{1,\tau}\mathbf{1} \cdot \{Yr > 2012\} + \gamma_{2,\tau}(P_{e_t} - P_{o_t}) + \gamma_{3,\tau} P_{o_t} + \gamma_{4,\tau}\mathbf{1} \cdot \{Yr > 2012\} \times Dist_i \\
& + \gamma_{5,\tau}(P_{e_t} - P_{o_t}) \times Dist_i + \gamma_{6,\tau}\mathbf{1} \cdot \{Yr > 2012\} \times (P_{e_t} - P_{o_t}) \\
& + \gamma_{7,\tau}\mathbf{1} \cdot \{Yr > 2012\} \times (P_{e_t} - P_{o_t}) \times Dist_i + \lambda_{i,\tau} + f_{my,\tau} + \epsilon_{it,\tau} \qquad (1.1)
\end{aligned}$$

$$P_{g_{it}} = x'_{it}\beta_\tau + \lambda_{i,\tau} + f_{my,\tau} + \epsilon_{it,\tau} \qquad (1.2)$$

$$Q_\tau\left(\epsilon_{\tau,it} | x_{it}, \lambda_{i,\tau}, f_{my,\tau}\right) = 0 \qquad (1.3)$$

$$Q_\tau\left(P_{g_{it}} | x_{it}, \lambda_{i,\tau}, f_{my,\tau}\right) = x'_{it}\beta_\tau + \lambda_{i,\tau} + f_{my,\tau} \qquad (1.4)$$

where the dependent variable, $P_{g_{it}}$, is retail gasoline price for city i in week t, x is our vector of regressors, and β_τ is the vector of parameters to be estimated. P_{e_t} is the weekly corn ethanol price, P_{o_t} is the weekly price of a gallon of oil, $Dist_i$ is the distance from city i to the ethanol production center in the Midwest, and $\epsilon_{it,\tau}$ is the error term with unknown distribution function and potential heteroskedasticity.[31] We estimate the relationship of x with $P_{g_{it}}$ for different values of τ which indexes the quantiles of the dependent variable. Thus, $Q_\tau\left(P_{g_{it}} | x_{it}, \lambda_{i,\tau}, f_{my,\tau}\right)$ denotes the τth conditional quantile of $P_{g_{it}}$ with $0 < \tau < 1$. Estimation and inference of β_τ is discussed in Galvao (2011). It is clear that the advantage of using a panel data (rather than cross sectional) quantile regression is that we can control for unobserved heterogeneity in the gasoline prices.

[31] Quantile regression is a semiparametric method because one does not need to specify the distribution function of the error term. The presence of heteroskedasticity is captured by the quantile regression coefficients. See Koenker (2005) for further details.

$\lambda_{i,\tau}$ control for city fixed effects. At the local level blender's decision to operate depends on the costs of its inputs, such as petroleum blendstock, ethanol, labor costs, etc. City fixed effects control for local unobserved production costs, variations in local environmental policies, and differences in local regulations. For example, Brown et al. (2008) finds that there are significant spatial differences in regulation and that those differences significantly affect gasoline prices.[32] In addition, some states require how the information about the ethanol content be labeled in retail outlets.

$f_{my,\tau}$ are month-by-year effects, where m is month (January-December) and y is year (2007-2014). Month-by-year effects, $f_{my,\tau}$, are monthly dummies for each year of the data sample. In other words, every month in a certain year is allowed to have a different impact from the same month in a different year.[33] They control for everything that was fixed within that time period and remove all of the fluctuations common across states and PADDs over time. For example, month-by-year effects control for variations driven by national level events as well as variations due to seasonality. Note that both city fixed effects and month-by-year effects are τ-dependent. With large number of city fixed effects, it is typical to impose the restriction $\lambda_{i,\tau} = \lambda_i$ for all quantiles. These traditional city-specific effects (λ_i) do not vary across quantiles and they estimate a location-shift effect that simply shifts the conditional quantile functions by λ.

The justification for the inclusion of relative prices of ethanol and oil in the regression is straightforward. We assume that ethanol is a substitute, though imperfectly, for petroleum blendstock. The incentive to blend ethanol is greater when the ethanol price and its associated transportation costs are smaller than the petroleum blendstock. As a result, we include not only the oil price as a control variable, but also the relative prices of corn ethanol and oil: $(P_{e_t} - P_{o_t})$. To make the interpretation of coefficients easier, we normalize the $(P_{e_t} - P_{o_t})$ variable by subtracting

[32]To the extent that there is seasonal variation in these regulations, we assume that seasonal variation in regulations are orthogonal to distance from ethanol refineries.

[33]Given the weekly observations, we determine the corresponding calendar month the weeks belong to generate month-by-year effects.

from it its post-2012 mean value. Identification for this coefficient comes from weekly variations in ethanol and PADD-level oil prices.

$Dist_i$ is distance from city i to ethanol sources and controls for ethanol transportation costs. Ethanol produced in a particular city (state) is no different from ethanol produced in other city (state). Because ethanol production is concentrated in the Midwest, our distance measure is the distance from each city to the ethanol production center in the Midwest. We find the centroid of the six largest ethanol producing states and designate it as the ethanol production center. The centroid of these ethanol producing states corresponds to a location in Iowa, which also happens to be the largest ethanol producing state. However, since ethanol still comes from other places, a blender will minimize its costs of production by purchasing ethanol from the closest ethanol refineries provided supply of ethanol is available. As will be discussed in the next section, we also present results using alternative measures of distance, such as the weighted average distances from cities to closest ethanol refineries.

We are mainly interested in the effects of distance on gasoline prices after 2012 when the ethanol policy started to bind. Hence, the coefficients of interest are those on $(Yr > 2012) \times Dist$ and $(Yr > 2012) \times (P_e - P_o) \times Dist$. From equation 1.1, if we take the derivative of retail gasoline price with respect to distance we get

$$\left.\frac{\partial P_g}{\partial Dist}\right|_{Yr>2012} = \gamma_4 + \gamma_7 (P_{e_t} - P_{o_t}) \tag{1.5}$$

This is the overall impact of distance on gasoline prices, where γ_4 is the direct distance effect. The interpretation of equation 1.5 is similar to "trade cost" in gravity models of trade. In the gravity models of trade, distance between two countries reduces the volume of trade between them. In our model, cost of ethanol to blenders increases with distance which is captured by γ_4. As the mandate started to bind and RIN prices started to increase in 2013, more ethanol has to be shipped to places outside the Midwest. To see the relationship between retail gasoline price and ethanol shipping

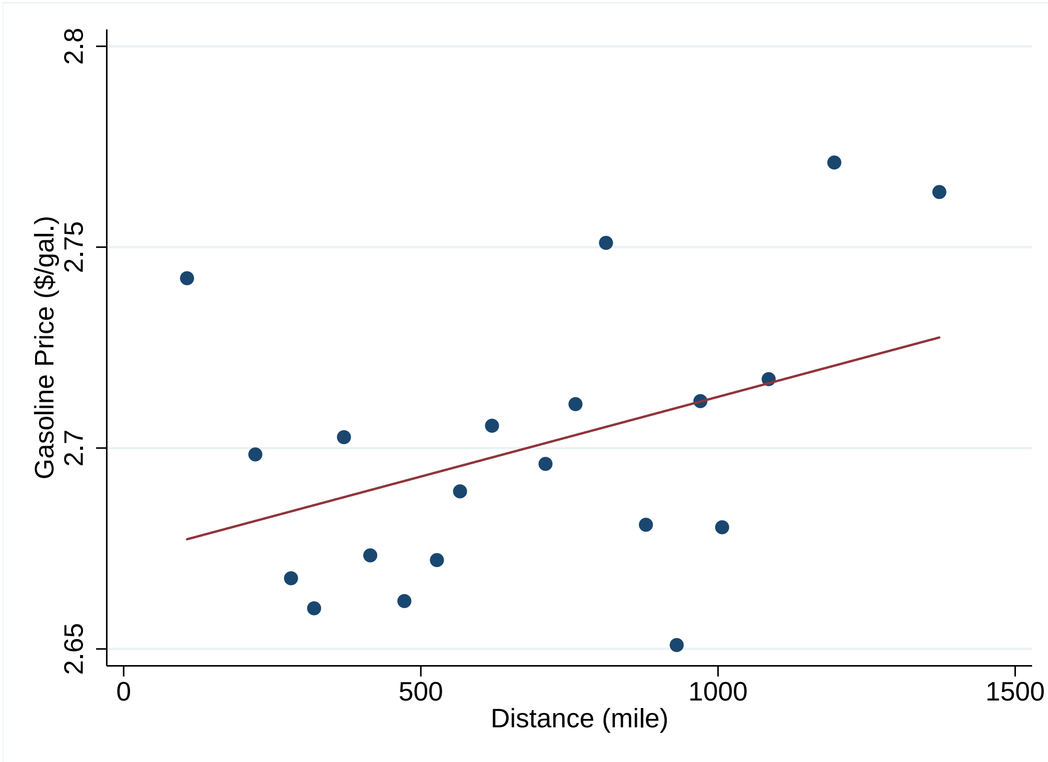

Figure 1.6: Relationship of Gasoline Price with Distance

Notes: Distance measure the distance from cities to ethanol production center in the Midwest. We bin the distances into several intervals of the same size and plot the average value of the gasoline price for each distance bin.

distance, we plot them in Figure 1.6. Note that distance is great circle distance from cities to the centroid of the largest ethanol producing states in the Midwest. Since we have thousands of observations, simple scatter plot would have become overcrowded and, therefore, not very useful in studying the relationship between the two variables. Therefore, in the Figure 1.6 we bin the distance variable into several intervals of the same size and plot the average value of the gasoline price for each distance bin. From the figure we can see a positive relationship between the two variables. However, as the equation 1.5 makes clear the effect of distance on gasoline prices also depends on the relative prices of corn ethanol and petroleum blendstock. We discuss the overall effect of distance on gasoline prices below.

Table 1.3: Main Regression Results

	(0.10)	(0.25)	(0.50)	(0.75)	(0.90)
$(Yr{>}2012)$	1.068***	1.014***	0.981***	0.954***	1.007***
	(87.50)	(88.97)	(66.41)	(62.76)	(61.37)
$(P_e{-}P_o)$	0.197***	0.166***	0.143***	0.0751***	0.0739***
	(28.57)	(28.31)	(19.33)	(9.85)	(9.02)
P_o	0.393***	0.386***	0.376***	0.326***	0.296***
	(62.43)	(69.73)	(55.27)	(45.58)	(38.07)
$(Yr{>}2012){\times}Dist$	0.0164***	0.0129***	0.00545	-0.0137**	-0.0404***
	(4.64)	(3.95)	(1.32)	(-3.27)	(-9.17)
$(P_e{-}P_o){\times}Dist$	-0.0187***	-0.0389***	-0.0524***	-0.0670***	-0.0614***
	(-4.37)	(-9.82)	(-10.05)	(-11.95)	(-9.50)
$(Yr > 2012)\times(P_e - P_o)$	-0.0557***	-0.0269**	0.0165	0.171***	0.249***
	(-5.38)	(-2.98)	(1.51)	(15.82)	(21.73)
$(Yr{>}2012){\times}(P_e{-}P_o){\times}Dist$	-0.0430***	-0.0508***	-0.0830***	-0.154***	-0.261***
	(-3.99)	(-5.37)	(-7.14)	(-13.01)	(-20.04)
$Constant$	0.801***	0.885***	1.043***	1.275***	1.396***
	(31.92)	(39.51)	(36.37)	(42.84)	(43.85)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Month-by-year effects	Yes	Yes	Yes	Yes	Yes
N	58,852	58,852	58,852	58,852	58,852

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

1.5 Results

Table 1.3 presents the regression results for different quantiles of retail gasoline price distribution. We are mainly interested in distance effect on retail gasoline prices after 2012. The coefficient on $(Yr > 2012) \times Dist$ is positive for $\tau < 0.75$. This means that ethanol shipping distance had positive impact on retail gasoline prices after 2012 when the RIN prices started to increase. However, this effect is statistically significant only at the lower tails of retail gasoline price distribution ($\tau < 0.50$). Thus, when retail gasoline price is low, cities farther from the ethanol production centers in the Midwest paid significantly higher gasoline prices than cities in upper Midwest. As the mandate became binding at the national level starting in 2013, more ethanol has to be shipped to far away places. Therefore, blending in those places may have occurred at higher costs due to the binding mandate and ethanol transportation costs. This result is intuitively clear: because E10 market in the Midwest has been saturated with ethanol, additional ethanol consumption due to the mandate must have come from places that have not yet hit the blend wall. This is because, even though the RFS is a national mandate, the penetration of ethanol across the U.S. has not been uniform. Figures 1.4 and 1.5 both suggest that the Gulf Coast, Rocky Mountain Region, and to some degree the West Coast likely absorbed more ethanol when the mandate started binding. Even if blenders choose not to blend ethanol to the required minimum level, a binding mandate means that blenders in far away places would have to pay significantly higher prices for RINs to meet their renewable volume obligations. RIN is a variable cost that increases the cost of producing finished gasoline. If a blender chooses not to blend ethanol to the required volume, then she shortfall in obligations must be met by purchasing RINs in the open market. If more gasoline is sold, more RINs have to be generated or purchased because the RFS mandate is proportionate to the gasoline consumption.

Importantly, the effect of transportation costs also depends on the relative prices of corn ethanol and petroleum blendstock used in the blending process. Note that P_o is per gallon oil price used to proxy for petroleum blendstock.[34] Cost of oil makes up about 2/3 of the cost of petroleum blendstock and the rest of the cost is made up of refining and distribution costs. The availability of relatively cheaper ethanol is expected to lessen the distance effect on gasoline price.[35] We plot the weekly variation

[34] Ethanol is blended with petroleum blendstock that is either conventional blendstock for oxygenate blending (CBOB) or reformulated blendstock for oxygenate blending (RBOB), with latter being more expensive to refine. See `http://wearethepractitioners.com/library/the-practitioner/2012/03/15/the-gasoline-bobs-cbob-and-rbob-%28and-carbob%29`. Last accessed: May 10, 2015.

[35] A gallon of ethanol contains 2/3 the energy of a gallon of petroleum blendstock. While relevant, in this paper we are not concerned with the retail price differentials between E10 (gasoline with up to 10% ethanol blend) and E0 (100% pure gasoline) sold in certain markets.

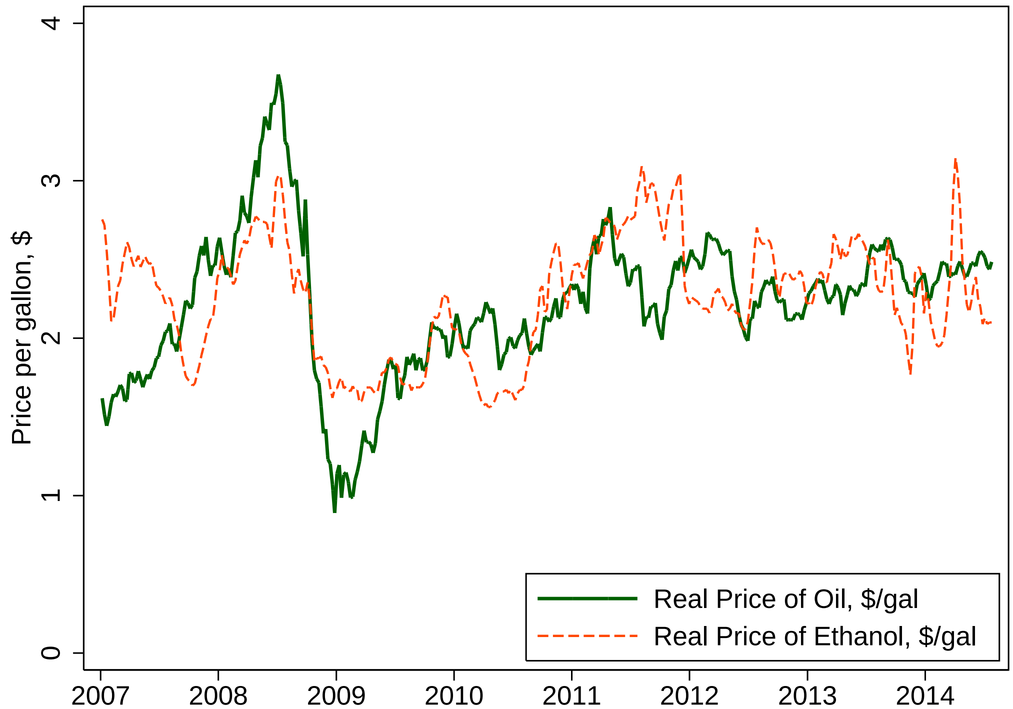

Figure 1.7: The Cost of Ethanol and Crude Oil

Notes: Ethanol price is the spot price at Iowa ethanol plants and oil price is the WTI spot crude oil price with delivery point in Cushing, Oklahoma.

of ethanol and crude oil spot prices in Figure 1.7. Ethanol price is the spot price of ethanol at Iowa ethanol plants. While petroleum products are mainly transported by cost-effective pipelines, ethanol delivery costs vary depending on shipping distances. In the past cold weather and increased crude oil shipments by rail was blamed for delays in ethanol shipments from the Midwest, leading to an increase in ethanol delivery prices. In New York Harbor, this has led to an increase in per gallon shipping costs of ethanol from usual 10 cents to about $1 in early 2014.[36] As Table 1.3 shows the coefficient estimate for $(Yr > 2012) \times (P_e - P_o) \times Dist$ is negative and statistically significant for all quantiles. We evaluate the post-2012 effect of distance on retail gasoline prices by

[36]See `http://www.wsj.com/articles/SB10001424052702303546204579439740561525518`. Last accessed: May 10, 2015.

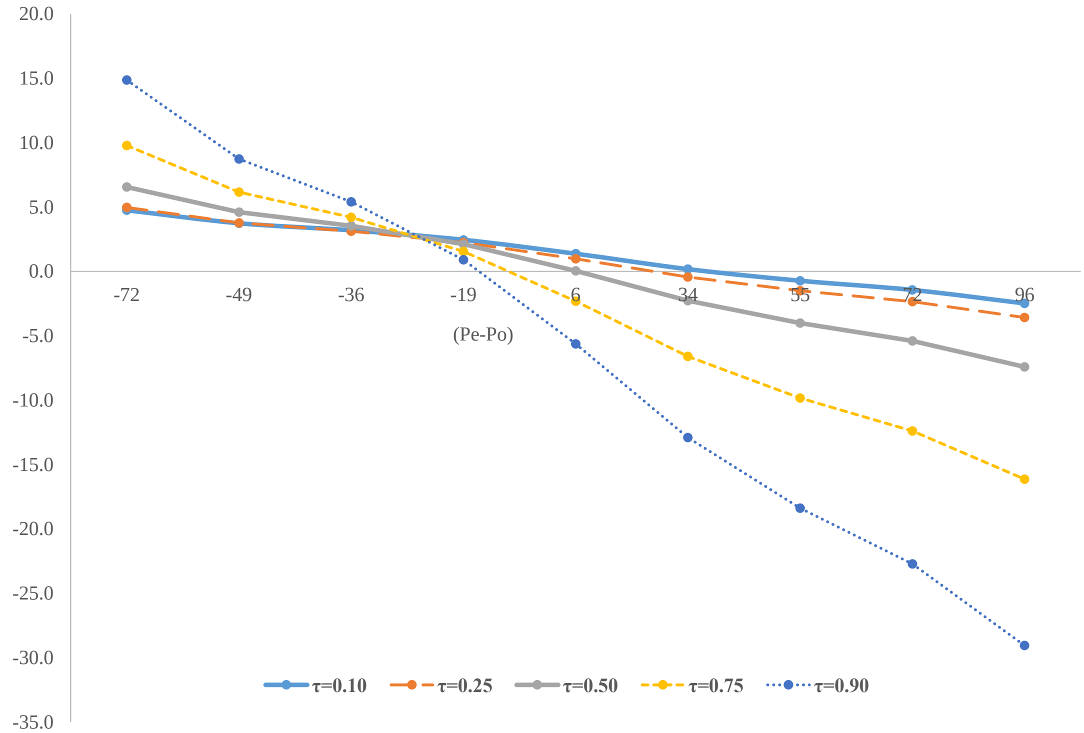

Figure 1.8: Changes in Retail Gasoline Price per 1,000 miles (cents/gal.)

Notes: This Figure shows the effect of distance from a city to an ethanol refinery on retail gasoline prices, as defined in equation 1.5. The overall distance impact depends on the relative costs of ethanol and petroleum blendstock as well, which is given on the horizontal axis.

controlling for the variation in relative prices of ethanol and petroleum blendstock below.

The overall impact of distance on retail gasoline prices, after the mandate became binding, is given by the equation 1.5 and presented graphically in Figure 1.8. The figure shows changes in gasoline prices per 1,000 miles against the various values of $(P_e - P_o)$. Note that the value on the horizontal axis for $(P_e - P_o)$ are demeaned by subtracting from it its post-2012 mean value, which is equal to $(\overline{P_e - P_o})\big|_{Yr>2012} = -\$0.15$ for our dataset. A movement to the left along the horizontal axis means relative ethanol to blendstock prices got lower than their post-2012 mean value. For instance, a value of -\$0.50 on the horizontal axis means relative price of ethanol to oil decreased by about \$0.65 from its mean value (e.g. $-0.65 - (-0.15) = -0.50$). This may occur, for example, when ethanol becomes cheaper than oil by \$0.65, or when oil price increases relative to ethanol by \$0.65, and/or combination of both. As Figure 1.8 shows, when the relative ethanol to oil prices move lower, the overall impact of distance on retail gasoline prices is positive. This result is intuitively sensible: ethanol is more appealing to blenders when the relative price of petroleum blendstock is high. If ethanol is costly to ship far away from the Midwest, then theory would predict that only when ethanol is very appealing to blend (e.g. the relative price of petroleum blendstock is high) would far away places fully blend. Since ethanol transport costs increase with distance, this means cities farther away from ethanol production centers face higher retail gasoline prices than cities closer to ethanol sources. For example, when $(P_e - P_o) = -\$0.50$, this translates into an additional cost of 4 to 9 cents per gallon of gasoline for every 1,000 miles depending on the distribution of gasoline prices. Similarly, back of the envelope calculations show that for a consumer living in Miami, Florida, which is about 1,450 miles away from the centroid of ethanol production center in the Midwest (i.e. Iowa), this translates into 5 to 13 cents more per gallon of gasoline when $(P_e - P_o) = -\$0.50$. We note that an increase in gasoline prices has a direct effect on transportation costs themselves as diesel fuel used for trains becomes more expensive.[37] Nonetheless, these point estimates seem high, therefore we focus on the significance of the result.

We observe differential impact as we move to the right along the horizontal axis. Positive values for $(P_e - P_o)$ imply ethanol becoming less competitive relative to petroleum blendstock. Surprisingly, when ethanol becomes more expensive than oil, distance effect on retail gasoline prices is negative. Though unexpected, this result is less likely to occur because gasoline prices tend to be high (as represented by higher quantiles in the graph), when oil prices are high. If ethanol is not competitively priced, then blending ethanol will not be profitable to blenders. Therefore, negative distance effect observed in the graph is unexpected and unlikely to happen.

[37] This is one manifestation of the market friction our paper is concerned with. The coefficient on $(Yr > 2012) \times (P_e - P_o) \times Dist$ will not be subject to that form of market friction, though, since it is differenced out by $(Yr > 2012) \times Dist$ for a given level of retail gasoline prices.

Table 1.4: Overall Distance Effect on Retail Gasoline Prices

	$\tau \leq 0.25$	$\tau \geq 0.75$
$P_e < P_o$	$+$	$+$
$P_e > P_o$	$\pm$	$-$

Notes: We define $\tau \leq 0.25$ and $\tau \geq 0.75$ as corresponding to lower and upper tails of retail gasoline prices, respectively. When $P_e < P_o$ (top two boxes), blending ethanol becomes attractive and distance effect is positive. In contrast, when $P_e > P_o$ and $\tau \geq 0.75$ (i.e. when ethanol becomes more expensive than oil and retail gasoline prices are already high), the distance has a negative effect on retail gasoline prices (bottom right box). We argue that this result is unlikely to occur because when oil prices are high, gasoline prices tend to be high as well.

To summarize the results, we present the effects of distance on retail gasoline prices using 2 by 2 table (see Table 1.4). We focus on the tails of retail gasoline price distribution. We define low retail gasoline prices as corresponding to the distribution of retail gasoline prices at and below the 25th quantile (i.e. $0 < \tau \leq 0.25$) and high retail gasoline prices $-$ at and above the 75th quantile (i.e. $\tau \geq 0.75$). When $P_e < P_o$ (top two boxes), the distance effect is positive and cities far from ethanol sources pay higher retail gasoline prices than cities closer to ethanol sources. This effect is more pronounced if the retail gasoline prices are already high. In contrast, when $P_e > P_o$, distance effect on retail gasoline price is generally negative. As explained above, we believe this negative distance effect is unlikely to happen. For $\tau \geq 0.75$, which corresponds to upper tail of gasoline prices, oil prices also tend to be higher and, therefore, negative distance effect seems counterintuitive.

A related question is could these results be driven by the existence of market power in the ethanol market? According to the latest analysis conducted by Federal

Trade Commission, the U.S. ethanol production industry seems unconcentrated.[38] We are not aware if there exists similar analysis about the RIN market. The sharp increase in RIN prices in 2013 fueled discussions about speculative activity in the RIN market. High RIN prices post-2012 could be the result of transaction costs or speculative activity by market participants. Because of lack of information about the RIN market, we are unable to study the factors behind a sharp spike in RIN prices in 2013. Therefore, although our results are consistent with the existence of market power in the ethanol market, we are unable to separate the effects of market power from the distance effects. What is certain is the existence of market frictions in the ethanol market due to distance between ethanol plants and blenders. Because of our difference-in-differences design, we take our results as causal evidence that the binding ethanol regulation exacerbated market friction that asymmetrically affected retail gasoline prices in the U.S.

1.6 Robustness Checks

The main regression results presented in Table 1.3 and discussed in the previous section, use distance from cities to the ethanol production center in the Midwest. Since distance is used to proxy for transportation costs of ethanol, we consider how robust our results are to different measures of distance.

Most ethanol plants are small-scale producers that are much smaller than oil refineries. Typically, demand for ethanol at the city level exceeds the supply by an individual ethanol producer. Hence, distance from a city to the single nearest ethanol refinery does not factor the need for additional ethanol from other nearby ethanol plants. Further, ethanol industry witnessed a number of its facilities having ceased production either temporarily or permanently due to various factors, including

[38] Federal Trade Commission: "2013 Report on Ethanol Market Concentration."

Table 1.5: Results Using Weighted Average Distance to the Closest Four Biorefineries

	(0.10)	(0.25)	(0.50)	(0.75)	(0.90)
$(Yr>2012)$	1.077***	1.032***	0.995***	0.955***	0.990***
	(87.86)	(90.87)	(86.43)	(75.10)	(59.45)
(P_e-P_o)	0.197***	0.160***	0.130***	0.0514***	0.0502***
	(29.49)	(28.55)	(23.84)	(8.51)	(6.42)
P_o	0.408***	0.393***	0.380***	0.321***	0.294***
	(63.12)	(70.14)	(70.73)	(53.23)	(36.98)
$(Yr>2012)\times Dist$	-0.0381***	-0.0101	-0.0166	-0.0449***	-0.104***
	(-3.93)	(-1.09)	(-1.76)	(-4.23)	(-7.15)
$(P_e-P_o)\times Dist$	0.00928	-0.0634***	-0.117***	-0.149***	-0.122***
	(0.70)	(-5.06)	(-9.15)	(-10.43)	(-6.44)
$(Yr>2012)\times(P_e-P_o)$	-0.0740***	-0.0442***	-0.0226**	0.106***	0.154***
	(-8.87)	(-5.95)	(-3.09)	(13.29)	(14.13)
$(Yr>2012)\times(P_e-P_o)\times Dist$	-0.242***	-0.207***	-0.151***	-0.266***	-0.482***
	(-8.13)	(-7.71)	(-5.60)	(-8.57)	(-10.23)
$Constant$	0.766***	0.856***	1.028***	1.280***	1.386***
	(29.91)	(37.68)	(45.45)	(51.78)	(42.74)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Month-by-year effects	Yes	Yes	Yes	Yes	Yes
N	58,852	58,852	58,852	58,852	58,852

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

drought.[39] Thus, using distance to a single closest refinery will underestimate the distance effect on gasoline prices. Instead, we opt to use a weighted average distance to the nearest ethanol refineries. We experimented with weighted average distances to the closest four to eight ethanol refineries. Table 1.5 presents the results from the regression using a weighted average distance to the closest four ethanol plants.

[39]For example, shortage of corn idled about 20 ethanol refineries in 2012-2013. See `http://www.usatoday.com/story/news/nation/2013/02/10/corn-shortage-idles-plants-nationwide/1906831/`. Last accessed: May 10, 2015.

The coefficients on one of the variables of interest, $(Year > 2012) \times Dist$, is negative for all quantiles, but statistically not significant at 25th and 50th quantiles. Regression estimates using a weighted average distance to closest five to eight ethanol plants yielded similar results. A closer inspection of the data shows that using a weighted average distance to closest four to eight ethanol plants underestimates the distance effect. If in the main regression specification the average distance from a city to the ethanol production center in the Midwest is 680 miles, it is only 160 miles when we use a weighted average distance to the nearest four ethanol refineries. Also, the weighted average distance estimates are significantly lower than the actual national average ethanol transport distance of approximately 680 miles as found in Strogen et al. (2012). However, if we evaluate the overall impact of distance, which also depends on the relative prices of ethanol and petroleum, distance has a positive impact on retail gasoline prices when $(P_e - P_o)$ falls.[40]

We also estimated an alternative specification where we define a dummy variable Far and set it equal to one for all the cities that are not in PADD 2 region (i.e. Midwest). This accounts for greater ethanol transport costs when ethanol is shipped to major demand centers outside the Midwest. The results are presented in Table 1.6. The coefficient estimate for post-2012 Far dummy variable, $(Year > 2012) \times Far$, is positive only at 25th and 50th quantiles, though, they are not statistically significant. On the other hand, the coefficients on $(Yr{>}2012) \times (P_e{-}P_o) \times Far$, are negative and statistically significant.

As further tests, we dropped PADD 1 and PADD 5 regions and compared the retail gasoline prices between PADD 2 and PADD 3 regions. The results are presented in Table 1.7. The coefficient on $(Year > 2012) \times Far$ is positive and statistically significant for all quantiles, except for $\tau = 0.90$. The other coefficient of interest, $(Yr > 2012) \times (P_e{-}P_o) \times Far$, is negative and statistically significant, except for $\tau = 0.50$. These estimates are consistent with the main results of the paper.

[40] When we use WTI crude oil prices instead of PADD-level oil prices, the results are qualitatively similar.

Table 1.6: Models of Gasoline Price with Cities Near vs. Far from Biorefineries

	(0.10)	(0.25)	(0.50)	(0.75)	(0.90)
$(Yr > 2012)$	1.067***	1.010***	0.992***	0.956***	1.022***
	(96.43)	(85.07)	(82.19)	(62.54)	(57.68)
$(P_e - P_o)$	0.193***	0.152***	0.118***	0.0555***	0.0645***
	(31.93)	(26.01)	(20.70)	(7.64)	(7.76)
P_o	0.400***	0.388***	0.373***	0.331***	0.315***
	(68.04)	(65.50)	(65.54)	(45.20)	(36.87)
$(Yr > 2012) \times Far$	-0.000386	0.00275	0.00282	-0.0113***	-0.0359***
	(-0.17)	(1.13)	(1.12)	(-3.50)	(-9.47)
$(P_e - P_o) \times Far$	-0.00652*	-0.0224***	-0.0320***	-0.0444***	-0.0354***
	(-2.26)	(-7.52)	(-10.78)	(-11.61)	(-7.84)
$(Yr > 2012) \times (P_e - P_o)$	-0.0649***	-0.0386***	0.00234	0.137***	0.205***
	(-8.45)	(-4.90)	(0.30)	(14.23)	(18.09)
$(Yr{>}2012){\times}(P_e{-}P_o){\times}Far$	-0.0725***	-0.0620***	-0.0701***	-0.126***	-0.245***
	(-11.01)	(-9.04)	(-10.32)	(-14.66)	(-24.15)
$Constant$	0.885***	1.329***	1.521***	1.764***	1.835***
	(36.46)	(52.75)	(60.51)	(55.69)	(50.49)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Month-by-year effects	Yes	Yes	Yes	Yes	Yes
N	58,852	58,852	58,852	58,852	58,852

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: We define Far dummy variable and set it equal to zero if a particular city is in PADD 2 region (Midwest). For all other cities in other PADD regions, it is set equal to one.

Table 1.7: Models of Gasoline Price with Cities in PADD 2 vs. PADD 3 Regions

	(0.10)	(0.25)	(0.50)	(0.75)	(0.90)
$(Yr > 2012)$	0.531***	0.508***	0.472***	0.467***	0.439***
	(41.13)	(31.87)	(29.39)	(32.10)	(26.46)
$(P_e - P_o)$	0.140***	0.0998***	0.0602***	-0.00529	-0.0109
	(20.38)	(13.08)	(7.83)	(-0.74)	(-1.27)
P_o	0.404***	0.400***	0.402***	0.384***	0.351***
	(55.42)	(48.85)	(50.73)	(52.46)	(39.56)
$(Yr > 2012) \times Far$	0.0259***	0.0379***	0.0398***	0.0176***	0.00644
	(10.39)	(11.45)	(10.82)	(5.07)	(1.54)
$(P_e - P_o) \times Far$	-0.00597	0.00172	-0.00816	-0.00526	-0.00288
	(-1.58)	(0.36)	(-1.65)	(-1.13)	(-0.52)
$(Yr > 2012) \times (P_e - P_o)$	-0.00279	0.0240*	0.0674***	0.204***	0.256***
	(-0.32)	(2.35)	(6.71)	(22.82)	(24.42)
$(Yr > 2012) \times (P_e - P_o) \times Far$	-0.0342***	-0.0481***	-0.0181	-0.0884***	-0.188***
	(-4.05)	(-4.81)	(-1.74)	(-9.28)	(-16.57)
$Constant$	1.260***	1.654***	1.801***	1.962***	2.117***
	(49.07)	(54.58)	(59.32)	(71.91)	(66.53)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Month-by-year effects	Yes	Yes	Yes	Yes	Yes
N	40,886	40,886	40,886	40,886	40,886

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: PADD 2 region is assumed to be closer to the ethanol sources, while PADD 3 region is assumed to be Far from ethanol sources in the Midwest.

Table 1.8: Results for Cities without 10% State Ethanol Mandates

	(0.10)	(0.25)	(0.50)	(0.75)	(0.90)
$(Yr > 2012)$	0.740***	0.694***	0.714***	0.752***	0.731***
	(58.07)	(42.23)	(49.66)	(50.02)	(40.90)
$(P_e - P_o)$	0.195***	0.167***	0.144***	0.0838***	0.0916***
	(27.76)	(20.09)	(20.16)	(11.18)	(9.96)
P_o	0.400***	0.387***	0.374***	0.318***	0.297***
	(63.14)	(50.24)	(57.67)	(46.07)	(34.86)
$(Yr > 2012) \times Dist$	0.0172***	0.0170***	0.00579	-0.0130**	-0.0364***
	(4.66)	(3.62)	(1.43)	(-3.16)	(-7.25)
$(P_e - P_o) \times Dist$	-0.0165***	-0.0436***	-0.0584***	-0.0821***	-0.0801***
	(-3.59)	(-7.44)	(-11.21)	(-14.60)	(-11.04)
$(Yr > 2012) \times (P_e - P_o)$	-0.0618***	-0.0255*	0.0251*	0.166***	0.247***
	(-5.77)	(-1.98)	(2.35)	(15.53)	(18.87)
$(Yr > 2012) \times (P_e - P_o) \times Dist$	-0.0418***	-0.0481***	-0.0881***	-0.147***	-0.262***
	(-3.69)	(-3.53)	(-7.78)	(-12.68)	(-17.81)
$Constant$	1.110***	1.204***	1.314***	1.497***	1.678***
	(45.50)	(40.02)	(50.67)	(55.38)	(51.51)
City fixed effects	Yes	Yes	Yes	Yes	Yes
Month-by-year effects	Yes	Yes	Yes	Yes	Yes
N	54,302	54,302	54,302	54,302	54,302

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression is run by dropping cities with 10% state ethanol mandates (Minnesota, Missouri, and Oregon).

A number of states have their own renewable fuel policies. These policies are generally more stringent than the RFS mandate at the national level. For example, Hawaii, Missouri, and Oregon require exactly 10% ethanol content for gasoline sold in those states (see Table 1.2). As a result, blenders in those states might not have much flexibility when to blend and how much to blend. Therefore, we reestimate our model by dropping cities in states with exactly 10% ethanol mandates (Missouri, Oregon, and Minnesota). The results presented in Table 1.8 did not change in a significant way and are of similar magnitude as the main results.[41] Perhaps, obligated parties (blenders and refiners) over-complied with the mandate and therefore, dropping states with more stringent ethanol policies did not alter our results significantly.

1.7 Conclusion

The 2007 renewable fuels standard (RFS) significantly boosted the demand for ethanol. Wholesale blending terminals, where ethanol is blended into gasoline before it is delivered to retail gasoline stations, are in the position to choose the amount of blending. The minimum quantity of ethanol required to be blended is regulated by RFS and is a yearly volume rather than a percentage of finished gasoline. This is a unique aspect of the policy for our study: a volumetric mandate permits blenders to have more flexibility in choosing their blending strategy within a year.

In the early years, the quantity of ethanol blended into fuel exceeded the mandated quantities each years since the RFS's inception in 2008. Therefore, mandate was most likely not binding during this period. Up until 2013 the price of ethanol renewable identification numbers (RINs), which is a better indicator of a binding mandate, has been consistently close to zero. Beginning with 2013, the situation was much different. An anticipation of higher blending mandates in 2013 and beyond, and an impending 10% blend wall meant that meeting the mandate by obligated parties (blenders and refiners) would be more difficult and expensive. Lack of infrastructure for blending ethanol and the limited access to the cost effective way of shipping ethanol throughout the U.S., had differentially affected the incidence of a policy across the country.

In this paper we look at the implication of a binding mandate on retail gasoline prices through the ethanol transportation cost channel. The existence of bottlenecks in ethanol infrastructure and access to ethanol blendstock across the regional markets may lead to unintended consequences. We find evidence that the RFS created a market friction in the ethanol industry due to transportation costs of moving ethanol

[41] Hawaii is not in the contiguous U.S. and, therefore, is not included in our analysis.

throughout the U.S. Using weekly retail gasoline price data from over 200 cities in the U.S. and a quantile difference-in-differences estimator, we find that distance from cities to ethanol production centers has resulted in differential impacts on gasoline prices over space. Cities farther from the ethanol sources paid higher gasoline prices relative to the cities in upper Midwest. As the mandate became binding starting in 2013, more ethanol has to be shipped to far away places. With yearly increases in the amount of ethanol consumption due to the mandate, more ethanol must be shipped and that additional blending must have come from places outside the Midwest at greater costs. Importantly, retail gasoline price impact of transportation cost of moving ethanol from the Corn Belt across to other states depends on the relative prices of corn ethanol and petroleum blendstock.

Our results highlight the spatial incidence associated with the mandated ethanol market. Ordinary least squares regression estimates the conditional mean and, therefore, is not adequate to capture distributional impact arising from dynamic market incentives. Because of our quantile difference-in-differences design, we take our results as causal evidence that the ethanol regulation led to market frictions that asymmetrically affected retail gasoline prices in the U.S. We do not attempt to find the total effects of a mandate on average gasoline prices. Rather, our results shed light on the incidence of the policy due to market frictions created by the lack of infrastructure in the ethanol industry. This may be of particular interest to policymakers in alleviating these market frictions from their market designs.

Chapter 2

Point Forecast Accuracy of Model Averaging in Carbon Dioxide Emissions Using U.S. State-Level Data

2.1 Introduction

Carbon dioxide (CO_2) emitted from fossil fuel (oil, gas, and coal) combustion is the largest contributor to global CO_2 emissions. Projections of CO_2 is of particular importance in evaluating policies to address CO_2 due to human activity. While literature on forecasting emissions is copious, reported forecasts may differ significantly due to differences in their model specifications and the estimation techniques.

Among the class of emissions forecasts, early works focused on modeling emissions based on Environmental Kuznetz Curve (EKC) hypothesis, where emissions first rise with income and then fall after a certain income level is reached (Holtz-Eakin and Selden (1995), Selden and Song (1994), Grossman and Krueger (1995)). Later work examined the EKC hypothesis using more flexible approaches (Schmalensee et al. (1998)). However, not all studies agree with the conclusions of the EKC hypothesis (Perman and Stern (2003), Stern (2004), Cole (2005)). More recent studies experimented with dynamic modeling approaches to emission projections with some success (Auffhammer and Steinhauser (2012)). While models and methods used to forecast CO_2 emissions are continually being perfected, there may be benefits from combining existing models.

Studies on forecast combination go back to at least Bates and Granger (1969) and Sanders (1963). In forecasting meteorological events, Sanders (1963) noted that averaging subjective individual forecasts did significantly better than the best individual forecast. The results from recent empirical and theoretical literature indicate that forecast combination typically leads to increased forecast accuracy, sometimes dramatically (Clemen (1989), Stock and Watson (2004), Timmermann (2006), Issler and Lima (2009)). Even simple averaging of forecasts are found to produce better forecasts on average than the forecasts generated from the best individual models (Timmermann, 2006). If the true data generating process is unknown, which is true in many situations, then pooling forecasts has the advantage of making use of a wider information set than is available to each individual model. This may lead to better forecast performance relative to that of individual model. Not surprisingly, forecast combinations have increasingly been used in forecasting financial and economic data.

However, despite the abundance of models and estimation methods used in forecasting emissions, application of forecast combination to CO_2 emissions is lacking. Indeed, one of the key recommendations of Intergovernmental Panel on Climate Change (IPCC) Expert Meeting in Boulder, Colorado, was to generate ideas for the evaluation and combination of projections from various modeling techniques.[1]

In this paper we evaluate the predictive accuracy of various individual models found in CO_2 emissions literature and their linear combinations. Using state-level data for the U.S., we show that combining multiple forecasts of CO_2 emissions can be

[1] IPCC, 2010: Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections. IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland.

useful alternative to individual model forecasts. We test the forecast accuracy and present evidence that the best forecast combination may outperform the forecasts from individual model specifications. Importantly, we find that the performance of the best individual forecast is not significantly better than that of the best performing forecast combination.

The individuals models used in this study have been chosen to represent differences in modeling approaches used as well as their significance in the studies on CO_2 emissions forecasts. While there are many other potential models to consider, we are constrained by their data requirements and the need to forecast their regressors. As for forecast combination, there are many candidate combination techniques to consider. We consider forecast combinations that have been applied in many empirical studies as well as recent advances in this area. Although alternative combinations may lead to better forecasting performance, our goal is to assess whether pooling multiple forecasts will improve forecasting CO_2 emissions relative to individual models. We consider combination techniques due to Bates and Granger (1969), Granger and Ramanathan (1984), simple equal-weights forecast averaging, and bias-corrected forecast averaging due to Issler and Lima (2009). Briefly, Bates and Granger (1969) suggested to combine multiple forecasts by weighting them inversely to their mean squared error (MSE), while in Granger and Ramanathan (1984) approach combination weights are obtained by regressing individual forecasts on their actual values. In equal-weights forecast averaging no combination weights are estimated. It is the simple average of individual forecasts. Bias-corrected average forecast is an extension of equal-weights forecast that seeks to remove time-invariant bias present in individual models. Estimation of these methods as well as individual models are discussed in more detail below.

The remainder of the paper is organized as follows. The next section presents a discussion of forecast combination problems and approaches to forecast combination. It also introduces individual model specifications considered in this paper. In section 2.3 we explain our empirical exercise and methodology. It also presents the dataset that is the basis of our study and discusses the reported results. Section 2.4 concludes.

2.2 Forecast Combination

In a recent survey, Timmermann (2006) discusses a number of potential reasons for forecast combination. First, mean squared forecast error (MSFE) can be minimized by combining individual forecasts due to gains from diversification. Second, individual forecasts may differ in how quickly they adapt to the new data if they are subjected to structural breaks. In this case, combining of individual forecasts may result, on average, in better forecast than forecasts obtained from individual models themselves. Third, because the true data generating process is usually unknown, individual model specifications are often misspecified. The diversification argument imply that combining forecasts helps reduce the misspecification biases that may be present in individual models.

For non-nested models, the plausibility of pooled forecasts is intuitively easy to understand. If two forecasts derive their properties from different information sets, the pooling forecasts allows one to use a wider information set. This, in turn, minimizes the quadratic loss function, such as mean squared error (MSE), leading to a better forecast performance. Surveys of empirical literature on forecast combinations agree that forecast combinations leads to increased forecast accuracy (Clemen (1989), Stock and Watson (2004)). As these studies show, even the simple averaging of predictors often dominates individual predictors.

For nested models, the benefits from model forecast combination are not clear-cut. Clark and McCracken (2009) found that forecast combination can be effective even for the nested models, but their effectiveness hinges on the assumption that population parameters are unknown and sample size is finite. If the decision maker knows the true population parameters, then one of the nested models encompasses the other model. Then, optimal forecast combination of these two models will assign either zero or unitary weight. In practical terms, population parameters are usually not known to the econometrician in advance.

2.2.1 The forecast combination problem

Here we follow Timmermann (2006) and briefly describe the forecast combination problem faced by a decision-maker. Given the set of N point forecasts, a decision-maker would like to combine those forecasts by minimizing some loss function, such as mean squared error (MSE) or mean absolute error (MAE):

$$\boldsymbol{\omega}^*_{t+h,t} = \arg_{\omega_{t+h,t}\in\Omega_t}\min \quad E[L(e^c_{t+h,t}(\boldsymbol{\omega}_{t+h,t}))|\hat{\boldsymbol{y}}_{t+h,t}] \tag{2.1}$$

where $\boldsymbol{\omega}_{t+h,t}$ are the estimated optimal weights for h-step ahead forecasts at time t, $L = L(e^c_{t+h})$ denotes some loss function as a function of forecast error from combination, and $\hat{\boldsymbol{y}}_{t+h,t}$ is a vector of forecasts. Assuming quadratic loss function, optimal weights for forecast combination are found by minimizing the MSE:

$$L(y_{t+h,},\, \hat{y}_{t+h,t}) = \theta(y_{t+h} - \hat{y}_{t+h,t})^2, \quad \theta > 0 \tag{2.2}$$

where $\hat{y}_{t+h}$ denotes h-step ahead forecast of a variable of interest. Since individual model forecasts are likely biased themselves, estimated weights can be biased as well. However, as noted in Timmermann (2006) information aggregation tends to reduce the forecast variance. Under MSE loss function, these two effects are easy to see:

$$L(\cdot) = E[e^2_{t+h,t}] = E[e_{t+h,t}]^2 + Var(e_{t+h,t})$$

In other words, while the estimated weights increase the forecast bias, combining multiple models may reduce the variance of the forecasts. In order to minimize the squared loss function, the decision-maker should consider trading off these two effects.

2.2.2 Diversification gain from forecast combination

The gains from forecast combinations can be explained similar to diversification gains in portfolio choice in the finance literature. Here we borrow from Timmermann (2006) to show the value of forecast combinations. Consider a decision maker with quadratic loss function who has access to two forecasts, $\hat{y}_1$ and $\hat{y}_2$. We assume forecasts errors are unbiased with $e_1 = y - \hat{y}_1 \sim (0, \sigma_1^2)$ and $e_2 = y - \hat{y}_2 \sim (0, \sigma_2^2)$, and their associated covariance is given by $\sigma_{12} = \rho_{12}\sigma_1\sigma_2$. ρ_{12} denotes the correlation between the two forecasts errors. If we assume combination weights are constrained to equal one, $(\omega, 1-\omega)$, the forecast error from the forecast combination is equal to the weighted average of the two individual forecasts:

$$e^c = \omega e_1 + (1-\omega)e_2 \tag{2.3}$$

The forecast error has an expected value of zero. The variance under forecast combination takes the form

$$Var(e^c) = \sigma_c^2(\omega) = \omega^2\sigma_1^2 + (1-\omega)^2\sigma_2^2 + 2\omega(1-\omega)\sigma_{12} \tag{2.4}$$

The decision-maker's objective is to minimize the forecast error variance in equation 2.4 which is easily solved through differentiation. The solution to the first order conditions yields the following weights

$$\omega^* = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}, \qquad 1-\omega^* = \frac{\sigma_1^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}} \tag{2.5}$$

We note that the weights have the same denominator, but the forecast error variance from the competing forecast enters their numerators. Thus, a more accurate forecast receives a larger weight and poor performing forecast receives a smaller weight. By substituting ω^* into the objective function, we get the expected value of MSE from the combination scheme:

$$\sigma_c^2 = \frac{\sigma_1^2\sigma_2^2(1-\rho_{12}^2)}{\sigma_1^2 + \sigma_2^2 - 2\rho_{12}\sigma_1\sigma_2} \tag{2.6}$$

We now can compare the forecast accuracy from combination of individual forecasts using their MSE. After some algebra, we see that $\sigma_c^2 \leq \min(\sigma_1^2, \sigma_2^2)$, which means combining two forecasts generally results in smaller MSE than that of individual model forecasts. Only under special cases, does the diversification gain disappear. Specifically, when (i) $\sigma_1 = 0$ or $\sigma_2 = 0$, or (ii) $\sigma_1 = \sigma_2$ and $\rho_{12} = 1$, or (iii) $\rho_{12} = \frac{\sigma_1}{\sigma_2}$, there is no diversification gain from combination of two forecasts.

Timmermann (2006) also compares the variances of forecast error from the optimal combination (equation 2.6) to forecast error variances from other common combination approaches. In combination scheme proposed by Bates and Granger (1969), combination weights are estimated inversely to their relative MSE as follows:

$$\omega_{inv} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}, \qquad 1 - \omega_{inv} = \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} \tag{2.7}$$

This produces the following forecast error variance:

$$\sigma_{inv}^2 = \frac{\sigma_1^2 \sigma_2^2 (\sigma_1^2 + \sigma_2^2 + 2\rho_{12}\sigma_1\sigma_2)}{(\sigma_1^2 + \sigma_2^2)^2} \tag{2.8}$$

The ratio of this forecast error variance to the value obtained using optimal weights above is equal to

$$\frac{\sigma_{inv}^2}{\sigma_c^2} = \frac{1}{1 - \rho_{12}^2} \left(1 - \left(\frac{2\sigma_{12}}{\sigma_1^2 + \sigma_2^2} \right)^2 \right) \tag{2.9}$$

Two conditions are possible depending on the values of forecast error variance from individual forecasts. For instance, if $\sigma_1 \neq \sigma_2$, Timmermann (2006) show that $\sigma_{inv}^2 > \sigma_c^2$ unless $\rho_{12} = 0$. In other words, when both models add additional information, optimal weights forecast combination will have smaller MSE than that of combination schemes developed by Bates and Granger (1969). If, however, $\sigma_1 = \sigma_2$, then MSE from both combination schemes are equal, which implies $\omega_{inv} = \omega^* = 1/2$.

Finally, the performance of optimal weights forecast combination is compared to that of simple average forecast combination. Simple average forecast combination assigns equal weights to each individual model forecasts. This produces the following MSE:

$$\sigma_{EW}^2 = \frac{1}{4}\sigma_1^2 + \frac{1}{4}\sigma_2^2 + \frac{1}{2}\sigma_1\sigma_2\rho_{12} \tag{2.10}$$

By comparing their respective MSE, we find that their ratio is equal to:

$$\frac{\sigma_{EW}^2}{\sigma_c^2} = \left(\frac{(\sigma_1^2 + \sigma_2^2 - 4\sigma_{12}^2}{4\sigma_1^2\sigma_2^2(1 - \rho_{12}^2)}\right)^2 \tag{2.11}$$

After some algebra, we can see that $\sigma_{EW}^2 > \sigma_c^2$ unless $\sigma_1 = \sigma_2$, in which case $\sigma_{EW}^2 = \sigma_c^2$. Hence, theoretically simple equal-weighted average forecast approximates the optimal forecast in MSE sense only when the forecast error variances from the two models are the same. Nevertheless, as discussed above, equal-weights forecast combinations performed well in many applications and because of its simplicity it remains as an attractive approach to forecast combination.

2.2.3 Forecast combination approaches

In this subsection we describe forecast combination approaches used in this paper. Specifically, we consider (1) equal weights forecast averaging, (2) bias-corrected forecast averaging suggested by Issler and Lima (2009), (3) forecast combination proposed by Bates and Granger (1969), and (4) Granger and Ramanathan (1984) forecast combination. As noted above, we focus on combination schemes that combines individual predictions linearly. While there many combination approaches to consider, even the small number of combinations considered here are sufficient to show the gains from combination to forecasting CO_2 emissions.

Equal weights forecast combination

Simple averaging of forecasts, $\frac{1}{N}\sum_{i=1}^{N} y_{t+h,t}^i$ is empirically shown to work well in a variety of applications. Results from empirical works show that simple average of forecasts works surprisingly well in many settings, often outperforming individual predictions and some other combination schemes that try to estimate "optimal weights"

(Stock and Watson (2004), Aiolfi et al. (2010)). One simple explanation for this equal-weighted "forecast combination puzzle" is that it does not require estimation of weights, while optimal weights require estimation of N weights that grow asymptotically with the number of forecasts (Issler and Lima (2009), Smith and Wallis (2009)).[2]

In addition, model instability arising from structural breaks may explain why simple pooling of forecasts may be successful than some other forms of combination schemes. As Hendry and Clements (2004) illustrated, when unanticipated structural breaks can occur later in period equal weights combination may fair better than both the individual projections and other forecast combination approaches. This is because weights based on prior performance are not affected by later breaks in the data. This may result in poorer outcomes for forecast combinations with estimated weights. Even when the individual models are misspecified average forecasts dominated other approaches (Hendry and Clements (2004)).

Bias-corrected average forecast

The techniques suggested by Issler and Lima (2009) is an extension of equal weights model averaging. They note that if forecasts from individual models are biased, then their simple average may be biased as well. Their approach corrects for time-invariant bias present in individual model forecasts. By construction this should result in improved forecast performance relative to equal weights forecast averaging. First, we need to estimate equal weights model averaging, which is then corrected by subtracting the bias-correction term as the following equation shows:

$$\frac{1}{N}\sum_{i=1}^{N}\hat{y}^{i}_{t+h,t} - \hat{B}$$

where $\hat{B}$ represents a market bias.

[2]So called "curse of dimensionality," where more weights need to be estimated as N increases, diminishes the consistency of the estimated weights themselves. See Issler and Lima (2009) for details.

Before bias-correction term is estimated, we express the forecast of a target variable, $\hat{y}^i_{t+h,t}$, as two-way decomposition of the forecast error as follows:

$$\hat{y}^i_{t+h,t} - y_t = k_i + \eta_t + \varepsilon_{i,t}$$

where k_i is individual model time-invariant bias, η_t – unforecastable component, and $\varepsilon_{i,t}$ is model-specific or idiosyncratic error term. Forecast combination diversifies the risk associated with $\varepsilon_{i,t}$, but cannot do the same for η_t. On the other hand, k_i can be eliminated by specifically introducing a bias-correction term into the forecast combination. In order to compute the bias correction term $\hat{B}$, the data is divided into three sub-periods: $t = 1, 2, ..., T_1, ..., T_2, ..., T$. The first sub-period covering, $t = 1, 2, ..., T_1$, is called "estimation" sample and is used to fit the individual models. The second sub-period, $t = T_1 + 1, ...T_2$, is called the "training" sample, where the forecast combination weights and bias-correction terms are estimated. As in Issler and Lima (2009), we first compute each model's time-invariant bias as

$$\hat{k}_i = \frac{1}{T_2 - T_1} \sum_{t=T_1+1}^{T_2} (\hat{y}^i_{t+h,t} - y_t)$$

Once the individual model biases are estimated, the average bias for N models is obtained by a simple average as

$$\hat{B} = \frac{1}{N} \sum_{i=1}^{N} \hat{k}_i$$

Finally, in the last sub-period or "evaluation" sample, $t = T_2 + 1, ..., T$, the equal weights forecast is corrected for a possible bias by subtracting the average bias: $\frac{1}{N} \sum_{i=1}^{N} y^i_{t+h,t} - \hat{B}$. Authors note that in large samples, as both N and $T \to \infty$, bias-corrected average forecast becomes an optimal forecasting instrument.

Bates and Granger forecast combination

In a seminal paper, Bates and Granger (1969) suggested using empirical weights based on each model's out of sample forecast variance. If the forecasts are unbiased and their errors uncorrelated, the estimated weights approach optimal weights. Following their methodology, in the first step we obtain out-of-sample forecasts and forecast errors to compute the mean squared forecast error (MSFE). Then, the weight for each model is inverted, $1/\sigma_i^2$, and normalized by the sum of the forecast variances across all N models,

$$\omega^i = \frac{1/\sigma_i^2}{\sum_{j=1}^{N} 1/\sigma_j^2}$$

where σ_i^2 is the MSFE from model $i's$ individual forecast. By construction, forecasts that performed well in the estimation sample are given greater weight in the combination exercise.

Granger and Ramanathan forecast combination

Unlike the other combinations schemes, this method uses an econometric approach to estimate forecast weights. Granger and Ramanathan (1984) considered three different regression methods to forecast combinations. In the first regression method, they regress the forecasts on actual values with no constant term. In the second case, weights are constrained to sum to one and forecasts are regressed on actual values with no constant term. Their third approach, which they call it their best method, the regression is estimated with constant and no restrictions on the weights. Here we consider only their best method that gives the smallest MSFE. Given N forecasts, the combination weights are obtained by the usual least squares estimator by regressing the target variable y_t on the N candidate forecasts:

$$y_t = \alpha + \beta_1 \hat{y}_t^1 + ... + \beta_N \hat{y}_t^N + u_t$$

The constant term adjusts for the bias present in individual forecasts. As with other combination schemes, the weights are obtained in the estimation sample and used in the evaluation period to compare the out-of-sample forecasting performances.

2.2.4 Individual models

In this subsection, we describe each individual model that enters the forecast combinations considered above as 'inputs.' The individual models used in this study have been chosen to represent differences in modeling approaches and econometric techniques present in empirical works on CO_2 emissions as well as tractability of their data requirements. More importantly, these models have been highly influential leading to many discussions in the subsequent literature on emissions. The first model we use is proposed by Holtz-Eakin and Selden (1995) who employed the following specification:

$$ln(c_{it}) = \delta_i + \gamma_t + \beta_1 ln(rgdppc_{it}) + \beta_2 ln(rgdppc_t)^2 + \epsilon_{it}$$

where $ln(c_{it})$ are log per capita carbon emissions for country i in year t, δ_i is a country fixed effect, γ_t is a year fixed effect, and $ln(rgdppc_{it})$ are log per capita real GDP for country i in year t. Holtz-Eakin and Selden (1995) test this general EKC specification using both linear and log-linear specifications and report similar results. According to the EKC hypothesis, emissions first rise with income and then decline after a country reaches a certain income level. Selden and Song (1994) and Grossman and Krueger (1995) both report an inverted U-shaped relationship between levels of economic development and various air pollutants. The "Kuznets" or inverted U-shaped relationship between economic development and emissions is by no means uncontroversial. Perman and Stern (2003), Stern (2004), and Cole (2005) question the existence of an inverted U-shaped relationship between income and emissions. Cole (2005) finds an inverted U-shaped relationship for CO_2 using the OECD-only sample, but when heterogeneity across countries is allowed, the income-emissions relationship is found to vary widely across countries.

The second model suggested by Schmalensee et al. (1998) also forecasts carbon emissions using the EKC relationship, but with more flexible income specification:

$$ln(c_{it}) = \delta_i + \gamma_t + F[ln(rgdppc_{it})] + \epsilon_{it}$$

where $F(\cdot)$ is a spline (piecewise linear) function. Schmalensee et al. (1998) use 8- and 10-segment splines with the same number of observations for each spline. We use 10-segment spline model following subsequent studies that try to replicate Schmalensee et al. (1998) model.[3]

In a recent study Auffhammer and Steinhauser (2012) forecast U.S. CO_2 emissions using state level data. They build a model universe using a small subset of variables found in existing reduced-form models. In addition to variables used in the previous two models above, they also include lagged emissions, population density, and several categorical variables in their specifications. Auffhammer and Steinhauser (2012) note that dynamic specifications with lagged emissions are appropriate in emissions projections because CO_2 emissions originate from a durable capital stock. These sparse set of variables lead to more than $27,000$ unique model specifications. The search over this model universe yielded the following specification with the lowest MSFE for aggregate CO_2 emissions:

$$ln(c_{it}) = \alpha + \rho_i ln(c_{i,t-1}) + \beta_1 ln(pdens_{it}) + \beta_2 oil_i + \epsilon_{it}$$

where $ln(pdens_{it})$ is log population density for state i in year t and oil is a categorical variable equal one for oil- or gas-producing states. The selection of the best model based on per capita MSFE resulted in a different functional form specification. If the goal is to forecast aggregate emissions, then selection based on the aggregate MSFE, rather than per capita MSFE, is more appropriate. It is likely that a different

[3]See Auffhammer and Steinhauser (2012), for instance.

set of best performing models will be chosen, for example as the sample size or forecast horizon is varied. Since our objective is to evaluate the performance of combining multiple forecasts in relation to individual models, we are not overly concerned over potential misspecification issue. In addition, combining multiple forecasts are generally robust to potential biases of unknown form (Timmermann, 2006).

Our final benchmark model is based on Yang and Schneider (1998) specification:

$$carbon_{it} = population_{it} \times \frac{rgdp_{it}}{population_{it}} \times \frac{energy_{it}}{rgdp_{it}} \times \frac{carbon_{it}}{energy_{it}}$$

where $carbon_{it}$ is the total carbon emitted in country i in year t, $population_{it}$ is population in country i in year t, $energy_{it}$ is the total energy consumption in country i in year t, and $rgdp_{it}$ is real GDP in country i in year t. In turn, their model is based on *IPAT* identity by Ehrlich et al. (1971). According to *IPAT* identity, $I = P \cdot A \cdot T$, I (impact or emissions) is decomposed into P (population), A (affluence, measured in per capita GDP), and T (technology index). The identity implies that emissions increase monotonically with P and A, but decrease with the level of T. Yang and Schneider (1998) use an extension of *IPAT* identity to decompose the emissions into four factors: population size, GDP per capita, energy intensity (total energy consumed per unit of GDP), and carbon intensity (average CO_2 emissions per unit of fossil fuel consumed).

2.3 Empirical Exercise

Our main goal is to evaluate the performance of forecasts from individual model specifications and their linear combinations. This section discusses the estimation method used in the empirical exercise. We use state-level data from 1960 to 2012 and conduct out-of-sample forecasts of per capita and total CO_2 emissions in the U.S. We obtain forecasts of state-level emissions first, which is then aggregated to obtain emission forecasts for the U.S. There are at least two reasons for forecasting using disaggregated data instead of directly forecasting the aggregate CO_2 emissions for the U.S. First, Lütkepohl (2011) and Marcellino et al. (2003) note that if the disaggregate data are heterogeneous and intertemporally related, forecasting components first and then aggregating the forecasts may lead to better forecasts. The dataset we have shows variation in per capita emissions and other variables both across states and time. Second, our objective is to compare the forecasts from reduced form specifications and their combinations. All the models we consider use disaggregated data. As is common in empirical literature, the empirical illustration in this paper involves short-term forecasts. Next, we explain the methodology of our empirical exercise in more detail.

2.3.1 Methodology

First, the data is divided into three sub-periods: 1960-1989, 1990-2004, and 2005-2012. The first sub-period, called "estimation" sample, is used for estimation of individual models. Then fitted models are used to obtain forecasts for the second sub-period which we call "training" sample. We use the forecasts for the period covering 1990-2004 to estimate the combination weights to be used for various combination approaches considered in this paper. The final sub-period has 8 observations and is referred to as "evaluation" sample. Out-of-sample forecasts for 2005-2012 are compared for each individual model and their combinations using the weights obtained in the training sample. We evaluate one-year ahead (h=1) through five-year ahead forecasts (h=5).

There are different approaches to forecasting depending on how the estimation window is chosen. We employ recursive expanding window approach where the initial estimation sample (1960-1989) is used to estimate individual models to produce h-step ahead forecasts. Then the estimation sample is increased by one more year covering 1960-1990 and individual models are re-estimated to produce h-step ahead forecasts for the next period. Thus, for 1990-2004 training sample we estimate 15 h-step ahead forecasts. The training sample forecasts are, in turn, used to estimate combination weights. The procedure to estimate those weights are discussed above in the subsection on forecast combination approaches. By their construction, equal-weights and its variation of bias-corrected average forecasts by Issler and Lima (2009) do not require estimation of forecast combination weights.

Once the weights are computed, we then conduct pseudo-out-of-sample forecasts for 2005-2012 as follows. Each individual specification is re-estimated using an expanding window to obtain h-step ahead forecasts for 2005-2012 evaluation sub-period.[4] We combine these h-step ahead individual forecasts with the estimated weights obtained in the training sample. Per capita emissions projections are multiplied by state population to get state aggregate emission forecasts. Aggregate CO_2 emissions for the U.S. is found by summing the total emissions over 50 states. Then individual forecasts and their combinations are compared to each other based on their root-mean squared forecast error (RMSFE) computed as follows:

$$\text{MSFE for Aggregate Emissions} = \frac{1}{8}\sum_{T=2005}^{2012}\sum_{i=1}^{50}(C_{T+h} - \widehat{C}_{T+h})^2$$

$$RMSFE = \sqrt{MSFE}$$

where C_{T+h} are total emissions for state i in year $T + h$.

MSFE and RMSFE for U.S. per capita emissions are estimated in a similar fashion. To do so, we divide the aggregate U.S. emissions by U.S. population to get per capita emissions for the U.S. Forecasts are then tested for significance of their predictive accuracy using formal statistical procedures. We tested the accuracy of forecasts using two loss functions found in the forecast evaluation literature: squared error loss and absolute value of loss. In the first approach, squared error losses from two competing forecasts, which correspond to MSFE above, are tested for equal predictive ability. In the absolute loss case, we test whether mean absolute errors (MAE) from competing two forecasts are the same. MAE is obtained as follows:

[4] Recursive one-step ahead estimation requires estimation of 23 regressions for each individual model for 1960-1989, 1960-1990, 1960-1991, etc. periods. With four individual models, we have estimated a total of 92 regressions.

$$\text{MAE for Aggregate Emissions} = \frac{1}{8} \sum_{T=2005}^{2012} \sum_{i=1}^{50} \left| C_{T+h} - \widehat{C}_{T+h} \right|$$

For models with contemporaneous explanatory variables we need projections of these variables for out-of-sample forecasts. While population projections can be obtained from the U.S. Census Bureau or other state agencies, projections of state personal income series are not readily available. In the following subsection, we describe our methodology used for right-hand-side variable predictions.

2.3.2 Projections of Explanatory Variables

In a series of studies Barro et al. (1991) and Barro and Sala-i Martin (1992) have examined the convergence across U.S. states and regional convergence within other countries. They find evidence of convergence across U.S. states where poorer states tend to grow faster than wealthy ones. We follow their approach and regress state average growth rates of per capita income over some time interval on the initial level of per capita income:

$$\frac{1}{T} \cdot ln\left(\frac{y_{it}}{y_{i,t-T}}\right) = \beta_0 + \beta_1 \cdot ln(y_{,t-T}) + u_{it,t-T}$$

where y_{it} is the real per capita personal income in state i at time t, $y_{i,t-T}$ is the real per capita personal income in state i at the beginning of the interval, and T is the length of the time interval. The estimated equation for the cross-section of states using data for 1960-2012 yields the following result with the standard errors in parentheses:

$$(1/52) \times [ln(y_{i,2012}) - ln(y_{i,1960}] = \underset{(0.002)}{0.029} - \underset{0.0001}{0.0001}[ln(y_{i,1960})]$$

The coefficient on initial per capita personal income is negative and statistically significant. This means that U.S. states display conditional β-convergence: poorer states grow faster than rich ones. We estimate series of cross-sectional regressions for different time intervals to predict the growth rates of per capita personal income.

Overall, the results are consistent with the results reported in Barro and Sala-i Martin (1992).

For population projections, we decided to make projections for both state population and personal income in order to replicate the problem a forecaster may encounter in making true out-of-sample forecasts. We estimate first order autoregressive (AR(1)) model for each state separately:

$$population_{it} = \beta_0 + \beta_1 \cdot population_{i,t-1} + e_{it}$$

Once we obtain population projections, we make population density predictions for each state under the assumption that state land areas remain constant over the forecast horizon. Population density projections are needed for forecasting Auffhammer and Steinhauser (2012) model specification.

For both Holtz-Eakin and Selden (1995) and Schmalensee et al. (1998) specifications, we need predictions for time and state fixed effects in order to conduct out-of-sample forecasts. For the former, we follow their approach and set the year fixed effects at last year's estimated value. However, this assumption rules out the effects of future technological changes on emissions. For Schmalensee et al. (1998) specification, we follow their steps and project the time fixed effects by regressing estimated time fixed effects on the following linear spline model:

$$\beta_t = \beta_0 + \beta_1 t + \beta_2 (t - 1970) \cdot \mathbf{1}[t \geq 1970]$$

This specification for projecting time fixed effects assumes that the trend after 1970 will continue into the future.[5]

Finally, we need projections of state fixed effects for out-of-sample forecasts. Alternatively, we could transform the data by demeaning the variables along the

[5]Schmalensee et al. (1998) also considered nonlinear trend model with $\beta_t = \beta_0 + \beta_1 + \beta_2 ln(t - 1940)$. This specification forecasts flattening time fixed effects into the future. While the authors report results from both specifications, they do not offer their preference for either specification. Therefore, we do not consider the nonlinear trend model here.

time dimension for each panel. This eliminates the need for projections of state fixed effects. However, the latter approach makes the computation somewhat difficult as the forecasting exercise considers various forecast horizons. Since we have large enough observations per panel, we estimate state fixed effects model, predict those fixed effects for the estimation sample and extend them into the forecast horizon.

Since it becomes cumbersome to forecast explanatory variables as the number of individual models to be used in forecast combination exercise is increased, we did not include other alternative specifications. Nonetheless, as it becomes clear in the next subsection, even with small number of forecasts used in this study, we are able to show the benefit of applying forecast combination to CO_2 emissions.

2.3.3 Data

Our objective is to evaluate the forecasting performance of combining multiple forecasts against the performance of individual models. To do so, we use U.S. state-level data from 1960 to 2012. The dataset is an annual data for 50 U.S. states from 1960 to 2012 and does not include Washington D.C. Thus, there are total of 2,650 observations for each variable, except for energy and carbon intensity growth rates. The data on energy and carbon intensity growth rates are given for 1990-2012 period.

We have collected the dataset from a variety of sources. Data for 1960-2010 estimates of annual fossil-fuel carbon dioxide emitted to the atmosphere (in million metric tons of carbon) for each 50 U.S. states are obtained from Carbon Dioxide Information Analysis Center at Oak Ridge National Laboratory.[6] We then combine this dataset with 2011 and 2012 U.S. state-level carbon dioxide emissions (in million metric tons of carbon dioxide) which we obtained from the Environmental Protection Agency.[7]

[6] See `http://cdiac.ornl.gov/CO2_Emission/timeseries/usa`. Last accessed: May 10, 2015.

[7] See `http://www.epa.gov/statelocalclimate/state/activities/ghg-inventory.html#four`. Last accessed: May 10, 2015.

Table 2.1: Descriptive Statistics, 1960-2012

Variable	Unit	Mean	Std.Dev.	Min	Max
Total CO_2 Emissions	mill.metric tons	96.86	101.55	3.61	721.42
Per capita CO_2 Emissions	metric tons	23.13	15.66	7.83	132.71
Per capita personal income	thous. US $	30.87	8.96	9.86	61.59
Population	thous. persons	4,875	5,374	229.00	38,000
Land Area	sq.miles	70,637	84,969	1,034	570,641
Population Density	per sq.mile	164.37	233.59	0.40	1,206
Energy Intensity	% change	-1.17	0.46	-1.70	-0.76
Carbon Intensity	% change	-0.47	0.53	-0.94	0.14
Total Observations		2,650	2,650	2,650	2,650

Note: Energy and carbon intensity growth rates are for 1990-2012 period.

We present the descriptive statistics for the variables used in our empirical exercise in Table 2.1. Typically, to examine the EKC hypothesis per capita emissions are regressed on real per capita GDP. Although GDP by state are preferred series, there is a discontinuity in the state GDP data at 1997 due to changes in industry specifications. Therefore, we use state personal income (in thousands of U.S. dollars) series instead. We note that other researchers have also used state personal income series when using state level data in forecasting emissions and studying income convergence across states.[8] We convert the state personal income series into 2012 U.S. dollars using consumer price index for all consumers. Consumer price index comes from the Bureau of Labor Statistics, while personal income and population by states are both taken from the Bureau of Economic Analysis.[9] We then divide state carbon emissions by

[8]See Auffhammer and Steinhauser (2012) for emissions, and Barro and Sala-i Martin (1992) for income convergence, for instance.

[9]Both data series are available at `http://www.bea.gov/iTable/index_regional.cfm`. Last accessed: May 10, 2015.

state population to generate per capita emissions (in metric tons of carbon) by state to be used in our empirical exercises.

Population density by state is obtained by dividing state population by their respective land areas (in sq.miles). Land area is the total area of a state excluding water areas and is taken from the U.S. Census Bureau.[10] We collected information whether a state is oil producing or not from the U.S. Energy Information Administration's historical crude oil production series.[11] In addition, for Yang and Schneider (1998) model we need energy and carbon intensity factors. In their paper, Yang and Schneider (1998) provide annual rates of change for each factor. We can use these rates in projections of CO_2 emissions without needing the initial values of each factor. For example, CO_2 emission projections in subsequent years will be calculated as the product of last period's CO_2 emissions and the sum of the growth rates of each four factors.

As the Table 2.1 shows there is a sufficiently large variation in both total CO_2 emissions and per capita CO_2 emission series over the study period. We observe this large variability both across space and over time. For example, per capita emissions ranged from 7.83 to 132.71 metric tons of CO_2 with a standard deviation of 15.66. Aggregate state-level emissions ranged from 3.61 to 721.42 million metric tons of CO_2 with a standard deviation of 101.55. Similarly, for other variables in the dataset we observe large variation both across states and years. In terms of total state emission levels, Vermont has been the state with the lowest total CO_2 emissions, while Texas remains to be the largest CO_2 emitter. In terms of per capita emissions, Wyoming has the highest CO_2 emission levels per person for each subsequent decade since 1960. The heterogeneity in per capita CO_2 emissions across the U.S. states is one of the reasons why we prefer to use state-level, rather than aggregated data, in our

[10]See `https://www.census.gov/geo/reference/state-area.html`. Last accessed: May 10, 2015.

[11]See `http://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_a.htm`. Last accessed: May 10, 2015.

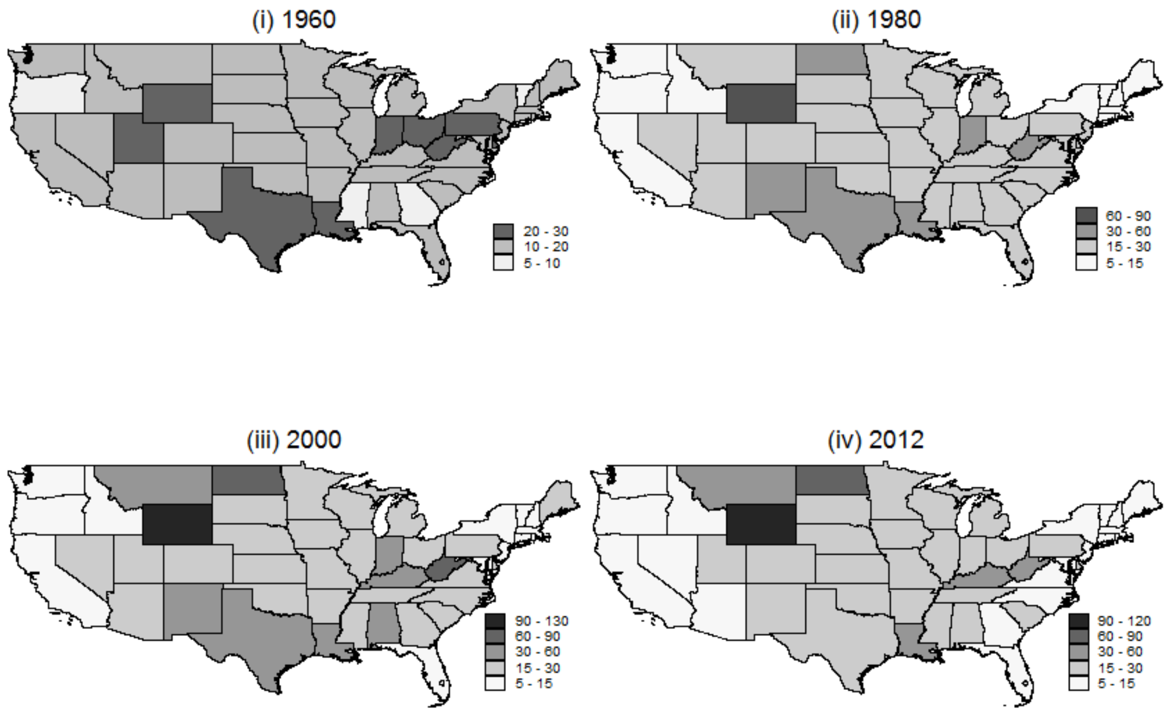

Figure 2.1: Per Capita CO_2 Emissions for Selected Years (metric tons of CO_2)

Source: Carbon Dioxide Information Analysis Center of ORNL and Environmental Protection Agency.

forecasting exercise. Figure 2.1 shows this heterogeneity in per capita emissions both across space and time.

2.3.4 Results

Here we present the results of forecast performance for out-of-sample forecasts from each individual model and their linear combinations. The methodology for obtaining out-of-sample forecasts are discussed in the Methodology subsection. We evaluate each individual model and their linear combinations based on the their RMSFE. Then, we compare the models and their forecast combinations to the specification with the lowest RMSFE.

The results of our empirical exercise for per capita CO_2 emissions are presented in Table 2.2 and for aggregate emissions in Table 2.3. First, we note that dynamic specification by Auffhammer and Steinhauser (2012) and structural identity specification by Yang and Schneider (1998) have smaller RMSFE than that of other individual models. These two specifications perform better, in terms of RMSFE, throughout the various forecast horizons. Second, all forecast averaging specifications have lower RMSFE than those of Holtz-Eakin and Selden (1995) and Schmalensee et al. (1998) specifications. Among all forecast combinations considered here, bias-corrected average forecast by Issler and Lima (2009) performs better in terms of RMSFE. It is well established that estimation of weights may be subject to bias, while equal weights forecast, which does not require estimation of weights, perform well in many applications (Clemen (1989), Stock and Watson (2004). It is not surprising that bias-corrected average forecast that uses equal weights forecast, coupled with bias correction term, performs well than the other combinations. Although model averaging by Granger and Ramanathan (1984) has a lower RMSFE than bias-corrected average forecast for one-year ahead (h=1) and two-year ahead (h=2) forecasts, for 3-year ahead and greater forecast horizons it does worse than the latter.

In the last five columns in Table 2.2 we present the percentage differences in RMSFE relative to the RMSFE from bias-corrected average forecast. For h=1, specifications by Auffhammer and Steinhauser (2012) and Yang and Schneider (1998) has 5 and 8 percentage points lower RMSFE. However, for h=2 through h=5, RMSFE for bias-corrected average forecast is smaller by 9-19 percentage points than that for Auffhammer and Steinhauser (2012) model. The improvement relative to Yang and Schneider (1998) specification is modest, about 2-7 percentage points, for h=2 and greater. Although bias-corrected average forecast was originally developed for cases with large number of forecasts and long data, the method is shown to work well in smaller number of models too (Issler and Lima (2009)). As noted in Issler and Lima (2009), the use of equal-weights, while avoids estimating forecast weights, may potentially increase bias. Bias-corrected average forecast corrects for bias present in

Table 2.2: RMSFE for Per Capita CO_2 Emissions

	Forecast horizon:					Difference (%):				
	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
Individual Models:										
Holtz-Eakin & Selden	1.31	1.67	1.90	2.28	2.48	66	61	57	43	35
Schmalensee et al.	1.67	1.92	2.23	2.51	2.85	111	85	84	58	55
Aufhammer & Steinhauser	0.75	1.13	1.40	1.87	2.18	-5	9	16	18	19
Yang & Schneider	0.73	1.08	1.29	1.68	1.87	-8	4	7	6	2
Forecast combinations:										
Equal-weighted forecast	1.04	1.40	1.66	2.06	2.32	32	35	37	30	26
Issler & Lima	0.79	1.04	1.21	1.59	1.84	0	0	0	0	0
Bates & Granger	0.83	1.28	1.77	2.11	2.30	5	23	46	33	25
Granger & Ramanathan	0.75	1.03	1.47	1.83	2.32	-5	-1	21	15	26

Note: Last 5 columns are percentage differences in RMSFE relative to that of bias-corrected average forecast from Issler & Lima model specification.

Table 2.3: RMSFE for Aggregate CO_2 Emissions

	Forecast horizon:					Difference (%):				
	h=1	h=2	h=3	h=4	h=5	h=1	h=2	h=3	h=4	h=5
Individual Models:										
Holtz-Eakin & Selden	408	526	600	729	797	63	59	53	42	34
Schmalensee et al.	525	609	708	795	907	110	84	81	55	52
Aufhammer & Steinhauser	235	358	446	600	702	-6	8	14	17	18
Yang & Schneider	230	342	414	541	606	-8	3	6	5	2
Forecast combinations:										
Equal-weighted forecast	327	443	530	660	745	31	34	35	28	25
Issler & Lima	250	331	392	514	595	0	0	0	0	0
Bates & Granger	261	407	565	674	740	4	23	44	31	24
Granger & Ramanathan	237	329	472	586	741	-5	-0.6	20	14	25

Note: Last 5 columns are percentage differences in RMSFE relative to that of bias-corrected average forecast from Issler & Lima model specification.

simple equal-weights forecast. When compared to simple average forecast, we can see that bias-correction lowered RMSFE by 26-37 percent for h=1 through h=5.

The results for aggregate CO_2 emissions in Table 2.3 are qualitatively similar to reported results for per capita emissions. Model averaging methods considered here all perform very well relative to specifications by Holtz-Eakin and Selden (1995) and Schmalensee et al. (1998) throughout the various forecast horizons. Individual model specification by Auffhammer and Steinhauser (2012) and Yang and Schneider (1998) have lower RMSFE for h=1 among all the individual models and their combinations. However, for h=2 and greater their competitiveness decreases in RMSFE sense. Bias-corrected average forecast proposed by Issler and Lima (2009) has lower RMSFE than that for Auffhammer and Steinhauser (2012) specification. The difference in RMSFE grows from 8 percent for h=2 to 18 percent for h=5. Relative to structural identity equation by Yang and Schneider (1998), the improvement in forecast performance is modest 3-6 percent.

Taken together, the reported results show that when the true data-generating process is unknown, combining multiple forecast can significantly improve out-of-sample forecasts. Even with the small number of forecasts considered in this paper, the advantage of combining multiple forecasts is clear. Improvement in forecast performance from model combinations, while modest, is encouraging. There are many different ways to combine individual forecasts and we only considered only a few of those methods. Nonetheless, the results from combining forecasts show that forecast combination may improve out-of-sample forecasts.

In addition to RMSFE comparisons, we also tested the out-of- sample forecast accuracy using a method suggested by Diebold and Mariano (1995). We present the test results in Tables 2.4 and 2.5. Diebold-Mariano test allows to compare two models' predictive ability and determine the best performing forecast. It tests whether the forecast accuracy of two models based on mean-square error (MSE) or other criteria, such as mean absolute error (MAE), are equal. Using out-of-sample forecasts

Table 2.4: Out-of-Sample Tests for Aggregate Emissions based on MSE

	MSE				
	h=1	h=2	h=3	h=4	h=5
Individual Models:					
Holtz-Eakin & Selden	0.000	0.000	0.000	0.003	0.003
Schmalensee et al.	0.042	0.023	0.000	0.000	0.000
Aufhammer & Steinhauser	0.488	0.149	0.003	0.001	0.000
Yang & Schneider	0.351	0.574	0.101	0.045	0.191
Forecast combinations:					
Equal-weighted forecast	0.000	0.000	0.000	0.000	0.000
Bates & Granger	0.249	0.000	0.000	0.000	0.000
Granger & Ramanathan	0.348	0.529	0.020	0.000	0.000

Note: The values are DM Test p-values. They test whether forecasts have the same predictive accuracy using MSE. Small p-value means rejection of equal forecast accuracy.

Table 2.5: Out-of-Sample Tests for Aggregate Emissions based on MAE

	MAE				
	h=1	h=2	h=3	h=4	h=5
Individual Models:					
Holtz-Eakin & Selden	0.000	0.000	0.000	0.000	0.000
Schmalensee et al.	0.013	0.000	0.000	0.000	0.000
Aufhammer & Steinhauser	0.82	0.334	0.003	0.000	0.000
Yang & Schneider	0.615	0.891	0.301	0.023	0.291
Forecast combinations:					
Equal-weighted forecast	0.000	0.000	0.000	0.000	0.000
Bates & Granger	0.424	0.000	0.000	0.000	0.000
Granger & Ramanathan	0.664	0.445	0.007	0.000	0.000

Note: The values are DM Test p-values. They test whether forecasts have the same predictive accuracy using MAE. Small p-value means rejection of equal forecast accuracy.

of aggregate emissions for 2005-2012, we compare the best combination forecast (bias-corrected average forecast) to other forecasts. Using the MSE indicator, the null hypothesis of equal forecast accuracy are rejected for h=3 through h=5 period ahead forecasts, except for Yang and Schneider (1998) specification. This means bias-corrected average forecast outperforms majority of individual model forecasts and the combined forecasts for h=3 and greater. Although bias-corrected average forecast is better than the forecast obtained from Yang and Schneider (1998) specification and has generally smaller RMSFE, Diebold-Mariano test failed to reject the null hypothesis of equal forecast accuracy. For h=1 and h=2, forecasting accuracy from Auffhammer and Steinhauser (2012), Yang and Schneider (1998), and the forecast combination due to Granger and Ramanathan (1984) are not statistically different from that of bias-corrected average forecast.

In terms of MAE, we are unable to reject the null hypothesis of equal forecast accuracy for bias-corrected average forecast and Yang and Schneider (1998) individual model forecast. For h=1, forecasts from Auffhammer and Steinhauser (2012), Yang and Schneider (1998), Bates and Granger (1969), and Granger and Ramanathan (1984) have similar predictive accuracy as that for bias-corrected average forecast. However, for h=3 through h=5 bias-corrected average forecast has significantly better forecast accuracy than the rest of the models.

Overall, the results confirm that the best combination model significantly outperforms the majority of individual models in terms of MSE and MAE tests. More importantly, the forecast accuracy tests show that the predictive performance of the best performing individual model is not statistically significant than that of the best combination.

2.4 Conclusion

Forecasting CO_2 emissions is of particular importance in evaluating policies to address CO_2 emissions. Literature on forecasting CO_2 emissions report forecasts that may differ significantly due to differences in modeling approaches and estimation techniques. Despite the variations in modeling techniques, to the best of our knowledge, application of forecast combination to CO_2 emissions has not be been evaluated before. As the empirical works show there can be gains from combining multiple forecasts. In this paper we evaluate the relative forecasting performance of various individual models and their linear combinations.

We find that among the class of forecast combinations considered in this paper, bias-corrected average forecast outperforms individual models in RMSFE sense. Consistent with forecast combination literature, the predictive accuracy of the best performing individual model is not significantly different from that of the best performing forecast combination. In particular, as the forecast horizon is increased the performance of the best performing individual model worsens relative to that of the best performing forecast combination (e.g. bias-corrected average forecast). Despite the relatively small number of models considered in this paper, the results of forecasting performance from forecast combinations are encouraging. Consistent with many empirical findings, forecast combination that uses a variation of equal weights forecast may result in improved forecast performance.

Our ability to increase the number of models to be combined is constrained by the need to produce out-of-sample projections of right-hand-side variables. As models to forecast emissions are continually being updated and perfected, combining better individual forecasts may result in even more improved forecasting performance. For example, the performance of forecast combination schemes can be further improved by including more models in the combination scheme if they expand the information set of existing models. But even with only four models used in the combination, the advantage of forecast combination is clear: forecast combination, on average improves the forecasting performance relative to that of the best individual forecast.

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