Economic Fundamentals of Gasoline Crack Spreads in the U.S.

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Abstract

I investigate the economic fundamentals of U.S. gasoline market and their links with the refining margin proxied by the ratio of gasoline and crude oil prices (crack ratio). I document distinct seasonal effects in stocks, production and consumption of gasoline and find that seasonally-adjusted variables have significant effects on the next month's seasonally-adjusted crack ratio. For instance, a positive one-sigma deviation from trend and seasonality of stocks is, on average, associated with a decrease in seasonally-adjusted crack ratio of 0.016-0.018, or, equivalently by a fifth of its standard deviation (0.08). Similarly, a one-sigma increase in adjusted net production (net imports) is typically followed by a decrease in crack ratio of 0.013-0.022 (0.012-0.017).

1 Introduction

The price of a commodity is ultimately determined by its supply and demand which often undergo intrinsic seasonal cycles. Many agricultural commodities, for instance, are harvested during a certain time of the year while their consumption levels are relatively constant. Other commodities have seasonal demand. For instance, consumption of electricity can be both higher and lower in summer depending on the country while consumption of motor gasoline in developed countries is typically determined by the individuals' driving habits which also vary in a predictable way across the year.

Seasonal fluctuations in demand and supply induce seasonality in prices and one can easily observe major fluctuations in the price of gasoline relative

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to the price of crude oil throughout the year. Large seasonal effects, however, mask finer interactions between the fundamentals and the prices. Indeed, given a certain change in price one cannot be sure if it is caused by a seasonal change in fundamentals or by an unexpected shock.

Identifying non-predictable aseasonal changes in fundamentals and their effects on prices is the subject of the current study. I explore the market of gasoline in the U.S. and identify strong annual patterns in consumption, production, stocks and the price of gasoline relative to crude oil price once trends in all the variables are eliminated. Having observed that, I introduce a simple procedure for removing the seasonality and verify its effectiveness.

I find that the deviations from the seasonal components in fundamental variables are significantly linked with the subsequent realizations of deseasonalized price ratio of gasoline and crude oil (crack ratio). For instance, a one-sigma positive deviation in seasonally-adjusted level of stocks is typically followed by a decrease in the next month crack ratio of 0.016-0.018. Since the sample standard deviation of seasonally-adjusted crack ratio is only 0.08 the effect is economically significant.

Similarly, a one-sigma positive shock to net production (net imports) is, on average, followed by a depreciation of gasoline relative to crude oil by 1.3-2.2% (1.2-1.7%) or, equivalently, a decrease in the crack ratio of 0.013-0.022 (0.012-0.017). The effects are both economically and statistically significant and I perform a number of robustness checks to verify that the results are not driven by a misspecification error.

The relationship between the prices of gasoline and that of crude oil is of considerable interest to the general public. A well-known study of Borenstein et al. (1997) found empirical support for a commonly held belief that retail gasoline prices tend to respond more promptly to oil prices increases (rather than to decreases). The finding has received considerable attention in the subsequent literature (for instance, Peltzman (2000) and Meyer and Cramon-Taubadel (2004)).

The impact of fundamentals on gasoline prices was recently studied by Kendix and Walls (2010) and Chesnes (2014) who addressed the impact of refinery shutdowns on the prices of finished petroleum markets using a proprietary dataset on outages of individual refineries. In contrast to these two studies I analyze aggregate variables and attempt to identify the effects of both supply and demand shocks.

The structure of the study is as follows. Section 2 introduces the data and the sample. Sections 3.1 and 3.2 describe the seasonal patterns in the data and the seasonal adjustment procedure used in the rest of the article. The effects of the seasonally-adjusted fundamentals on the seasonally-adjusted crack ratio are explored using basic regressions in Section 3.3. The findings are verified using alternative models in Section 3.4 and using different specifications in Section 3.5. An interpretation for the documented effects is suggested in Section 3.6. Finally, Section 4 concludes.

2 Data and trends

2.1 Data

The study is based on the data provided by the U.S. Energy Information Administration (EIA). I use the following fundamental variables of the U.S. gasoline market: refinery and blender net production of finished motor gasoline (*prod*), prime supplier sales volumes of finished motor gasoline (*cons*), stocks of total motor gasoline (*stocks*), and, finally, imports and exports of total motor gasoline (*imp* and *exp*). Total gasoline refers to both finished motor gasoline (gasoline ready to be sold in retail market) and motor gasoline blending components (wholesale gasoline not necessarily meeting the retail specifications).[1]

I use well-known benchmark spot prices for both gasoline and crude oil. Gasoline price is the price of conventional gasoline blendstocks (CBOB) at the New York Harbor (*nyg*) while the oil price is the price of West Texas Intermediate crude oil in Cushing, Oklahoma (*wti*).[2]

Stocks are in million barrels (MMbbl) while production, consumption, exports and imports all are in million barrels per day (MMbbl/d). Gasoline price is converted to dollars per barrel to be directly comparable with crude oil price. The fundamental variables are monthly while prices, in principle, are available at daily frequency. I use average monthly prices in the analysis. All series start being available in July 1986 since the gasoline price is not available before.

[1] Appendix B contains details on the variables used in the study

[2] The acronym CBOB stands for *Conventional Blendstock for Oxygenate Blending*. It is wholesale gasoline which meets the requirements for *conventional gasoline* after blending with oxygenates (currently ethanol). Please see Appendix A for details.

2.2 Trends in prices

The top plot in Figure 1 shows the spot prices of gasoline at the New York Harbor and WTI crude oil in Cushing, Oklahoma starting in June 1986 in weekly frequency. From the late 1980 to the late 1990s crude oil price stays around 20$ per barrel with the only exception of a short increase to around 40$ during the conflict in Iraq in 1990. Over those years the average premium in the gasoline price over the crude oil price is about 4$ or, roughly, 20%.

[Figure 1 about here.]

In the 2000s crude oil price experiences a period of steady growth and reaches 140$ per barrel in the summer of 2008. Gasoline spot price generally follows the trend though gasoline becomes significantly more expensive in the fall of 2005, summer 2006 and the first half of 2007. During those periods the spread reaches or even exceeds 20$ per barrel which is significantly higher than its average of roughly 7-8$ per barrel from 2000 to the middle of 2008.

In the second half of 2008 both prices fall by roughly 100$ with the spread being quite stable during the period. During 2009 and 2010 the prices rebound back to the levels of 100$ per barrel for gasoline and roughly 90$ for crude oil. The spread averages 7$ during the period. Starting from 2011 the spread increases substantially and becomes 25$ per barrel with the price of gasoline fluctuating around the level of 120$ and the crude oil price being 95$ on average.

The crack spread (the difference of the prices) is shown in the middle plot of Figure 1. The spread is relatively stable from 1992 to 2000 and is relatively more volatile in 1988-1992 and 2005-2009. The nominal spread is not well-suited for the analysis since it both increases on average (11$ vs 4.4$ per barrel) and becomes more volatile (volatility of weekly changes increases roughly by a factor of 3) in the second half of the sample starting in 2000. It is worth noting that the spread becomes negative in 2006 and 2008.[3]

An alternative way to look at the price is to inspect their ratio

$$sr_t = nyg_t/wti_t. \tag{1}$$

[3] Appendix B examines the occurrences of negative spread values and the significant increase in the spread starting in 2011.

which is referred to as spread (or crack) ratio from now on and is shown in the bottom plot in Figure 1. The behavior of the ratio is more homogeneous across time compared to the spread. The ratio substantially deviates from its mean level of 1.2 both in the first and the second part or the sample. For instance, it increases substantially just before the Iraq campaign in August 1990. Visually, the difference between pre-2011 and post-2011 levels is less evident.

2.3 Trends in fundamentals

The time series of the fundamental variables along with the crack ratio since 1983 are shown in Figure 2. A visual inspection of the time series clearly indicates that all the fundamental series are non-stationary due to the presence of trends and that consumption and production are clearly seasonal. Postponing the discussion of seasonal patterns till the next section we briefly overview the long-term trends in the variables.

U.S. gasoline consumption (displayed on the third plot from the bottom) in Figure 2 is currently around 8.2-9.2 MMbbl/d. It was steadily growing in the 1980s until the Gulf War in 1990-1991. After the conflict (1992-1993) the growth in consumption resumed and continued till 2007–2008 when the consumption was dramatically affected by the oil price spike and the financial crisis. In 2008 the consumption started to fall and then stabilized at levels lower by 0.5 to 1.0 MMbbl/d compared to the peak pre-2008 values of 8.9 to 9.6 MMbbl/d.

[Figure 2 about here.]

The U.S. production of gasoline (third plot from the top in Figure 2) was typically lower than the consumption until 2008–2009. The deficit was covered by imports which started to grow notably around 1995 (second plot from the bottom in Figure 2). However, imports started to decrease in 2007-2008 while exports (the bottom plot in Figure 2) started to increase rapidly in 2009-2011 and are likely to outgrew imports in 2014.

The stocks shown on the second plot of Figure 2 are likely to be seasonal and are rather stable in absolute terms. However since the consumption has risen the stocks relative to consumption have declined. While in the 1980s the stocks were holding around 30-40 days of supply on average across the year in the 1990s and 2000s the range became 22 to 30 days.

The increase in exports in 2009-2011 coincided with the increase in the U.S. domestic crude oil production started approximately around the same time (please refer to Figure 3). As discussed above, the trends of gasoline consumption and imports reversed few years before (around 2007-2008). I interpret those events as structural breaks and limit the sample to a 15-years period from the beginning 1993 to the end of 2007.[4] As discussed briefly in the beginning of Section 3.6 the choice of sample period is by no means critical to the findings of the study.

[Figure 3 about here.]

3 Analysis

3.1 Seasonal patterns

I eliminate the trends in all the variables by subtracting centered 12-month moving averages from all the observations. More specifically, if X is the variable of interest its detrended version X^d is constructed as

$$X_t^d = X_t - \frac{1}{12}\sum_{i=0}^{11} X_{t-i+5} \qquad (2)$$

In other words, the trend is constructed as an average of the observations with lags ranging from -6 to +5. The detrended variables are shown in Figure 4. It is evident that all the variables are seasonal. Moreover, seasonal patterns in consumption and production are rather stable while the annual cycles in the other variables are clearly less stable across the sample.

[Figure 4 about here.]

To identify the typical annual fluctuations I normalize the detrended variables by their trends to obtain the percentage deviations and, finally, compute average seasonal fluctuations for all calendar months. Figure 5 shows the resulting seasonal profiles.

Consumption tends to be low very (-7% from the trend) in January and then gradually increases until June and August when it typically reaches the highest levels of around +4%. Then it falls sharply in September till neutral levels and stays neutral till December. Seasonality in driving patterns is similar as illustrated by the dashed line in the middle plot which shows the average

[4]While all the series are available from June 1986 the observations up to 1993 are not discarded. They are used for computing the trends and constructing the initial estimates of seasonalities which require 6 months and 5 years of data accordingly.

percentage deviations from the trend of vehicle-miles traveled variable reported by the Federal Highway Administration.

[Figure 5 about here.]

Production is also low in January (-3% from the trend) and decreases even further in March reaching -4%. It quickly picks up in April till the neutral level and reaches the maximum in June (+3%). Then it gradually decreases reaching a local minimum near the trend level in October and gradually increases till the end of the year (+2%). Production troughs in January–March and October are caused by planned refinery shut-downs (so-called turnarounds). I find that refinery utilization rate has exactly the same seasonality as production as indicated by the bottom plot of Figure 5.

The stocks, in opposite, are high in the beginning of the year (+6%) and then decrease in spring, especially from February to March when many refineries are undergoing maintenance while the consumption is healthy. In April–June the increased production is keeping up with the demand and the stocks stay at approximately neutral levels. They decrease in August (-4%) as producers anticipate the seasonal fall in the demand in autumn and start to build up again in November when the refineries ramp up production again after completing repairs.

I also explore the autocorrelation and partial autocorrelations of the detrended variables (Figure 6). Consumption and production both have significant positive partial autocorrelation at the 12th lag as well as significant autocorrelations at lags which are the multiples of 12 which is a clear indicator of annual seasonality. Similar patterns hold for stocks, imports and exports, however partial autocorrelations at 12th lag are much smaller in magnitude for those variables.

[Figure 6 about here.]

3.2 Seasonal adjustment

Aiming to uncover the effects of aseasonal fluctuations in fundamentals on the subsequent crack ratios I use a simple filtering procedure. I assume that the expected seasonal component is given by an average of observations in the same calendar month in the preceding 5 years. It is inspired by periodical reports published by the EIA which often compare current fundamentals to their observed values in the preceding years.[5]

Let X^d be the detrended variable of interest constructed from the original series via (2). Then its seasonally-adjusted version X^a is constructed as

$$X_t^a = X_t^d - \frac{1}{L}\sum_{i=1}^{L} X_{t-12i}^d \tag{3}$$

where L is the number of lags used. I report the results for $L = 5$ and the results are very similar for L ranging from 2 to 5 ($L = 1$ corresponds to seasonal differencing).

The filtered variables are shown in Figure 7. The seasonalities clearly present in the detrended variables seem to be eliminated by the seasonal adjustment procedure except, possibly, for stocks which appear as having cycles in the second half of the sample. To assess more formally whether the seasonalities are removed I normalize the variables to have unit standard deviations and compute the averages across all calendar months. I find that for all the variables the standardized monthly averages do not exceed 0.3 of their respective standard deviations and that the vast majority of points lie between -0.2 to 0.2 standard deviations.

[Figure 7 about here.]

The summary statistics of seasonally-adjusted variables are shown in Table 1. The sample standard deviations and ranges of consumption and production reduce approximately by one half indicating that the seasonal variations in those variables account for a large percentage of the total variation and that the seasonal variations have a stable structure well-captured by the adjustment procedure. The similar effect is observed for stocks while for the price ratio, exports and imports the ranges and standard deviations are either unaffected or even increasing. This indicates that either the seasonality has a more complex structure than assumed by the seasonal moving-average filter (3) or that the unpredictable component effectively dominates in those variables.

[Table 1 about here.]

[5]For instance, U.S. Energy Information Administration (February 20, 2014). *This Week in Petroleum* reports always include a plot of crude oil and finished products stocks with their five-year ranges highlighted.

Comparing autocorrelation profiles of detrended and seasonally-adjusted provides further evidence supporting the fact that the applied seasonal adjustment procedure is effective. Indeed, Figure 8 shows that neither of the variables have significant autocorrelations at lags greater than 3. In particular, high positive partial autocorrelations present in detrended consumption and detrended production (Figure 6) are clearly eliminated in the adjusted variables.

[Figure 8 about here.]

3.3 Effects of the adjusted fundamentals

I find that production, consumption, stocks and imports adjusted for trends and seasonality are significantly related to the subsequent crack spread ratios filtered in the same way. More specifically, I document the effects of the adjusted standardized fundamentals

$$\mathbf{X}_{as} = \{\mathrm{sr}_t^{as}, stocks_t^{as}, prod_t^{as}, \mathrm{cons}_t^{as}, imp_t^{as}, exp_t^{as}\} \tag{4}$$

on the adjusted crack spread ratio sr_{t+1}^a next month within a linear model

$$sr_{t+1}^a = \sum_{X \in \mathbf{X}_{as}} \beta_X X_t + \varepsilon_{t+1} \tag{5}$$

The explanatory variables in the set $\mathbf{X}_{as}$ are standardized to make it easier to compare the effects across different variables: each coefficient can be interpreted as an impact of one-standard deviation shock to the corresponding variable.

In this section I report the coefficients in equation (5) obtained with ordinary least squares. The results are robust with respect to the specification of the error term as discussed in Section 3.4. In addition to the joint regression having all the adjusted variables as explanatory variables I also run regressions using subgroups of related variables as predictors. This is done to highlight the explanatory power of specific variables and to study the robustness of coefficient estimates. In particular, I regress the adjusted crack spread ratio sr_{t+1}^a only on stocks, only on production and consumption, and, finally, only imports and exports (all explanatory variables are lagged, adjusted and standardized similarly to the joint regression (5)).

The results are presented in Table 2. In the joint regression (see specification (1) in Table 2) the coefficients on the lagged crack ratio, stocks, production, consumption and imports are all statistically significant with the R-squared of 0.34 . Except for consumption all the coefficients are statistically significant at the confidence level of 0.01 while that of consumption is significant at 0.05. The largest coefficient estimate is that of lagged crack ratio (0.023). When the crack ratio increases by its sample standard deviation (0.08) its value in the next month increases, on average, by one-third times the standard deviation. The effect is likely to be caused by a significantly positive autocorrelation of the adjusted crack ratio (0.45). When used as a single predictor lagged crack ratio explains 16% of the variation in the next month crack ratio.

[Table 2 about here.]

Of all adjusted fundamental variables adjusted stocks have the largest linear effect on the crack ratio in the subsequent month. On average, when adjusted stocks increase by one sample standard deviation (5.62 MMbbl) the crack ratio in the subsequent month decreases by 0.017. It is an economically significant effect since the sample standard deviation of the adjusted crack ratio ratio is only 0.08. In other words, a positive one-standard deviation shock to stocks is associated, on average, with a decrease in the crack ratio next month by roughly one-fifth of its sample standard deviations. In a regression including only stocks (specification (2) in Table 2) the coefficient roughly doubles in magnitude (from -0.017 to -0.032) while the standard error of the estimate remains the same. R-squared of the standalone regression is roughly 0.2.

The estimate for adjusted production implies that when it equals its sample standard deviation (0.14 MMbbl/d) the crack ratio next month decreases, on average, by 0.015 or, equivalently, the price of gasoline relative to crude oil decreases by 1.5%. Similarly, a one-sigma shock to consumption relative to its trends and seasonality (0.12 MMbbl/d) is typically followed by an increase in the crack ratio by 0.01. In other words, a positive one-sigma shock to production (consumption), on average, decreases the crack ratio next month by roughly one-fifth of its standard deviations (increases the crack ratio by one-eighth of its standard deviations). In a regression having only production and consumption as predictors (specification (3) in Table 2) the coefficient on consumption becomes highly significant and both coefficients slightly increase in magnitude: that of consumption from 0.01 to 0.015 and that of production from -0.015 to -0.018. In this regression the adjusted R-squared is 0.07.

The coefficient on lagged imports is negative and statistically significant while that of imports is positive and not significant in the joint regression. Their magnitudes imply that a one-sigma increase in adjusted imports (0.09 MMbbl/d) is on average associated with a decrease in crack ratio by 0.013 while a one-sigma increase in adjusted exports (having sample standard deviation of 0.03MMbbl/d) is, on average, followed by a an increase in crack ratio of 0.009. In a regression with just imports and exports as regressors (specification (4) in Table 2) the estimates as well as their standard errors remain the same and the R-squared equals 0.05.

3.4 Robustness checks

I perform the following checks to assess the robustness of the results. First, I compute the standard errors using heteroskedascity- and autocorrelation-robust covariance matrix estimator of Newey and West (1987). Second, I reestimate the regression (5) using a number of models for serial correlations in disturbances and report the results for the best-fitting one. Finally, I estimate a least absolute errors regression (LAE) with the same input and response variables as in (5) to assess whether reported OLS estimates might be biased because of outliers.

The results of the alternative procedures are shown in Table 3. The first column (OLS) displays the results of OLS estimation discussed above. In the second column (NW) the standard errors are recomputed using Newey-West estimator. I report the results for the bandwidth parameter m set to 3 which is a result of an automatic selection procedure suggested in Newey and West (1994). The standard errors of coefficients on production and stocks slightly increase and the corresponding p-values increase from below 0.01 to below 0.05. The other standard errors are unchanged except that the standard error of the coefficient on imports decrease. I find that the exact choice of the bandwidth m from a range of 1 to 12 does not affect the p-values in a major way except that for $m = 1, 2$ the coefficient on consumption becomes insignificant at 0.05 confidence level (the coefficient estimate increases from 0.005 to 0.006).

[Table 3 about here.]

The third column in Table 3 shows the estimated coefficients in model (5) for the best fitting specification of the error term ε_t from a panel of seasonal autoregressive–moving-average (SARMA) models. I consider models with the number of autoregressive and moving-average terms ranging from 0 to 2 for both seasonal and non-seasonal components excluding, however, all the models having more than 3 terms in total.[6] The estimation is via maximum-likelihood and the best model is selected based on its Bayesian Information Criterion (BIC). Of all the tested models I find that the best fitting one is an autoregression

$$(1 + 0.25L^{12} + 0.11L^{24})(1 - 0.25L)\varepsilon_t = \nu_t \tag{7}$$

where the variance of the error term ν_t is 0.0031. Its BIC statistic equals -470.34.

Specifying the error term ε_t in model (5) as a SARMA process (7) results in coefficient estimates (reported in the third column of Table 3) quite different from those obtained with OLS (the first column in the same table). Most notably, the coefficient on exports increases by one-third (0.009 to 0.012) and becomes highly statistically significant. The estimated effects of imports, on opposite, decreases by half (from 0.013 to 0.06) and becomes insignificant. The coefficients on production and consumption slightly decrease (in absolute terms) and remain significant. Finally, the coefficient on lagged crack ratio decreases from 0.023 to 0.014 and becomes insignificant.

Since the estimates of regression coefficients obtained for OLS and SARMA specifications are based on minimizing squared model errors the estimates may be contaminated by outliers either in response or explanatory variables. To assess whether this might be the case I estimate the model (5) using a least absolute errors (LAE) regression. The resulting coefficients are obtained by minimizing absolute model errors rather than squared ones which makes the obtained estimates robust to outliers.

The estimates resulting from the LAE regression (shown in the last column of Table 3) have three notable differences with the estimates obtained with OLS (first column in the same table). First, the coefficient on exports in-

[6] A general ARMA$(p, q)(P, Q)_{12}$ model for a variable ε_t is

$$\left(1 - \sum_{i=1}^{P} \Phi_i L^{12i}\right)\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)\varepsilon_t = \left(1 + \sum_{i=1}^{Q} \Theta_i L^{12i}\right)\left(1 + \sum_{i=1}^{q} \theta_i L^i\right)\nu_t \tag{6}$$

where L is the lag operator and the noise term ν_t on the right-hand side is stationary and serially uncorrelated. I consider the models with parameters p, P, q, Q satisfying $0 \leq p, P, q, Q \leq 2$ and $P + p + Q + q \leq 3$. The acronym "SARMA" is chosen for the models of type (6) in to highlight the fact that the models of interest involve seasonal terms.

creases from 0.009 to 0.016 and becomes significant. Second, the coefficient on production decreases (in absolute value) from -0.015 to -0.019. Third, the standard error of the coefficient on imports increases and the coefficient becomes insignificant keeping almost the same value (0.014 vs 0.013). The estimated effect of consumption slightly decreases and the other estimates are virtually unaffected. The results of the LAE regression indicate that there is a possibility that OLS estimates for the coefficients on exports and production are underestimated while the coefficients on consumption are overestimated.

The evidence produced by the alternative specifications or estimation methods presented in Table 3 suggests that lagged adjusted stocks and lagged adjusted production are the most relevant predictors for the adjusted crack ratio both by magnitude and by statistical significance. Each one-sigma increase in adjusted stocks is, on average, associated with a decrease in crack ratio by 0.016-0.018 which is a fifth of its sample standard deviation (0.08). An average effect of a similar one-sigma increase in lagged adjusted production is slightly smaller (-0.011 to -0.019). Both relationships are unquestionably significant and there is a possibility that the effect of production is underestimated since the outlier-robust estimate is the largest by magnitude and is highly significant (-0.019).

The evidence on the effects of consumption, exports and is, however, mixed. The coefficient of consumption is marginally statistically significant for three out of four methods (OLS, NW, SARMA) and is not significant within the outlier-robust LAE-estimation. The estimates of a coefficient on imports ranges from -0.013 and being highly significant to -0.006 and being insignificant. A similar pattern holds for exports and one can observe that either factor tends to be significant when the other one is not.

3.5 Net variables and statistical significance

The estimated coefficient on lagged imports estimated with OLS is large in absolute terms (-0.013) and highly significant while that of exports is smaller (0.009) and insignificant (Table 3). The opposite pattern holds for SARMA estimates: the coefficient on imports equals -0.006 and is insignificant while that of exports is highly statistically significant and equals 0.013. This suggests that net imports (imports less exports) might be a more robust explanatory variable rather than exports and imports separately.

I check whether this is the case and also use net production (production less consumption) as an explanatory variable instead of disaggregated consumption and production. The model specification is

$$sr^{a}_{t+1} = \beta_0\, sr^{as}_{t} + \beta_1\, stocks^{as}_{t} + \beta_2\, netprod^{as}_{t} + \beta_3\, netimp^{as}_{t} + \varepsilon_{t+1} \qquad (8)$$

where, as before, I standardize all the explanatory variables. Clearly, the estimated coefficients on net imports ($netimp^{as}_{t}$) and net production ($netprod^{as}_{t}$) correspond to average effects on the crack ratio next month associated with one-sigma shocks to these new variables.

I use the same four estimation procedures as in Section 3.4, namely ordinary least squares, OLS with Newey-West standard errors, maximum-likelihood estimation for the best-fitting SARMA model for residuals, and, finally least average errors regression. The bandwidth parameter for Newey-West estimator is set to 1 as suggested by the selection procedure of Newey and West (1994). The best-fitting SARMA model for residuals ε_t is $(1 + 0.18L^{12} + 0.10L^{24})(1 - 0.25L)\varepsilon_t = \nu_t$ with the estimated variance of ν_t being 0.0032. This model is very close to the model (7) selected for the disturbances ε_t in a regression (5) using disaggregated variables (4).

The results are shown in Table 4. All the fundamental variables are highly statistically significant for the first three methods, namely ordinary least squares (specification “OLS” in Table 4), Newey-West with the automatically selected bandwidth parameter (specification “NW” in the same Table) and a regression with seasonal ARMA disturbances (“SARMA”). For least average regression (specification “LAE” in Table 4) lagged stocks and net imports are insignificant while net production is significant at 0.05 confidence level.

[Table 4 about here.]

Whether net or disaggregated variables are used in the specification has little effect on coefficient estimates for lagged stocks and lagged crack ratio. Indeed, in the regression having net variables (5) the coefficient on adjusted lagged stocks ranges from -0.016 to -0.017 (Table 4) while in the regression (8) with disaggregated predictors the coefficient varies from -0.016 to -0.018. Similar pattern holds for the coefficient on the lagged crack ratio. The standard errors of coefficients on lagged stocks and lagged crack ratio in the least average regression increase from 0.008 in the disaggregated regression (5) to 0.010-0.011 in a regression using net variables.

In the regression having net variables as predictors the estimated coefficient on net production varies from -0.013 (SARMA) to -0.022 (LAE) (please see Table 4) and a similar patter holds for net imports: LAE estimate is the highest (in absolute terms) while the one for SARMA is the lowest. Notable differences between OLS and LAE estimates for net production and imports agrees with the fact that the estimates for disaggregated variables obtained used those two methods are also different (please see Table 3).

The effects of net imports are indeed more robust than those associated with imports and exports alone. While the estimated coefficients on imports and exports in Table 3 are jointly significant in only one specification (SARMA) the coefficient on net imports are significant in 3 out of 4 specifications (Table 4). The estimated effect of one-sigma shock to lagged net imports (-0.012 to -0.019) is also higher than these of exports and imports alone (0.09 to 0.014 in absolute value).

Net production is a sum of a relatively more significant predictor (production) and a less significant one (consumption) (please see Table 3). As a result, net production seems to be slightly less significant than production alone except for SARMA regressions where net production becomes highly significant when neither production nor consumption are. That being said, the magnitudes of the estimated coefficients on net production reported in Table 4 (-0.016 to -0.022) are higher than those of production and consumption alone (0.08 to 0.015 in absolute value as shown by Table 3) and the net variable is significant across all four estimation methods being highly significant in two of them.

The results of the regressions including net production and net imports strengthen the evidence that all of the considered fundamentals have significant statistical relationships with the subsequent crack ratios. Indeed, while the results of disaggregated regressions may lead one to question whether adjusted consumption, imports and exports are significantly related to the subsequent crack ratios, both net imports and net production have larger estimated effects on crack ratios than disaggregated variables and are unquestionably statistically significant.

3.6 Interpretation of results

In a model where next month crack spread ratio is explained with lagged disaggregated variables (5) the estimated coefficients do vary considerably when one changes the set of explanatory variables (please see Table 2), the specification of the error term or the loss function for the modelling errors (Table 3). One could easily observe, however, that the signs of all the estimates are remarkably stable: none of the coefficient estimates ever changes sign.

The obtained evidence on the effects of lagged adjusted fundamental on the adjusted crack ratio can be summarized as follows: higher adjusted stocks, production and imports are, on average, associated with a decrease in crack ratio next month while higher consumption and exports tend, on average, to be followed by a lower crack spread. I find that those effects are very stable across time. For instance, joint regressions (5) on five-year samples starting in 1993 and ending in 2012 yield exactly the same signs.

Since the crack ratio proxies the profitability of refining (assuming gasoline is the single output of the process) the signs are consistent with the following interpretation: positive adjusted production and consumption capture unexpected shocks to supply and demand respectively while positive adjusted stocks capture unexpected increases in supply relative to demand. Finally, adjusted imports (exports) capture relative aseasonal fluctuations in imports (exports) caused by relative shortages (overproductions) of gasoline in the domestic market.

Let us consider adjusted production. Assuming it indeed captures unexpected shocks to gasoline supply one would expect it to be negatively associated with the deseasonalized crack ratio which captures the profitability of refining. Indeed, an unexpected increase in gasoline supply leads to a relative overproduction of gasoline and hence lowers the profitability of refining which is captured by the crack ratio. Hence one would observe a negative coefficient in a regression of adjusted crack ratio sr^a_{t+1} on the adjusted production prod^{as}_t.

Similarly, a positive relationship between lagged adjusted consumption next month is consistent with an interpretation of the variable as capturing unexpected shocks to gasoline demand. Indeed, an unexpected increase in gasoline demand would raise the gasoline price and hence increase the refining margin proxied by the crack ratio.

An unexpected positive increase in stocks could be interpreted as an unexpected decrease in gasoline demand, an unexpected increase in gasoline production or a combination of both. In all cases the crack spread would decrease because supply increases relative to demand. It is also possible that an increase in stocks could be a result of increasing futures prices relative to spot prices.

Storing gasoline for prolonged periods of time, however, is not common since the product tends to degrade.

The observed negative association between lagged imports and consequent crack ratios suggests that it is plausible that imports typically increase following an initial shortage of gasoline. Indeed, a shortage of gasoline would increase the domestic crack ratio and make importing more profitable. The imports would grow increasing the supply which would, in turn, lead to a decrease in the crack ratio. This hypothesis is supported by the results of a regression of adjusted imports on lagged adjusted crack ratio: I find that the crack ratio has a significant positive coefficient in this regression.

A positive association between lagged adjusted exports and the adjusted crack ratio could be due to a similar mechanism. An increase in exports could be a consequence of relative overproduction of gasoline which would increase exporting margins. An increase in exports would correct the overproduction and lower the crack ratio. This hypothesis is also supported by the data: lagged adjusted production (which presumably captures supply shocks has a significant positive effect on imports).

The suggested interpretation is not definitive and the same observed effects could be a result of different economic mechanisms. The robustness of reported effects clearly calls for additional investigations.

4 Conclusion

The gasoline market in the U.S. has pronounced seasonal patterns: consumption, production and the refining margin tend to be higher in summer while the stocks follow the inverted pattern. I show that seasonality in the variables can be eliminated using a straightforward procedure and explore the effects of the lagged adjusted fundamentals on the adjusted crack ratio using several linear models.

The directions of the identified effects are remarkably stable. An increase in lagged adjusted stocks, production or exports predicts, on average, a decrease in (adjusted) crack ratio. Lagged consumption and exports have, on average, an opposite effect on the crack ratio. The same effects are observed in other sample periods.

The magnitude and statistical significance of the observed effects, however, varies from one variable to another one and depends on the estimation method. The main complication in the analysis is serial correlation of disturbances within the linear model. I use Newey-West standard errors and a fitted seasonal ARMA model for disturbances to verify the robustness of OLS estimates based on an assumption of no serial correlation.

The evidence on stocks is the least controversial: a one-standard deviation increase in adjusted stocks is, on average, associated with a decrease in the adjusted crack ratio next month of 0.016–0.018 or, equivalently, gasoline depreciates relative to crude oil by 1.6–1.8%. The effect is economically significant since the standard deviation of the adjusted crack ratio is only 0.08. A one-sigma increase in lagged production is followed, on average, by a decrease in crack ratio of 0.015–0.019 and the effect is also statistically significant.

A similar shock to lagged consumption, on average, increases crack ratio by 0.008-0.0010 but the estimates are not always significant. The estimates for coefficients on exports and imports vary greatly and I find that net imports (imports less exports) is a more robust predictor of the adjusted crack ratio than imports and exports alone: a one-sigma increase in net adjusted imports is followed, on average, by a decrease in crack ratio by 0.012-0.017.

The signs of the observed relationships agree with an interpretation of adjusted production and adjusted consumption as unexpected shocks to supply and demand of gasoline correspondingly. Indeed, one would expect that a positive supply shock decreases the refining margin while a positive demand shock increases it. Similarly, interpreting adjusted stocks as unexpected increases in supply relative to demand agrees with the evidence. Adjusted imports (exports) are predicted by adjusted crack ratio (production) so that the variable can be thought of as capturing atypically large imports (exports) following a shortage of gasoline (overproduction of gasoline).

The work can be extended in a multitude of directions. First, it would be natural to consider other finished products in addition to gasoline. The average gasoline yield in the U.S. is roughly 45% while that of diesel is roughly 30%. Clearly, an analysis including both gasoline and diesel would give a more complete picture of the market.

Next, it would be interesting to study regional rather than aggregate data. For instance, half of the refining capacity is located in Gulf Coast while the Northeast has little of its own and depends critically on gasoline transported from elsewhere. Hence it is reasonable to expect that exports and imports of those regions contain more information relevant to prices compared to the aggregate data.

Another extension would be to study futures prices in addition to spot prices. Since the fundamentals affect the spot crack ratio with a lag it would be interesting to check whether futures prices incorporate the information more rapidly. Furthermore, one could study the effects of fundamentals on higher-order moments in addition to the price. Effects on both historical and risk-neutral moments implied from option quotes would be of interest.

The findings of the study lay a foundation for the development of more complex models. One possibility is modelling the variables jointly in reduced-form within a vector autoregression (VAR) model which would allow to study the interactions between the variables in more detail (Kilian, 2010). Creating a structural model for the gasoline market is another possibility. A dynamic model able to reproduce observed seasonal patterns in production and stocks as an outcome of refineries' planning problem would be a major step forward.

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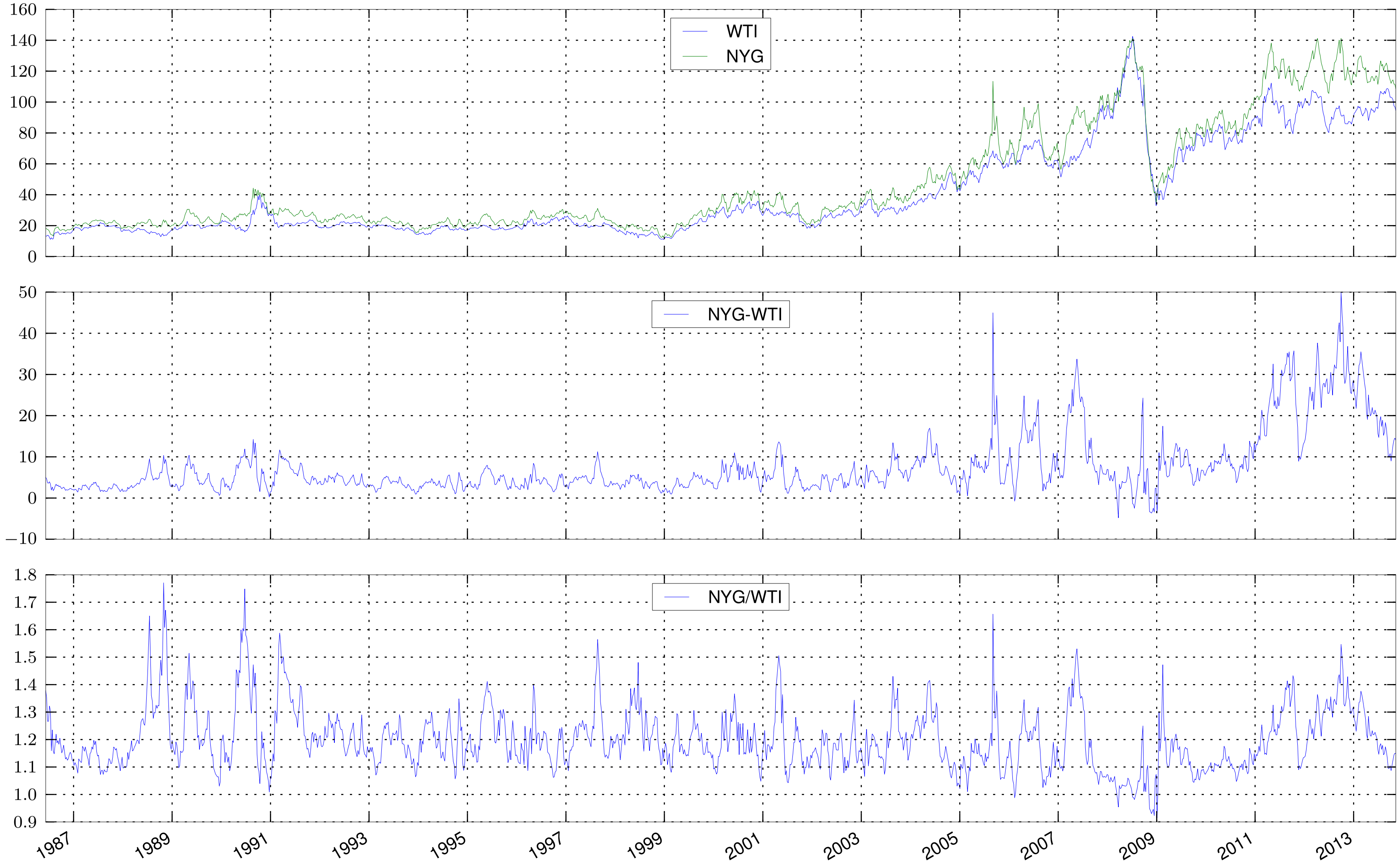

Figure 1: Weekly average spot prices of WTI crude oil in Cushing, OK and CBOB gasoline at New York Harbor (top plot). The spread and the ratio of the two prices (center and bottom). Prices in dollars per barrel. Source: U.S. Energy Information Administration (EIA).

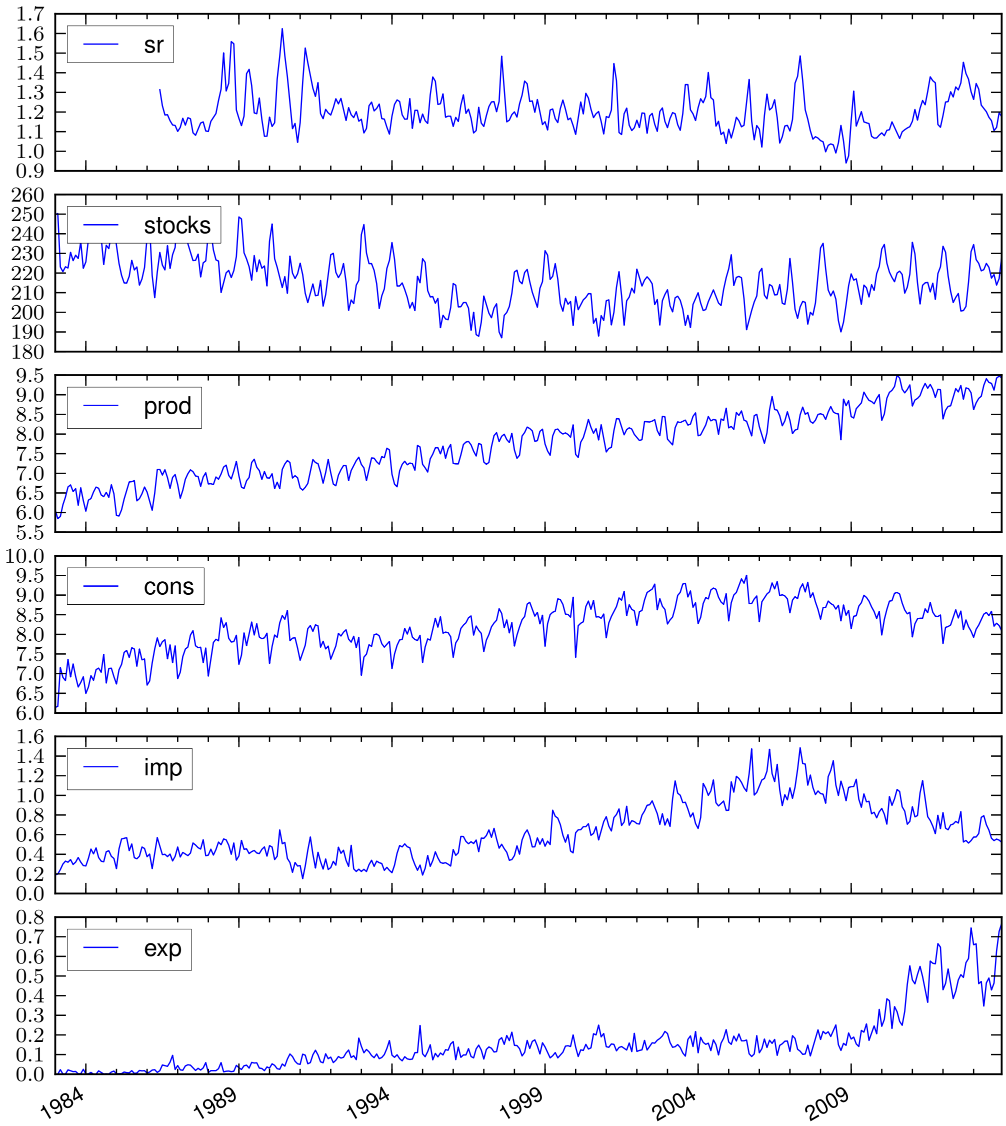

Figure 2: Crack ratio and the fundamental variables of U.S. gasoline market since 1983. Top to bottom: crack ratio (sr), stocks, production, consumption, imports and exports Crack ratio is the spot price of CBOB gasoline at New York Harbor divided by the WTI crude oil spot price (please see Section 2.1 or Table 1 for the exact definitions of the other variables). All series in MMbbl/d except for stocks which are in MMbbl and the crack ratio (unitless). Data: U.S. Energy Information Administration (2014).

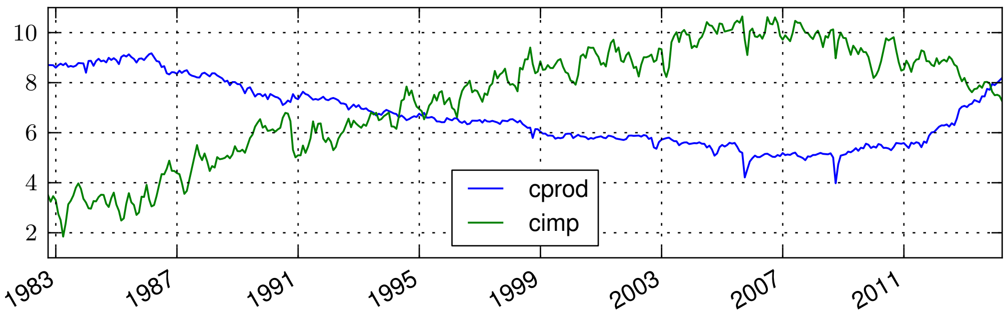

Figure 3: Domestic production and the imports of crude oil in the U.S (in MMbbl/d). The exports are less than 0.5 MMbbl/d and are not shown. Data: U.S. Energy Information Administration (2014).

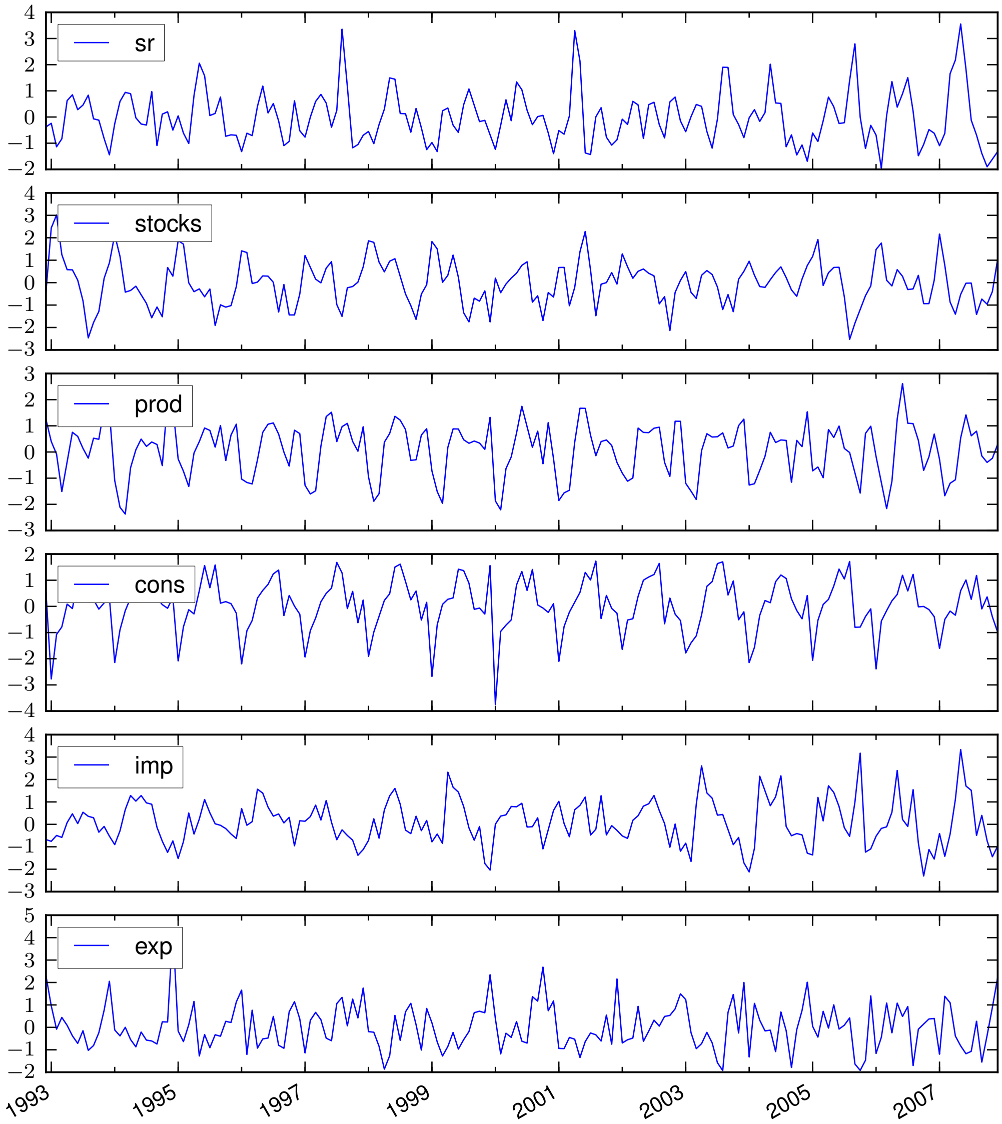

Figure 4: Detrended crack ratio and detrended fundamentals of the U.S. gasoline market. Top to bottom: crack ratio (sr), stocks, production, consumption, imports and exports. Detrended series are obtained by the formula $X_t^d = X_t - \frac{1}{12}\sum_{i=0}^{11} X_{t-i+5}$. Crack ratio is the spot price of CBOB gasoline at New York Harbor divided by the WTI crude oil spot price (please see Section 2.1 or Table 1 for the exact definitions of the other variables). All series in MMbbl/d except for stocks which are in MMbbl and the crack ratio (unitless).

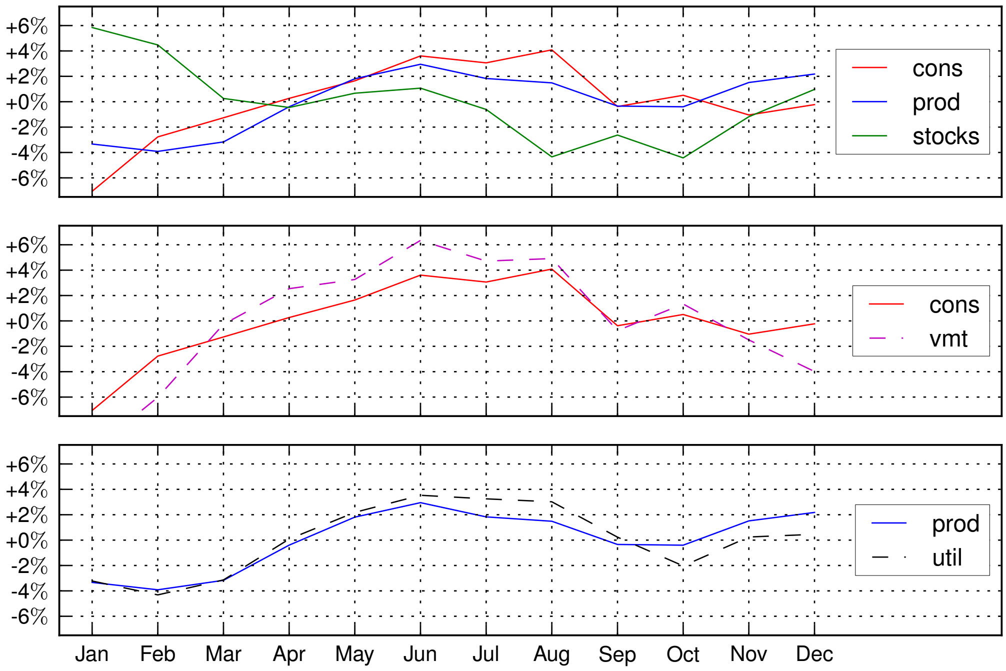

Figure 5: Seasonal patterns of gasoline market fundamentals: consumption, production and stocks (top), consumption and U.S. vehicle-miles traveled (middle), production and refinery utilization (bottom). The plots are obtained by normalizing the detrended variables by their trends and computing the averages for all calendar months.

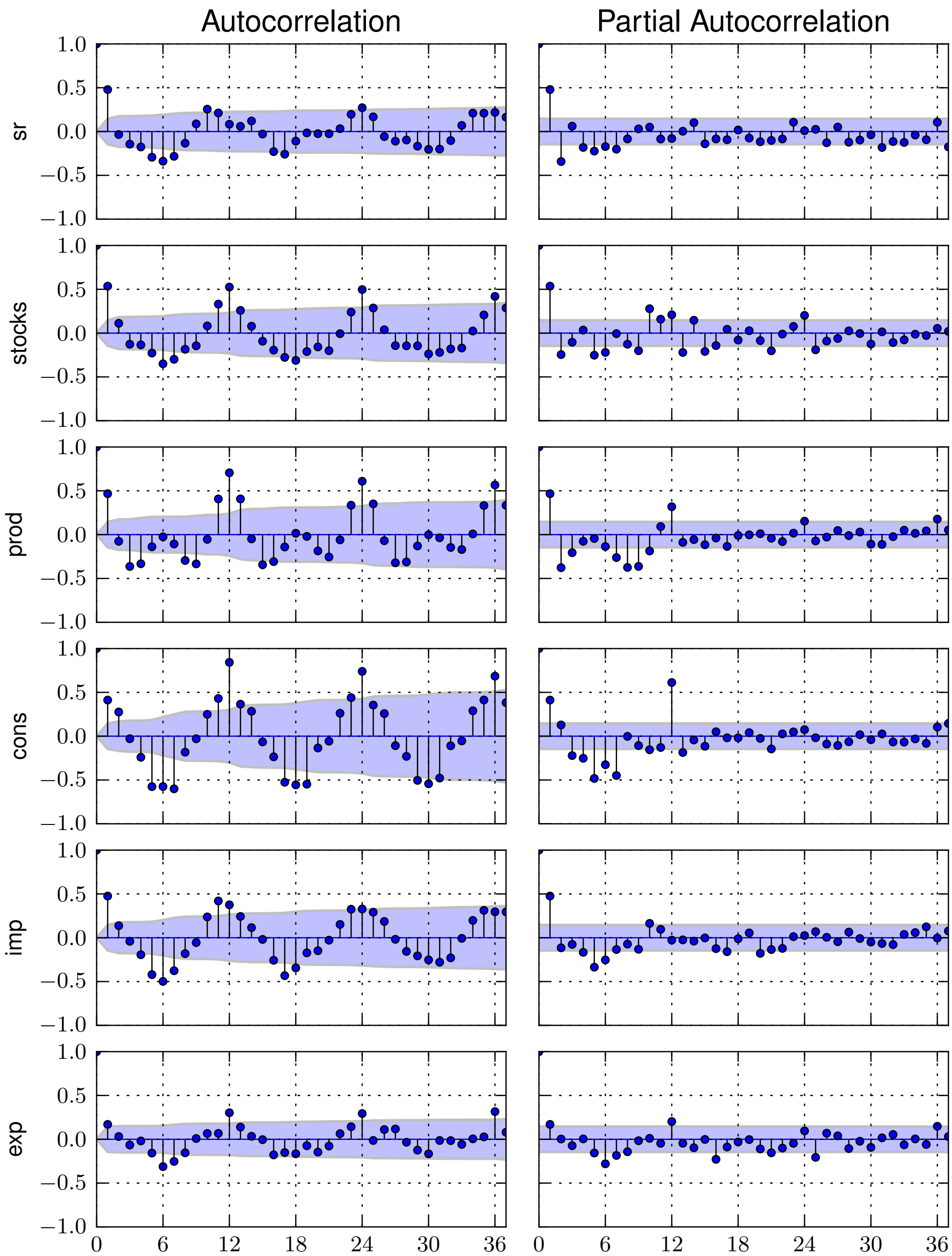

Figure 6: Autocorrelations and partial autocorrelations of detrended U.S. gasoline market fundamentals and the detrended crack ratio. Top to bottom: crack ratio (sr), stocks, production, consumption, imports and exports. Detrended series are obtained by the formula $X_t^d = X_t - \frac{1}{12}\sum_{i=0}^{11} X_{t-i+5}$. Crack ratio is the spot price of CBOB gasoline at New York Harbor divided by the WTI crude oil spot price (please see Section 2.1 or Table 1 for the exact definitions of the other variables).

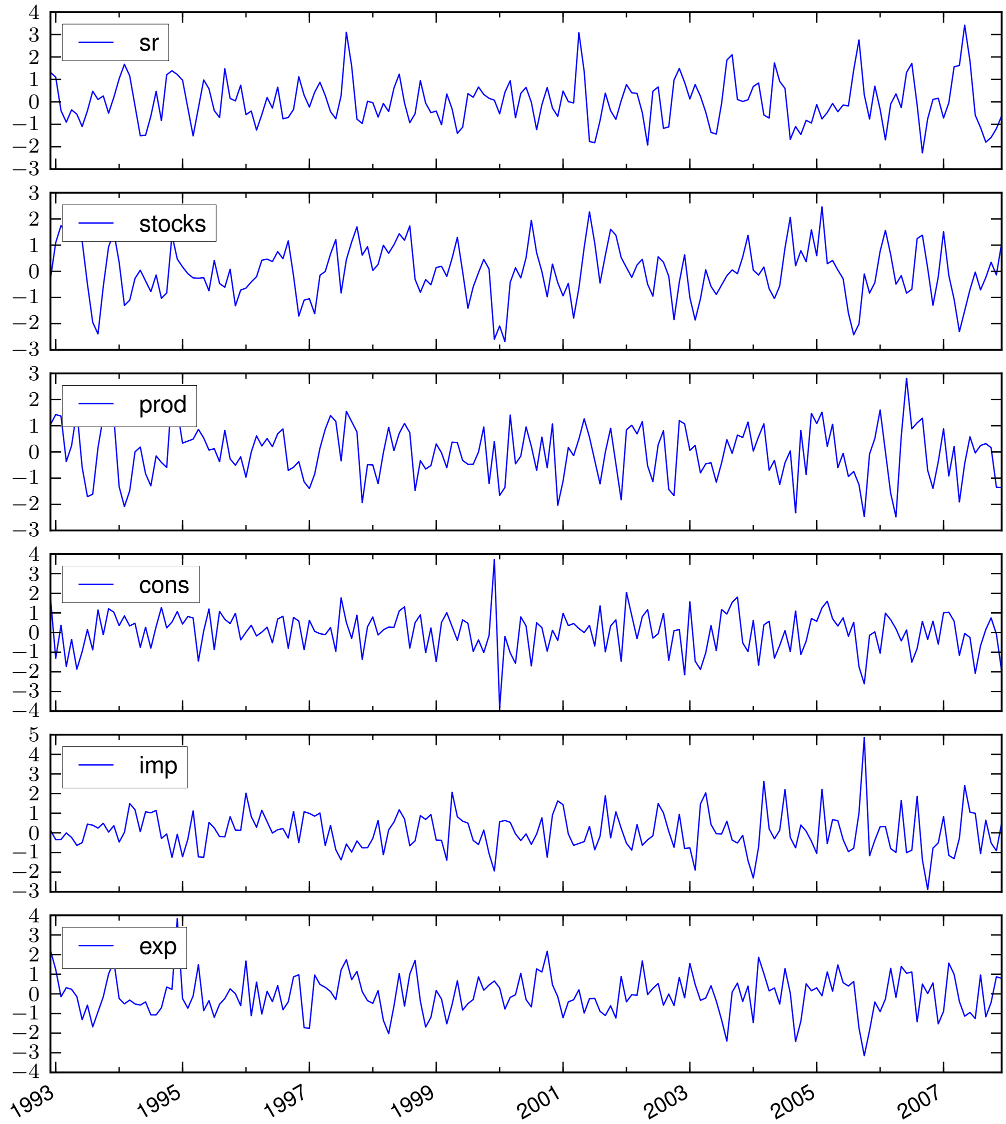

Figure 7: Seasonally-adjusted crack ratio and seasonally-adjusted fundamentals of the U.S. gasoline market. Top to bottom: crack ratio (sr), stocks, production, consumption, imports and exports. Seasonally-adjusted series X^a are obtained from the detrended ones X^d via $X^a_t = X^d_t - \frac{1}{L}\sum_{i=1}^{L} X^d_{t-12i}$. Crack ratio is the spot price of CBOB gasoline at New York Harbor divided by the WTI crude oil spot price (please see Section 2.1 or Table 1 for the exact definitions of the other variables). All series in MMbbl/d except for stocks which are in MMbbl and the crack ratio (unitless).

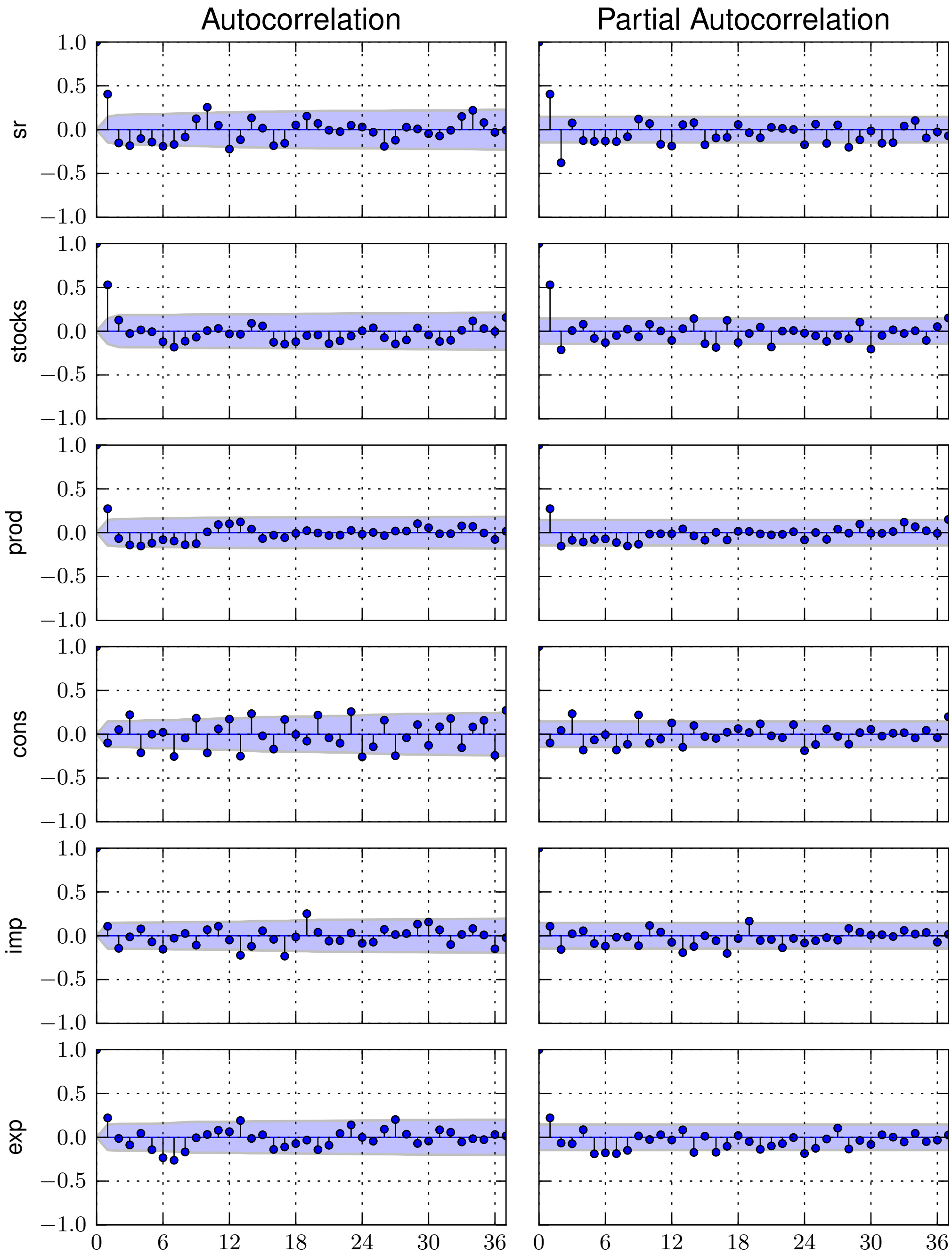

Figure 8: Autocorrelations and partial autocorrelations of seasonally-adjusted U.S. gasoline market fundamentals and the seasonally-adjusted crack ratio. Top to bottom: crack ratio (sr), stocks, production, consumption, imports and exports. Seasonally-adjusted series X^a are obtained from the detrended ones X^d via $X^a_t = X^d_t - \frac{1}{L}\sum_{i=1}^{L} X^d_{t-12i}$. Crack ratio is the spot price of CBOB gasoline at New York Harbor divided by the WTI crude oil spot price (please see Section 2.1 or Table 1 for the exact definitions of the other variables).

A Motor gasoline specifications

Retail motor gasoline is obtained by mixing gasoline blendstocks and certain additives so that the resulting product meets the relevant regulatory criteria. In the U.S. finished gasoline specifications are controlled by a number of overlapping federal and state laws that changed quite dramatically over the last 20 years. In this section we overview the most important qualities of motor gasoline and the regulations that shaped the gasoline market in the U.S.

The most important property of motor gasoline is its octane rating. The higher it is the less likely it is that the mix of the air and gasoline vapors within a cylinder will auto-ignite when being compressed. Higher compression is desirable from the energy efficiency perspective and since higher-octane blendstocks are typically more expensive the range of additives was used throughout the history to raise octane numbers of lower-octane gasoline.

As early as in the 1920s so-called tetraethyl lead (TEL) was found to increase the octane number when added to gasoline. It had become so widespread that in the 1970s almost all gasoline consumed in the world was leaded. Around this time it was found to be toxic which led to the full ban by the developed countries in the 1990s and the 2000s.

While leaded gasoline was banned in the U.S. in 1995 it was effectively replaced by the unleaded one much earlier. In fact, the consumption of unleaded gasoline surpassed that of leaded gasoline in 1982. The replacement was possible due to the widespread adoption of methyl tertiary buthyl ether (MTBE) as a replacement for TEL.

In addition to being an octane booster MTBE is an *oxygenate* which means it contains oxygen atoms which become available when the fuel-air mixture starts burning. The presence of additional oxygen allows fuel to burn more completely which reduces carbon monoxide and organic emissions. Alcohols such as methanol and ethanol are also oxygenates with high octane ratings and fuel ethanol production was steadily increasing in the U.S. since the early 1980s.

Oxygenate blending was significantly endorsed by the reformulated finished gasoline (RFG) and the winter oxygenated fuel (oxyfuels) programs initiated by the Environmental Protection Agency (EPA) in the 1990s (Figure 9). Both programs aim at improving air quality in designated areas by imposing additional requirements on the motor gasoline sold there. In particular, those

	Mean	SD	Range	Min.	Max	Skew	Kurt.
				Untransformed			
sr	1.19	0.08	0.46	1.02	1.49	0.89	1.26
$stocks$	208.63	10.31	57.66	187.02	244.68	0.50	0.51
$cons$	8.48	0.52	2.55	6.96	9.50	-0.37	-0.45
$prod$	7.91	0.45	2.30	6.66	8.96	-0.42	-0.45
imp	0.70	0.31	1.30	0.19	1.49	0.37	-0.69
exp	0.14	0.04	0.18	0.07	0.25	0.41	-0.41
				Detrended			
sr^d	-0.00	0.08	0.42	-0.15	0.27	0.90	1.31
$stocks^d$	-0.10	8.00	44.42	-20.26	24.16	0.15	0.11
$cons^d$	0.01	0.28	1.56	-1.07	0.49	-0.78	0.99
$prod^d$	0.02	0.23	1.17	-0.56	0.61	-0.41	-0.48
imp^d	0.01	0.11	0.60	-0.25	0.36	0.38	0.35
exp^d	0.00	0.03	0.21	-0.06	0.14	0.73	1.34
				Seasonally-adjusted			
sr^a	0.00	0.07	0.41	-0.17	0.25	0.56	0.73
$stocks^a$	-0.14	5.62	28.93	-15.10	13.84	-0.17	0.04
$cons^a$	0.00	0.12	0.89	-0.45	0.44	-0.39	1.25
$prod^a$	-0.00	0.14	0.77	-0.36	0.41	-0.14	-0.28
imp^a	0.01	0.09	0.68	-0.25	0.43	0.71	2.47
exp^a	-0.00	0.03	0.22	-0.10	0.12	0.17	0.85

Table 1: Summary statistics of transformed and untransformed variables. Series: crack ratio (sr) – the spot price of CBOB gasoline at New York Harbor (in \$ per barrel) divided by the spot price of WTI crude oil in Cushing, OK, U.S. stocks of total gasoline ($stocks$), U.S. total gasoline production ($prod$), U.S. finished motor gasoline consumption as given by the prime supplier sales volumes ($cons$), U.S. total gasoline imports and exports (imp and exp). Detrended series X^d are obtained from the original variables by the formula $X_t^d = X_t - \frac{1}{12}\sum_{i=0}^{11} X_{t-i+5}$. Seasonally-adjusted series X^a are obtained from the detrended ones via $X_t^a = X_t^d - \frac{1}{L}\sum_{i=1}^{L} X_{t-12i}^d$. Stocks are in million barrels (MMbbl) while production, consumpion, exports amd imports are in million barrels per day (MMbbl/d). Total gasoline refers to finished motor gasoline and motor gasoline blending components. All series are monthly and the sample spans from 1993 till 2007.

Table 2: Estimated effects of lagged seasonally-adjusted fundamentals on seasonally-adjusted crack ratio (sr^a_{t+1}). The explanatory variables (all – seasonally-adjusted, lagged, standardized): crack ratio (sr^{as}_t), stocks, production, consumption, imports and exports (please see Table 1 for the exact definitions of the variables). All series are monthly and the sample spans from 1993 till 2007. Standard errors are in parenthesis

	Dependent variable:			
	sr^a_{t+1}			
	(1)	(2)	(3)	(4)
sr^{as}_t	0.023**			
	(0.005)			
$stocks^{as}_t$	−0.017**	−0.032**		
	(0.006)	(0.005)		
$prod^{as}_t$	−0.015**		−0.018**	
	(0.005)		(0.005)	
$cons^{as}_t$	0.010*		0.015**	
	(0.005)		(0.005)	
imp^{as}_t	−0.013**			−0.014*
	(0.005)			(0.005)
exp^{as}_t	0.009			0.008
	(0.005)			(0.005)
Observations	180	180	180	180
R^2	0.360	0.197	0.084	0.057
Adjusted R^2	0.338	0.192	0.074	0.047
Residual Std. Error	0.059	0.065	0.070	0.071
F Statistic	16.347**	43.857**	8.161**	5.403**
Note:				*p<0.05; **p<0.01

Table 3: Estimated effects of lagged seasonally-adjusted fundamentals on seasonally-adjusted crack ratio (sr^a_{t+1}). The explanatory variables (all – seasonally-adjusted, lagged, standardized): crack ratio (sr^{as}_t), stocks, production, consumption, imports and exports (please see Table 1 for the exact definitions of the variables). Estimation procedures: ordinary least squares (OLS), OLS with Newey-West standard errors with 3 lags (NW), maximum-likelihood with best-fitting seasonal ARMA disturbances (SARMA), least absolute errors regression (LAE). All series are monthly and the sample spans from 1993 till 2007. Standard errors are in parenthesis.

	Dependent variable:			
	sr^a_{t+1}			
	OLS	NW	SARMA	LAE
	(1)	(2)	(3)	(4)
sr^{as}_t	0.023**	0.023**	0.014	0.024**
	(0.005)	(0.005)	(0.008)	(0.007)
$stocks^{as}_t$	−0.017**	−0.017*	−0.016**	−0.018*
	(0.006)	(0.007)	(0.006)	(0.008)
$prod^{as}_t$	−0.015**	−0.015*	−0.011*	−0.019**
	(0.005)	(0.007)	(0.005)	(0.007)
$cons^{as}_t$	0.010*	0.010*	0.009*	0.008
	(0.005)	(0.005)	(0.004)	(0.006)
imp^{as}_t	−0.013**	−0.013**	−0.006	−0.014*
	(0.005)	(0.004)	(0.004)	(0.007)
exp^{as}_t	0.009	0.009	0.012**	0.016*
	(0.005)	(0.005)	(0.004)	(0.006)
Observations	180	180	180	180
Note:			*p<0.05; **p<0.01	

Table 4: Estimated effects of lagged seasonally-adjusted fundamentals on seasonally-adjusted crack ratio (sr^a_{t+1}). The explanatory variables are (all – seasonally-adjusted, lagged, standardized) crack ratio (sr^{as}_t), stocks, net production (production less consumption) and net imports (imports less exports). Net variables were computed from the variables already adjusted for trends and seasonality (please see Table 1 for the exact definitions). Estimation procedures: ordinary least squares (OLS), OLS with Newey-West standard errors with 1 lag (NW), maximum-likelihood with best-fitting seasonal ARMA disturbances (SARMA), least absolute errors regression (LAE). All series are monthly and the sample spans from 1993 till 2007. Standard errors are in parenthesis.

	Dependent variable:			
	sr^a_{t+1}			
	OLS	NW	SARMA	LAE
	(1)	(2)	(3)	(4)
sr^{as}_t	0.024**	0.024**	0.015	0.023*
	(0.005)	(0.005)	(0.008)	(0.010)
$stocks^{as}_t$	−0.017**	−0.017**	−0.017**	−0.016
	(0.005)	(0.007)	(0.006)	(0.011)
$netprod^{as}_t$	−0.016**	−0.016*	−0.013**	−0.022*
	(0.005)	(0.006)	(0.005)	(0.010)
$netimp^{as}_t$	−0.017**	−0.017**	−0.012**	−0.019
	(0.004)	(0.005)	(0.005)	(0.011)
Observations	180	180	180	180
Note:				*p<0.05; **p<0.01

programs established a minimum oxygenate content measured by the weight of oxygen. For instance, the 2.1% threshold required by the reformulated gasoline program could be achieved by blending in 12% by volume of MTBE or 6% of ethanol. In 1997 when the RFG specification was widely adopted the share of RFG in total U.S. consumption became roughly 30%.

[Figure 9 about here.]

Following a discovery of MTBE in groundwaters of Santa Monica, California in 1995 the state ruled in 1999 to ban the chemical by 2002. Many other states followed suit and MTBE was almost phased out in the U.S. by 2006. At the same time the use of ethanol as an oxygenate started to increase and surpassed that of MTBE in 2003. This growth in fuel ethanol consumption was further supported by the adoption of the Renewable Fuel Standard (RFS) program in 2005.

Essentially the RFS set the targets for the consumption of renewable biofuels in the U.S. The program was expanded in 2007 and the revised targets for 2022 required aggressive growth in the consumption of corn and especially cellulosic ethanol. As a result, consumption and production of fuel ethanol have grown dramatically from roughly 0.2-0.3 MMbbl/d in 2005 to 0.8-0.9 MMbbl/d in 2011. Since the commercial production of cellulosic ethanol has not picked up this growth is due to the traditional corn ethanol technology.

The ethanol consumption targets in the RFS program are in absolute terms and are based on an optimistic scenario for the gasoline consumption growth made before 2007-2008. In reality U.S gasoline consumption has significantly declined in 2008 and plateaued since then. This left the industry in a situation commonly referred to as the “blend wall”, namely an inability to blend in the required amounts of ethanol due to the fact that the vast majority of vehicles in the U.S. are not suited for running on gasoline having more than 10% ethanol.

One of the disadvantages of ethanol as a fuel is its tendency to absorb moisture. When the concentration of water within ethanol becomes large enough they will separate forming two different layers of liquids. This is the main reason why ethanol blending is typically done at the truck rack just before the finished gasoline is shipped to retail gas stations. As a result, gasoline traded in the wholesale markets in not oxygenated.

Specifications for unoxygenated gasoline blendstocks commonly traded in the U.S. wholesale markets are derived from the specifications for the resulting oxygenated finished gasoline. For instance, blendstocks which meet the reformulated finished gasoline (RFG) specification after oxygenation is referred to as *reformulated blendstock for oxygenate blending* (RBOB). Gasoline futures traded on CME/NYMEX with delivery in the New York Harbor since 2005 (ticker RB) are based on this specification. Similarly, CBOB refers to unoxygenated gasoline which meets the requirements for *conventional gasoline* (CG) which is the default specification for finished motor gasoline in the U.S.

Reformulated gasoline currently accounts for around 35% of total gasoline consumption in the U.S. RFG areas currently include a number of densely populated counties on the East Coast from Baltimore to Boston as well as Chicago, St. Louis, Fort Worth, Dallas, Houston and California.[7] Gasoline sold in California must also meet stricter criteria imposed by the California Air Resources Board and is referred to as CaRFG. The corresponding wholesale unoxygenated product is labelled CARBOB.

[Figure 10 about here.]

As a result of an amendment to the Clean Air Act passed in 1990 the Environmental Protection Agency also regulates volatility (in a physical sense) of gasoline sold in the U.S. depending on area and time of the year. Volatility of a liquid is measured by its Reid Vapor Pressure (RVP). The higher the RVP the more volatile the liquid and the lower its boiling temperature. Gasoline with higher RVP is slightly cheaper, evaporates more easily and is more suitable for cold weather.

NYMEX gasoline future contract (having RBOB as an underlying commodity) specifies the maximum RVP for the underlying gasoline depending on the delivery month in accord with the regulations relevant for the New York area. Current specification of gasoline futures requires the maximum RVP of the delivered gasoline to be 15.0 from November till the end February and 9.0 from April till September 15. In March and from September 16 to November the limit is 13.5.

[7] Figure 10 shows the map of gasoline specifications required across U.S. as of June 2014.

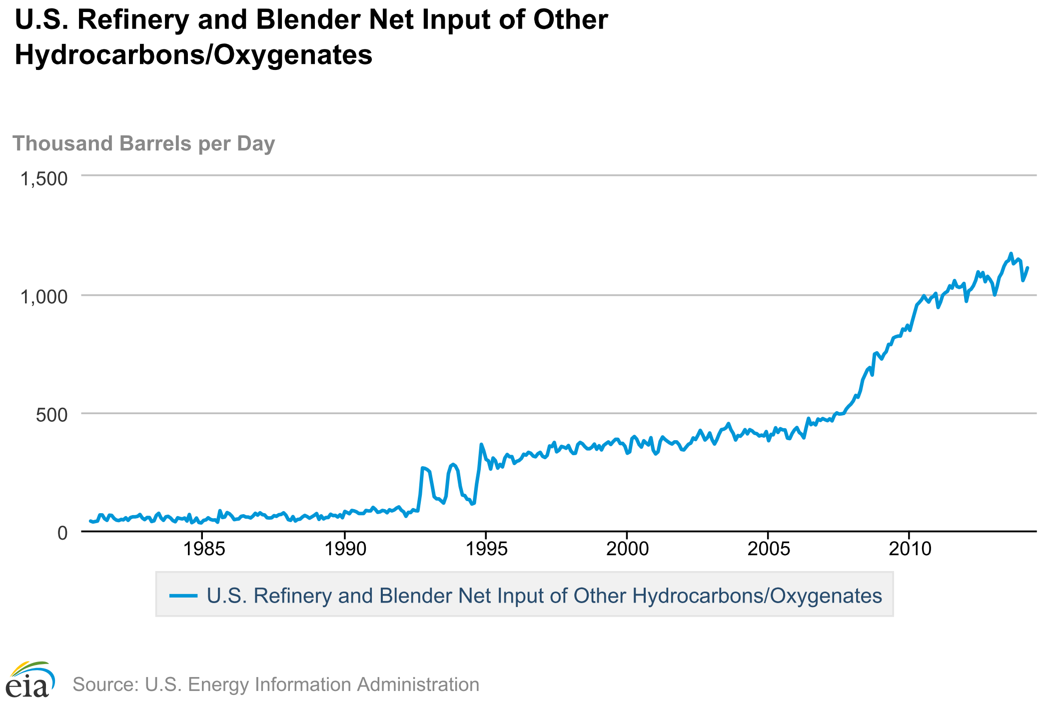

Figure 9: U.S. Refinery and Blender Net Input of Other Hydrocarbons/Oxygenates (Thousand Barrels per Day)

B Data provided by U.S. Energy Information Administration

The U.S. Energy Information Administration (EIA) collects and aggregates information on energy production, consumption, imports/exports and prices across all energy sectors in the U.S. including crude oil, refined products and renewable fuels. To obtain the data it requires the agents involved in production, processing or transportation of abovementioned products to submit weekly, monthly and annual reports. The entities obligated to report include refineries, storage facilities, blenders, pipeline operators and renewable fuels plants as well as importers and all companies involved in maritime transportation of crude oil or petroleum products across the PAD districts (explained below).

For instance, all refineries within the U.S. must submit the monthly report (form EIA-810) by the 20th day of the next month The form has five sections pertaining to 1) operating capacity of atmospheric distillation units and their maximum capacities at the beginning of the month 2) average sulfur content

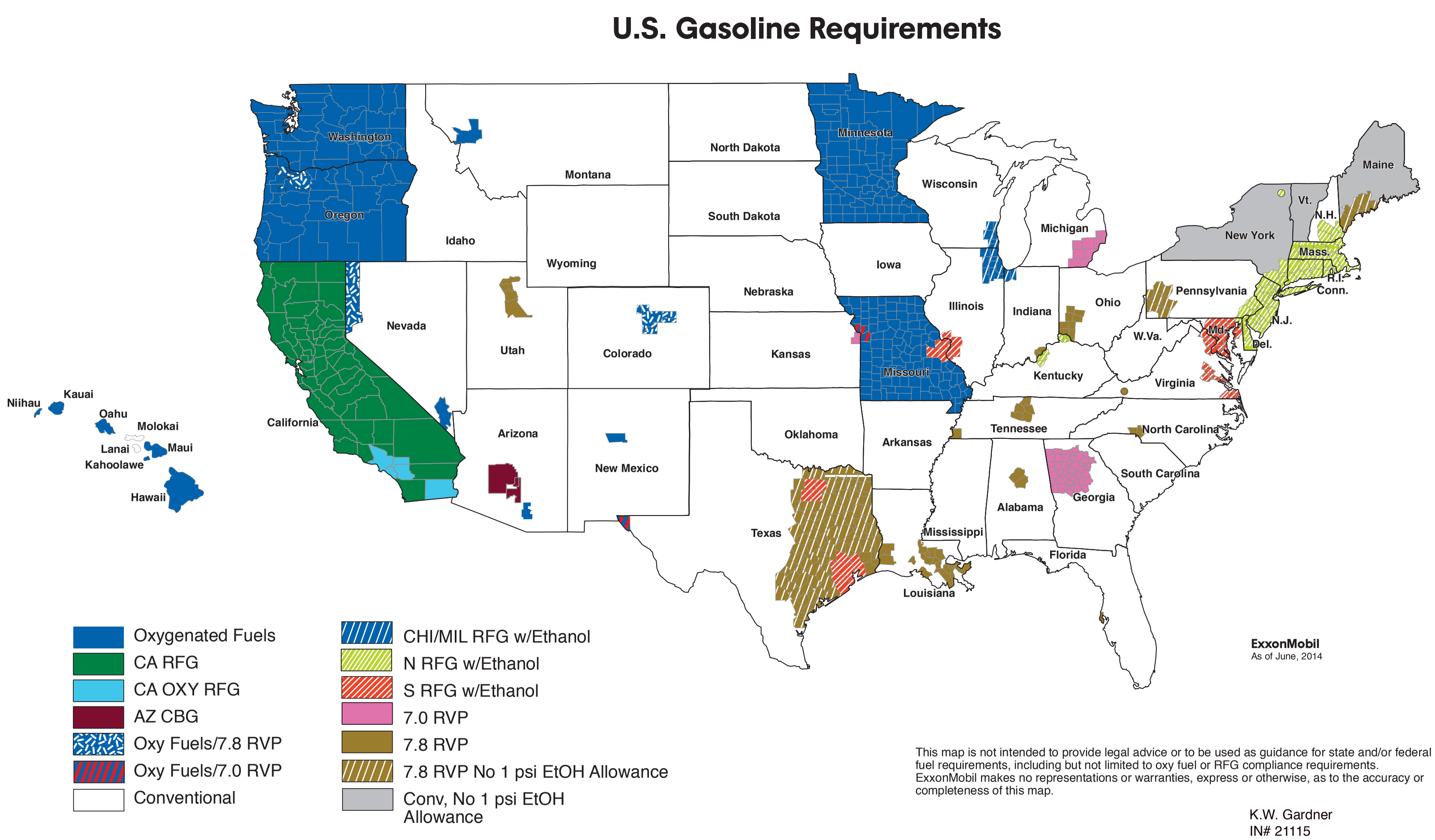

Figure 10: Map of gasoline specifications in the U.S. as of June 2014. Reproduced with the permission of K.W. Gardner

and API gravity of crude oil feedstocks 3) inputs of crude oil to ADUs and advanced processing units (e.g. crackers or naphtha reformers) 4) beginning and ending stocks, receipts, inputs, production, shipments across a detailed categorization of petroleum and related products 5) storage capacities for crude oil and the refined products.

The reported numbers are typically aggregated regionally across so-called Petroleum Administration for Defense Districts (PADDs) which were originally invented by the state agency with the same name responsible for rationing gasoline supplies during the Second World War. Consolidated statistics are disseminated in a number of periodical reports (such as Petroleum Supply Monthly and Refinery Capacity Report) and are available from EIA's website.

Refinery and blender production of finished products is available at monthly frequency starting from 1982. It is computed by taking out net inputs from the reported production numbers. In addition, data for blenders and refineries separately is available from 2005. Since then the production of finished gasoline has clearly shifted from refineries to standalone blenders without refining capacity: in 2013 blenders accounted for 75% of the total production versus 35% in 2005.

Speaking of demand proxies the common practice, according to EIA, is to use the *product supplied* quantities which essentially captures the disappearance of products from so-called primary supply chain consisting of refineries, blenders, large bulk storage terminals and pipelines. To be more precise, the key inputs to the U.S. product supplied are net production (+), stock changes (−), imports (+) and exports (−). Once a product left the primary market it enters the smaller-scale distribution network which includes retail gas stations and heating oil dealers as well as small bulk plants.[8] Since it takes time for a product to go through the secondary system before it is bought by an end user the actual consumption may be slightly different from the product supplied.

Arguably the best proxies for consumption itself are given by *prime supplier sales volumes* which are obtained directly using a separate survey (EIA-782C) rather then implied from aggregate data. EIA defines a prime supplier as a "...a firm that produces, imports, or transports any of the selected petroleum products across State boundaries and local marketing areas and sells the prod-

[8] EIA defines smaller bulk plants as those having less than 50000 bbl in capacity and receiving products only by truck or rail. A typical capacity of a gasoline tanker truck is 190-240 bbl

uct to local distributors, local retailers, or end users". The changes in gasoline product supplied and prime supplier sales volumes are highly correlated (0.88) but the levels diverge with a systematic trend.

The direct data on crude oil purchase prices paid by refineries is available for U.S. since 1974 and by PADDs starting from 2004. Those prices include all costs associated with transporting the oil to a refinery. Purchase costs can be also proxied by well-known benchmark prices (such as WTI spot and futures prices). In addition, for crude oils produced within the U.S. there are first purchase prices available either by crude oil stream, API gravity or state while for imported oil there are prices reported by crude stream, API gravity and the exporting region/country.

For gasoline there are also well-known benchmark prices including spot and futures prices for RBOB blendstocks at New York Harbor, spot CBOB at the same location, spot CBOB at the Gulf Coast and, finally, spot CARBOB at Los Angeles. EIA also provides detailed regional retail prices prices by grade (regular, midgrade, premium) and formulation (regular, conventional) as well as average monthly refiner sales prices by area, grade and sales type (for resale or to end users).

Alternative spreads Inspection of alternative crack spreads can explain two peculiarities of gasoline crack spread constructed using the spot price of gasoline at the New York Harbor and that of WTI crude oil, namely occurrence of negative values and a significant increase in the spread starting in 2011.[9] The increase in the spread is likely to be related to relative depreciation of WTI price compared to other price benchmarks. Occurrence of negative spread values, at least in 2008, is likely to be caused by the fact that the price of heating oil (which is a complementary product in the production of gasoline) was unusually high in the same year.

First I examine the alternative spot crack spread constructed using the Brent spot price instead of WTI spot price. Prior to 2011 I find no notable differences between the two spreads. The average difference between them from 1984 to 2011 is 0.65$ (per barrel) with WTI-based spread being smaller on average. However, the average of the Brent-based spread after 2011 is only 9.34$ which is much smaller than the average of the WTI-based spread (25$

[9]There are multiple periods when this spread is negative. It happens briefly in February 2006 and repeatedly in 2008. In March 2008 the spread is negative for one week (-5$ per barrel), then it is again negative in the first half of July (-2.5$ to -1.5$), and, finally, the spread stays below zero for one month in November 2008 (-3.5$ to -2.5$).

per barrel) and more in line with the historical spread levels before 2011.

The analysis of crack ratios instead of spreads leads to the same conclusion. The average difference between the ratios is only -0.06 before 2011 is while for the period starting from 2011 it is 0.18. The correlations between the changes of the two time series are not very different for the two subperiods (0.81 vs 0.78). The time series of the two crack ratios are shown in Figure 11.

[Figure 11 about here.]

The likely reason for the divergence of Brent and WTI crack spreads are the logistical constraints depressing the WTI benchmark. Borenstein and Kellogg (2012) argue that in 2011 the insufficient pipeline capacity to move crude oil from the new fields in the U.S. Midwest and Canada led to a relative depreciation of WTI prices compared to the global oil market. Since Brent crude oil price spread behaves similarly to WTI price spread before 2011 the former is probably a better benchmark for the gasoline traded in the New York Harbor starting in 2011.

The relative irrelevance of WTI price after 2011 is supported by the data on historical refineries' purchasing prices provided by the EIA.[10] Indeed, purchasing prices for the refineries in the Gulf Coast (PADD2) and the Midwest (PADD3) diverged substantially starting from 2011.

It is hard to identify the single reason why the NYG/WTI crack spread has become negative in 2008 as it was an eventful year for U.S. gasoline and crude oil markets. Firstly, in July 2008 the oil price itself reached the all time high of roughly 143.68$ as shown on the bottom plot of Figure 12. It is debated whether or not the market was somehow distorted in summer 2008 and detachment of WTI crude oil price from the supply/demand fundamentals is a possible reason for the negative crack spread.

[Figure 12 about here.]

Secondly, in addition to the oil price peaking in July the U.S. oil production and the refining industry were clearly affected by the hurricane Ike which hit the Gulf Coast on September, 13. In addition to the clearly identifiable spread

[10]The exact name of the dataset is "Refiner Acquisition Cost of Crude Oil". Aggregated U.S. monthly data is available from 1974 while separate data for each of the PADDs is available from 2004.

spike immediately after the storm there could have been longer-term effects which could contribute to the spread becoming negative in November.

Finally, the negative gasoline crack spread in 2008 could be related to the relative deficit of diesel fuel in 2008. The top plot in Figure 12 shows the heating oil crack spread against the gasoline crack spread computed using spot prices of finished products at the New York Harbor and the spot price of WTI crude oil. Clearly, diesel spread was exceptionally high in 2008 and since diesel cannot be produced without producing gasoline as well it is plausible that negative crack spread was caused by a relative overproduction of gasoline.

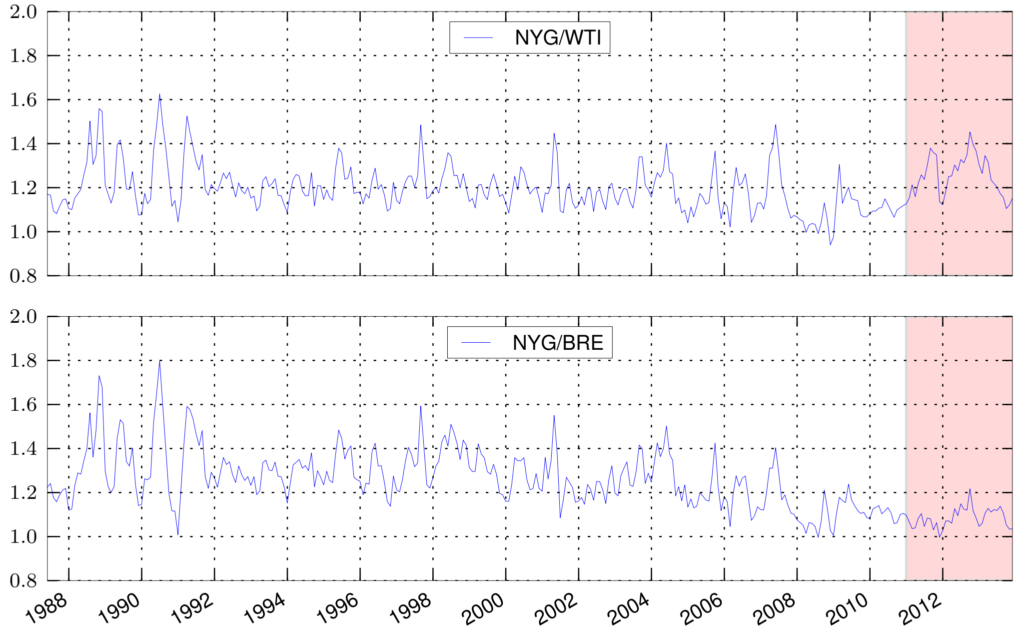

Figure 11: The ratio of the monthly gasoline spot price at the New York Harbor and monthly average WTI spot price (top). A similar ratio with the Brent spot price instead of WTI spot price (bottom) Highlighted is the divergence between the two starting in 2011. Data: U.S. Energy Information Administration (EIA).

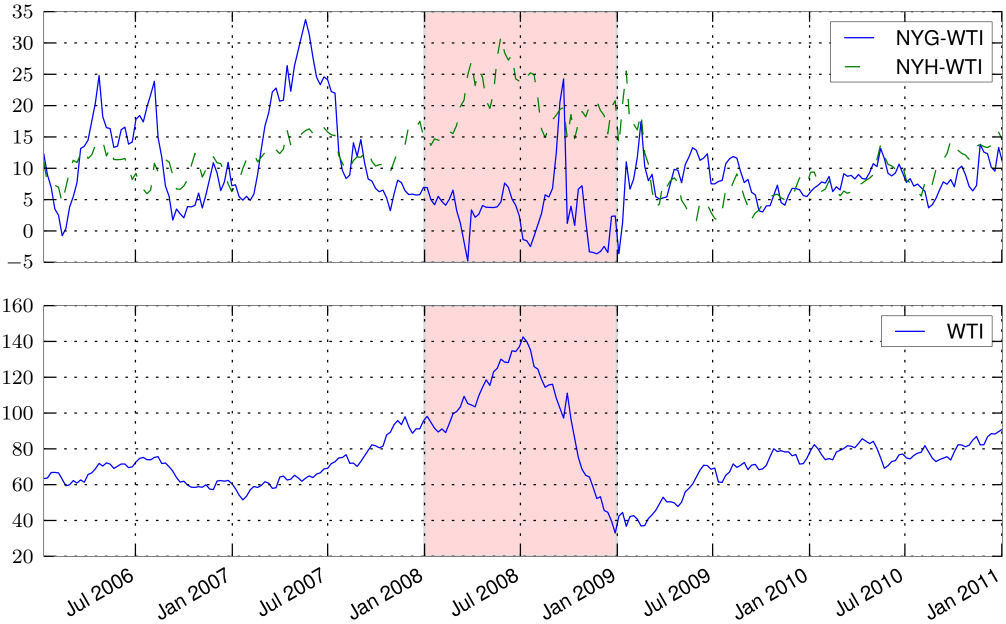

Figure 12: Gasoline and heating oil spot crack spreads from 2005 to 2011 (top). WTI spot crude oil price (bottom). Crack spreads are computed using spot prices at New York Harbor and WTI spot crude oil price. Highlighted region corresponds to 2008. Data: U.S. Energy Information Administration (EIA).