Empirical Assessment of Baseline Conservation Tillage Adoption Rates and Soil Carbon Sequestration in the Upper Mississippi River Basin

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1. Introduction

In recent years, there has been a widespread discussion about the policies that might be adopted to foster the use of farming practices that sequester carbon in agricultural soils (e.g., Antle and McCarl, 2002). Among these practices, conservation tillage (CT) is regarded as one of the most effective in increasing carbon content in many agricultural soils. Since scores of farmers use CT without policy intervention, a key question associated with any policy designed to increase the adoption of CT to induce higher carbon sequestration is the amount of carbon that can be directly credited to the program versus that which would have occurred anyway (Antle and McCarl (2002), Thomassin (2003), Murray (2004)). To answer the question, the baseline which represents "business as usual" (BAU) conditions is needed to rightfully account for the *additional* carbon generated due to a policy, i.e. the carbon that would be sequestered in addition to the amount that would have been sequestered in the absence of the carbon purchasing project.

This study proposes a methodology for estimating a BAU baseline for the adoption of CT in corn and soybean production and the associated carbon sequestered and empirically implements the procedures in the Upper Mississippi River Basin (UMRB) region in the central U.S. An integral component of the methodology developed is the explicit acknowledgment that there is an uncertainty in the baseline originating from the use of an econometrically estimated model. As a consequence, rather than representing the baseline as a series of point estimates associated with baseline tillage and carbon sequestered, our method allows presenting the results in the context of probabilities of adoption and distributions of carbon sequestered.

The paper is organized as follows. Section 2 describes the study region and data. In sections 3, we present the methodology for estimation of the baseline and apply it for UMRB. In section 4, we summarize the main findings and discuss limitations.

2. Study region and data

The UMRB is a large watershed at the head of the Mississippi River covering parts of the central U.S. Cropland and pasture are the dominant land uses in the UMRB, which account for about two thirds of the total area. The watershed is comprised of 14 sub-watersheds that coincide with the boundaries of U.S. Geological Survey Hydrologic Units, commonly referred to as 4-digit Hydrologic Unit Codes (HUCs) (Figure 1).

The primary data used in the study is the 1997 Natural Resource Inventory (NRI) (Nusser and Goebel, 1997). The NRI is a statistically based database that was updated every five years from 1982 to 1997 for the entire non-federal land in the U.S. with information such as soil type, landscape features, cropping histories, and conservation practices. Each NRI "point" represents an area, generally ranging from a few hundred to several thousand acres in size, which is assumed to consist of homogeneous land use, soil, and other characteristics. The 1997 NRI contains information for 1982, 1987, 1992, and 1997. However, CT use information is provided only in 1992 and hence the 1992 data are initially used to fit CT adoption models. After the CT adoption models are estimated with 1992 NRI data, they are calibrated for use with 1997 NRI data.

The study uses over 28,000 NRI points that are reported in corn or soybean production in 1997 (Table 1). Overall, our sample covers 90% of the total UMRB cropland under corn and soybeans.

3. Estimation of the CT and carbon sequestration baseline.

We follow five steps in developing the baselines: 1) econometrically estimate a CT adoption model for each sub-region of the UMRB, 2) calibrate the estimated model to the most recent data on CT adoption rates available, 3) combine the adoption model estimates with field specific carbon sequestration estimates to generate a baseline assuming that all explanatory variables in the model remain fixed at 1997 levels, 4) generate confidence intervals around these point estimates , and 5) relax the BAU assumption and generate baseline estimates under a variety of assumptions about changes in explanatory variables. The remainder of the section details the five steps outlined.

3.1. Econometric estimation of a CT adoption model draws heavily on the empirical estimates and methods developed in Kurkalova et al. (2005) and Sengupta et al. (2005). The basic model from Kurkalova et al. (2005) assumes that a farmer adopts conservation tillage when $\pi_1 > \pi_0 + P$, where π_1 represents the net returns to farming using CT, π_0 is the net returns to the conventional practice, and P is a risk premium needed for adoption. Assuming a binary choice, an additive logistically distributed error, ε, with standard deviation multiplier, σ, to represent omitted variables, a linear net returns function, $\boldsymbol{\beta}\mathbf{x}$, and a premium function P(**z**), the probability of adoption is

$$\begin{aligned}\Pr\left[adopt\right] &= \Pr\left[\pi_1 \geq \overline{\pi}_0 + P + \sigma\varepsilon\right] \\ &= \Pr[\boldsymbol{\beta}\mathbf{x} \geq \overline{\pi}_0 + P + \sigma\varepsilon] \qquad (1) \\ &= \Pr[\varepsilon \leq \frac{\boldsymbol{\beta}\mathbf{x}}{\sigma} - \frac{\overline{\pi}_0}{\sigma} - \frac{P(\mathbf{z})}{\sigma}],\end{aligned}$$

where **x** and **z** are vectors of explanatory variables including a range of soil and land characteristics and the bar on $\overline{\pi}_0$ denotes that this variable is known. The coefficients of the net returns to the CT can be recovered from maximum likelihood estimates of the model.

In addition to the specification (1), Sengupta et al. (2005) also consider a specification that describes the probability of adopting conservation tillage as a function of the difference in the net returns between conventional and conservation tillage. In this case, instead of viewing the returns to conventional tillage as being known and that to CT being unknown, it is assumed that the average returns to both tillage methods are known. Then the model can be written as

$$\begin{aligned}\Pr\left[adopt\right] &= \Pr[\boldsymbol{\beta}\mathbf{x} \geq \bar{\pi}_D + P + \sigma\varepsilon] \\ &= \Pr[\varepsilon \leq \frac{\boldsymbol{\beta}\mathbf{x}}{\sigma} - \frac{\bar{\pi}_D}{\sigma} - \frac{P(\mathbf{z})}{\sigma}],\end{aligned} \tag{2}$$

where $\bar{\pi}_D$ denotes the difference in net returns to conservation and conventional tillage. In this specification, $\boldsymbol{\beta}\mathbf{x}$ represents the point-specific deviation in the increment in returns to CT over conventional till from the average, rather than the total return to CT. We refer to models (1) and (2) as *level* and *difference* models, respectively.

In estimation, the data from the NRI are augmented with information on net returns, climatic data and farm characteristics as detailed in Kurkalova et al. (2005). The conventional tillage net returns and, where needed, the CT net returns, are constructed for each NRI point through farm budget analysis, specifically by combining county-specific average yield data, state-specific price data, and region-, tillage-, and rotation-specific cost data. Finally, each NRI point is assigned to a weather station based on the county of location, and 1975-94 weather station data are used to construct growing season average temperature and precipitation data. Summary statistics for the data used in CT model estimation and baseline simulation are reported in Table 2.

Separate tillage models are fit to each of the 4-digit HUCs constituting UMRB to represent the distinct features of each area's climate, landforms, and cropping practices. The information on the procedures followed and the resulting properties of the estimators are available in Sengupta et al (2005).

*3.2. Calibration of the estimated models to the most recent data on tillage adoption rates available for the region***.** The latest available 1997 NRI dataset does not have any information on the use of CT beyond 1992. Thus, we use the 1997 region-average CT use estimates derived by Kurkalova and Carriquiry (2005) from Agricultural Resource Management Survey (ARMS) data (http://www.ers.usda.gov/data/arms/) and county-level estimates reported by Conservation Technology Information Center (http://www.ctic.purdue.edu/CTIC/CTIC.html) to calibrate the 1992-estimated CT adoption model. Specifically, the models (1) or (2) used with 1997 NRI are assumed to have the additional additive shift parameters. The values of the parameters are chosen so that the region-average model-predicted rate of adoption of CT is equal to that derived from the CTIC and ARMS data.

3.3. Business as usual baseline is estimated as follows. We first assess the carbon sequestration potential of each cropland NRI point using the Erosion Productivity Impact Calculator (EPIC) model (Williams, 1990) and then combine the carbon estimates with the estimates of the probabilities of CT adoption from the calibrated model. The NRI point level carbon sequestration estimates are computed as the annual average difference of the total soil carbon pool under two scenarios: one assuming 30 years of CT and the other assuming 30 years of CT.

Our per acre estimates of carbon sequestration potential are at the lower end of those reported in the literature. While our maxima are in agreement with West and Post (2002), the means in our sample are lower, which is consistent with the way we model both conventional and conservation tillage. Instead of comparing extremes, i.e. conventional till and no-till as

West and Post (2002) do, we deal with the whole spectrum of tillage systems. On the CT side, we consider ridge till and mulch till in addition to no-till. Similarly, on the conventional tillage side, we model conventional tillage both with and without moldboard plowing, yet this distinction is known to significantly impact soil carbon content (Almaras et al., 2000). Another reason for lower and sometimes negative estimates of carbon sequestration is that not all soils are expected to sequester carbon when conventional tillage is replaced with CT (Lal, 2001). Particularly, a reduction in tillage intensity on the soils with high clay content and colder and/or wetter climates may lead to crop failure and thus to a reduction in soil carbon content.

The baseline watershed-level CT adoption rate is estimated as

$\sum_{i\in\{watershed\}} p_i a_i \Big/ \sum_{i\in\{watershed\}} a_i$, where p_i is the probability of adopting CT at the i-th NRI point, and a_i is the number of acres represented by the point. The baseline soil carbon sequestration in each of the watersheds is estimated as

$$\sum_{i\in\{watershed\}} p_i c_i a_i \, . \qquad (3)$$

Here c_i is the EPIC-estimated annual change in soil carbon content due to the change in farming practices from conventional to conservation tillage. In estimating the BAU baseline, we assume that all explanatory variables in the models remain unchanged in the future. This assumption is relaxed later as described in section 3.5.

3.4. Confidence intervals and distributions around baseline point estimates are generated using a bootstrap-like procedure of Krinsky and Robb (1986). The approach builds on the observation that maximum likelihood estimators of the discrete choice (logit) model are asymptotically unbiased and distributed as multivariate Normal random variables. Therefore, random draws from the multivariate Normal distribution with the mean equal to the estimates of the model parameters and variance equal to the estimated variance-covariance matrix of the parameters can be treated as the draws from the multivariate distribution of the parameters of the model. With a large number of draws, Monte-Carlo techniques can be used to describe the distributions of any smooth functions of the parameter estimators.

To implement the procedure, we first randomly generate the parameters of the CT models. Next, we calibrate the CT models to the region-average CT adoption rates and use calibrated models to predict the probabilities p_i of CT adoption at each NRI point in the analysis. Then we use formulas (3) to estimate the baseline in every watershed in the analysis. We repeat this process for 10,000 draws and then summarize the empirical distributions of the quantities of interest using Monte-Carlo techniques.

The results for the BAU scenario are summarized in Table 3 and in Figure 2. Interestingly, we found tight confidence bounds on the baselines both for each watershed and for the UMRB area as a whole, both for CT adoption rates and for carbon sequestration. As expected, the baseline point estimates differ significantly across watersheds reflecting the differences in soils, landscape, and other factors affecting crop production and conservation tillage adoption, as well as in the area under crops (Figure 2).

3.5. Baseline estimates for non-BAU scenarios are obtained by first estimating the trends in several explanatory variables of the CT adoption model and then using the estimates to estimate the trend in CT adoption. Specifically, we use Census of Agriculture (http://www.nass.usda.gov/census/) county-level data to estimate the 1992 to 1997 change in four explanatory variables of the CT adoption model: proportion of county cropland operated by tenants, proportion of county operators working off farm, county-average farm operator age, and proportion of county operators that are male, separately for each county in the analysis.

The estimates of the changes are then used to predict the values of the four explanatory variables in 2007 under the assumption that the identified linear trend will continue. The baselines computed when the four 1997 explanatory variables are replaced with the predicted 2007 values are summarized in Figure 3. We find that if the identified linear trend in the farmer characteristics continues, we may expect the UMRB baseline to increase, though the difference in the 1997 and 2007 baselines varies significantly by watershed (Figure not reported).

To investigate the effect of changes in fuel prices, which contribute to other explanatory variables, the net returns to conventional tillage and those to CT, we use our estimates of the fuel costs. An increase (decrease) in fuel prices by 50% is modeled as a decrease (increase) in the net returns to conventional tillage by $0.5 \cdot (f_0 - f_1)$, where f_0 is the 1997 fuel cost under conventional tillage and f_1 is that under CT. Somewhat surprisingly, we do not find a significant effect of the fuel price changes on the baselines as reflected in the large overlap of the corresponding histograms in Figure 4. As with other baselines, the results vary significantly by watershed (Figure not reported).

4. Caveats and Summary

This paper proposes a methodology for developing a carbon sequestration baseline resulting from the adoption of CT. The results of applying the method to a major crop production area in the central United States are reported for two major crops in the region, corn and soybeans. The approach to estimation of carbon sequestration baseline developed in this study should be readily transferable to other geographic areas and sequestration activities, both in the agricultural sector and forestry.

In brief, the methodology begins with the econometric estimation of CT adoption model. Second, due to limitations in the data, we calibrate the model parameter estimates to more recent data on tillage adoption rates available for the region, and combine the model estimates with field specific carbon sequestration estimates obtained from the EPIC model to generate a BAU baseline. Given the sampling uncertainty resulting from an econometric procedure, we estimate confidence intervals for the BAU baseline estimates. Finally, we recognize that the BAU baseline may not be the best estimator of the "without policy" baseline as changes in various exogenous variables may drive changes in the underlying adoption rates of CT, even in the absence of carbon promoting policies. Thus, we derive baselines estimates under changes in farmer characteristics and fuel prices.

A number of interesting and robust results appear. First, we note that there are wide variations in the BAU baselines across the fourteen sub-watersheds in the study region. Given the wide heterogeneity of soils, weather, crop rotations, and adoption rates of conservation tillage, this is probably not surprising. However, it does point out the importance of using models that capture the full spatial heterogeneity of soil, weather, and other characteristics in establishing baseline estimates. A second, and encouraging, finding is that the confidence intervals derived for the baseline are uniformly tight. This suggests that even if point estimates with no confidence bounds were considered in establishing baselines, there would be relatively little chance of greatly over- or understating the total carbon sequestered. This, of course, may not hold true in other applications.

A third finding of note is that the BAU can change considerably when explicit recognition is taken of the fact that average farmer characteristics will be changing in the future. In our particular case, recognition of these changes using Census of Agriculture data results in an increasing carbon sequestration trend under the baseline. The changes are large and clearly indicate that if account is not taken of these non-policy changes, the baseline would be incorrectly specified. The final non-policy variable we consider in estimating baseline carbon adoption rates is the effect of fuel prices. Unlike farmer characteristics, we do not have a clear prediction as the magnitude or even direction of the change of fuel prices. While initially somewhat surprising, this result is consistent with the fact that fuel prices, while an important part of the cost of farming, are only one of many costs.

Several caveats are worth noting. First of all, as for any analyses of carbon sequestration in agricultural soils, our results are contingent upon the state of the art in physical simulation of carbon processes. As the EPIC model improves and is calibrated to the newest field trial data, the empirical results obtained may change. Also, the absence of reliable data on net returns and costs of production precluded us from expanding our analysis to the crops other than corn and soybeans. There may be significant carbon sequestration potential available from those crops. Work is currently underway to incorporate sorghum and wheat areas in future analyses of carbon sequestration potential in the UMRB.

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Table 1. UMRB cropland analyzed: selected statistics

Watershed	Corn area, 1000 acres	Soybean area, 1000 acres	NRI points
7010	704	538	555
7020	2,645	2,769	2,501
7030	269	41	198
7040	1,144	524	1,263
7050	505	0	217
7060	1,663	513	1,429
7070	654	0	331
7080	5,605	4,377	6,436
7090	2,536	759	2,409
7100	2,920	2,861	3,351
7110	888	1,290	1,326
7120	1,948	1,355	2,339
7130	4,231	3,772	4,511
7140	1,398	1,480	1,877
UMRB	27,110	20,277	28,743

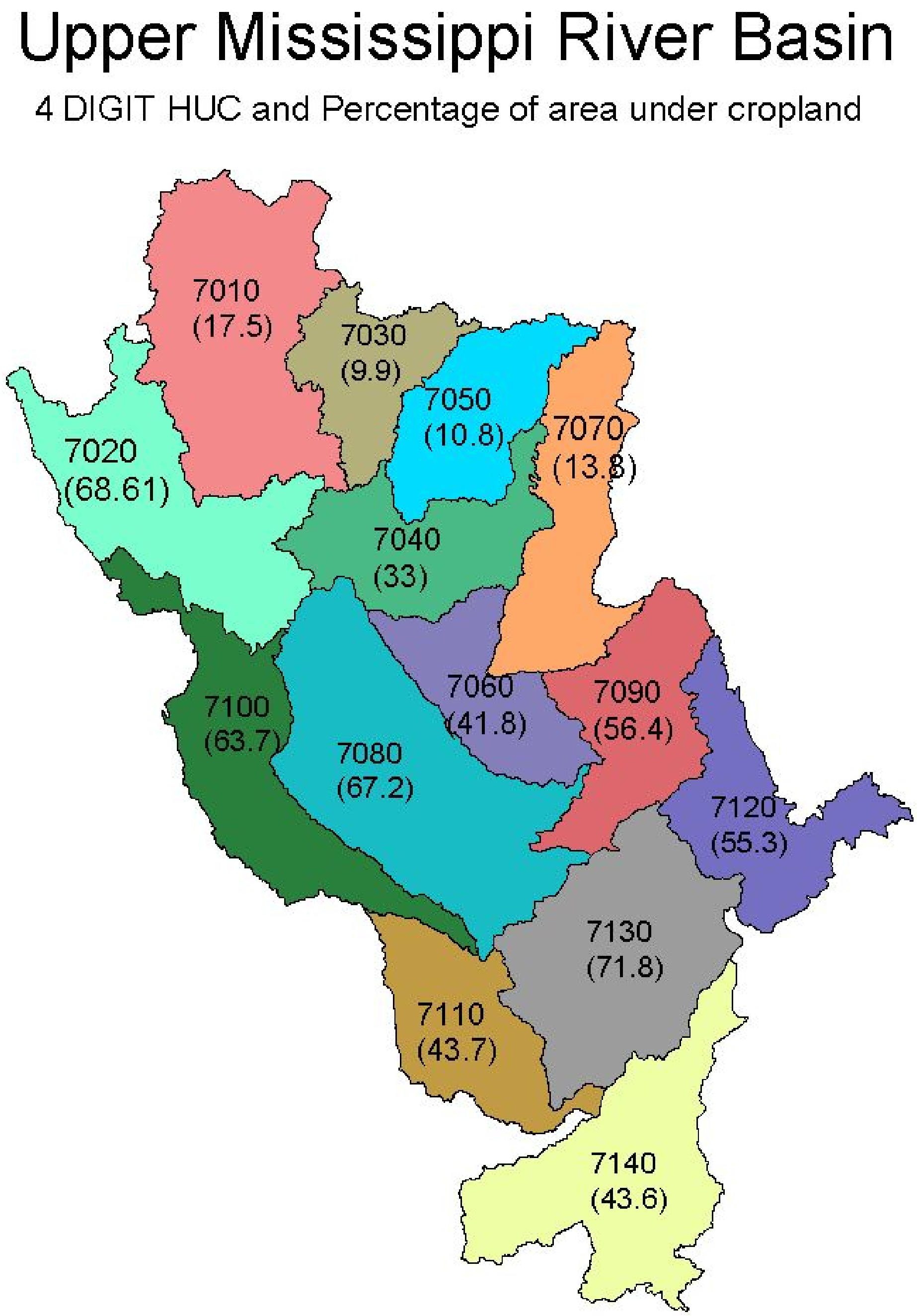
Table 2. Summary statistics for the data used in conservation tillage adoption model

Variable	Mean	Standard deviation	Minimum of watershed means	Maximum of watershed means
Net returns to conventional tillage, $ per acre	110	29	56	154
Net returns to conservation tillage, $ per acre	119	28	70	162
Land slope, percent	28%	32%	15%	60%
Soil permeability, inches per hour	1.3	1.7	0.9	3.0
Soil available water holding capacity, percent	21.1%	3.2%	19.0%	22.0%
Erodibility index	6	10	3	14
Organic matter	4.3	5.4	2.5	6.4
Soil acidity	6.52	0.48	6.01	7.06
Mean of daily maximum temperature over growing season, Fahrenheit	78.6	2.7	74.8	82.4
Mean of daily minimum temperature over growing season, Fahrenheit	55.5	2.8	50.8	59.3
Mean of daily precipitation over growing season, inches	0.123	0.015	0.113	0.135
Variance of daily precipitation over growing season, inches squared	0.097	0.020	0.082	0.110
Proportion of county cropland operated by tenants	0.162	0.063	0.039	0.209
Proportion of county operators working off-farm	0.526	0.051	0.469	0.604
County average farm operator age, years	52.5	1.7	50.1	54.8
Proportion of county operators that are male	0.970	0.012	0.949	0.981
County rural code (0 to 9, 9 is for completely rural)	5.4	2.4	3.3	7.1

Table 3. Baseline conservation tillage adoption in the UMRB

Watershed	Minimum	5th percentile	50th percentile	95th percentile	Maximum	Standard Deviation
7010	0.086	0.234	0.312	0.369	0.467	0.043
7020	0.151	0.201	0.247	0.295	0.328	0.028
7030	0.143	0.200	0.264	0.340	0.403	0.043
7040	0.181	0.217	0.265	0.319	0.440	0.031
7050	0.317	0.371	0.432	0.495	0.553	0.038
7060	0.226	0.385	0.461	0.556	0.834	0.059
7070	0.178	0.314	0.400	0.523	0.856	0.069
7080	0.487	0.527	0.578	0.630	0.674	0.031
7090	0.191	0.327	0.391	0.468	0.860	0.056
7100	0.368	0.453	0.513	0.574	0.633	0.037
7110	0.292	0.353	0.422	0.493	0.550	0.043
7120	0.393	0.434	0.473	0.512	0.548	0.024
7130	0.471	0.502	0.537	0.573	0.609	0.022
7140	0.380	0.422	0.463	0.505	0.554	0.025
UMRB	0.424	0.445	0.463	0.481	0.508	0.011

Figure 1.



Upper Mississippi River Basin
4 DIGIT HUC and Percentage of area under cropland
7010
(17.5)
7020
(68.61)
7030
(9.9)
7050
(10.8)
7070
(13.8)
7040
(33)
7060
(41.8)
7090
(56.4)
7100
(63.7)
7080
(67.2)
7120
(55.3)
7130
(71.8)
7110
(43.7)
7140
(43.6)

Figure 2. BAU baseline, by watershed

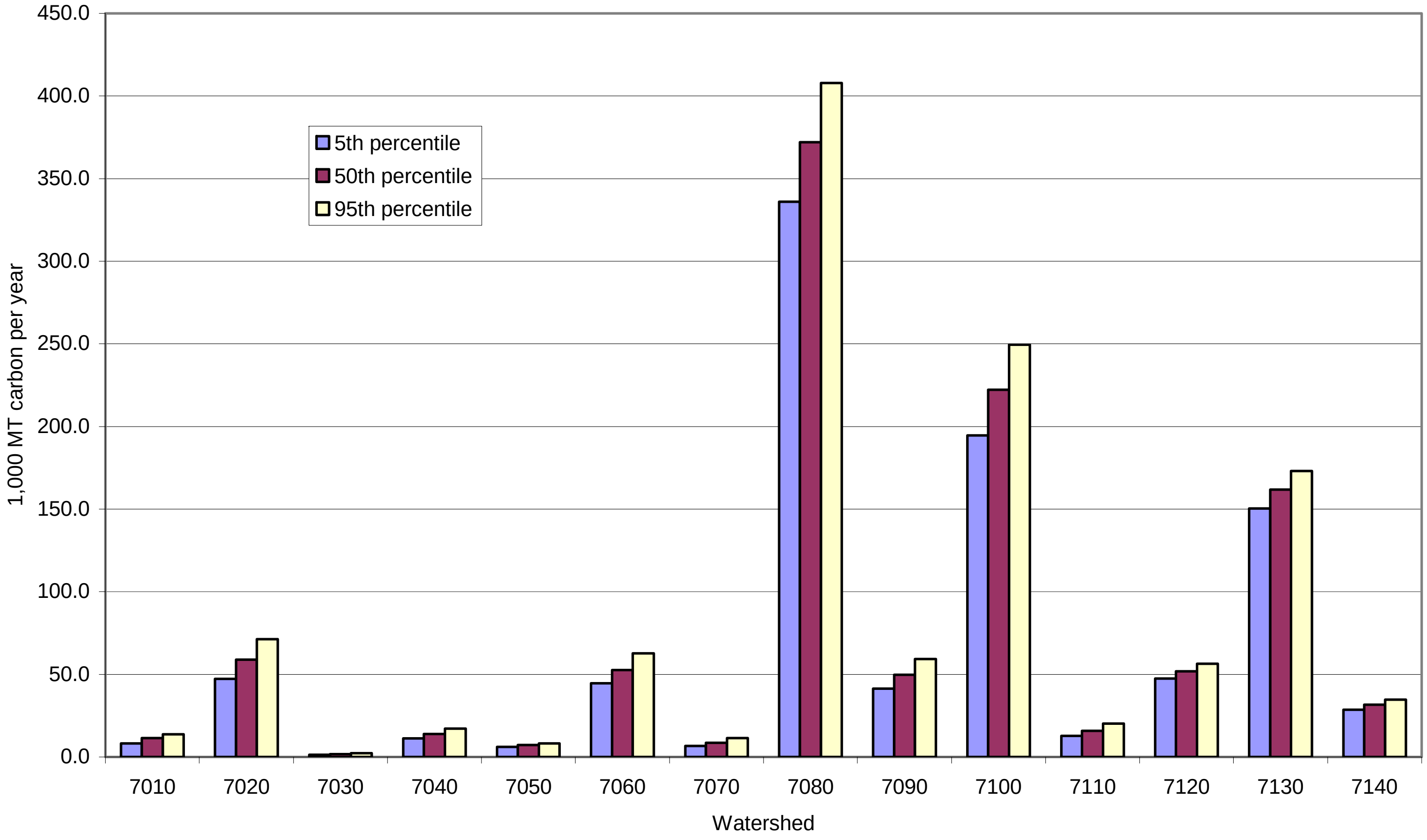


Figure 3. Effect of changes in farmer characteristics on UMRB baseline: 1997 versus 2007

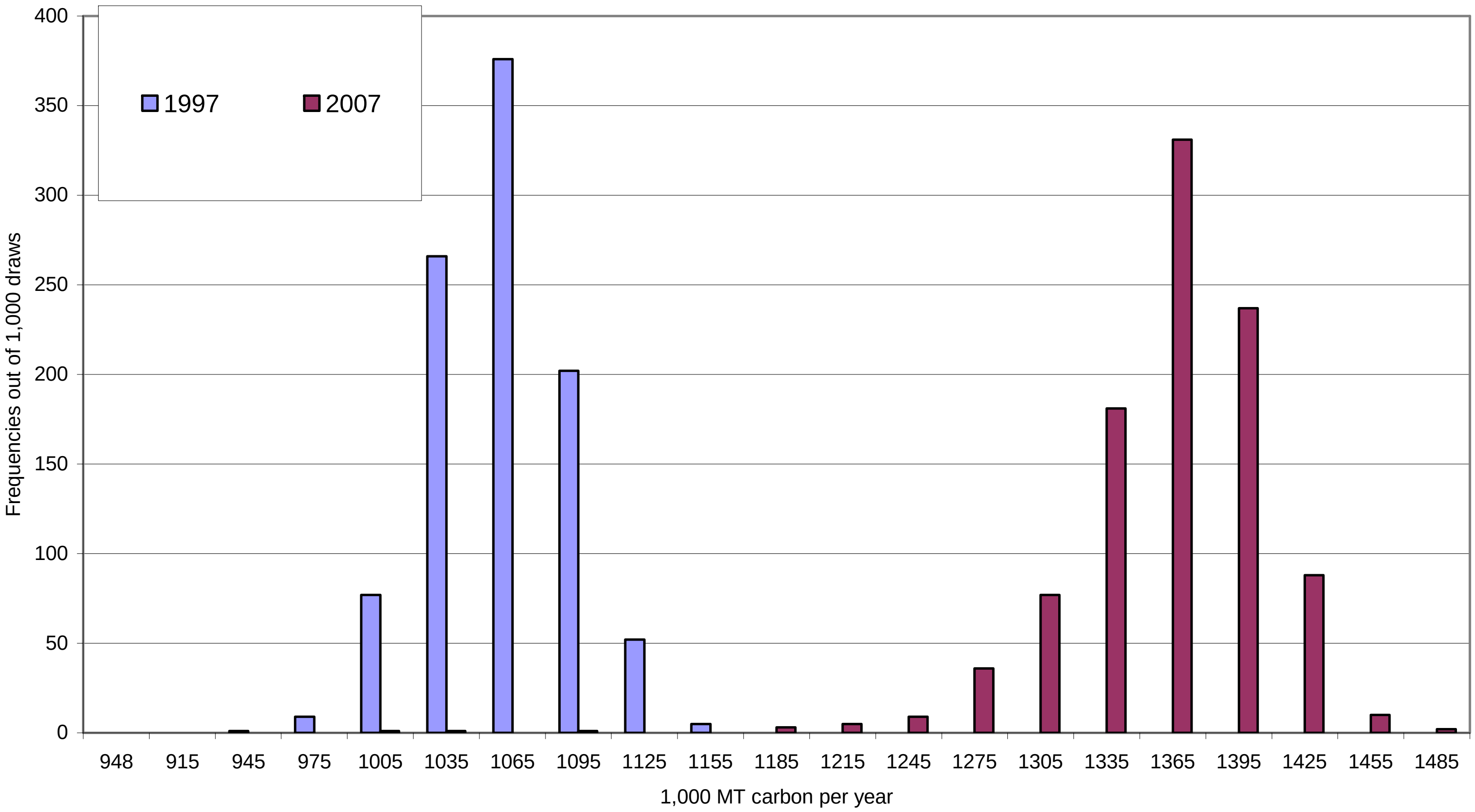


Figure 4. Effect of fuel prices on UMRB baseline