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A Simulation of Factors Impeding Water Quality Trading

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Abstract. While there is substantial evidence that nonpoint sources have lower nutrient reduction costs than point sources, experience with water quality trading (WQT) reveals a common theme: little or no trading activity. The success of WQT seems, in part, to depend on the structure of the market created to bring buyers and sellers together to transact exchanges. To examine the ways that various market imperfections may affect the performance of a WQT market, a model is constructed which simulates a hypothetical point-nonpoint market. This paper focuses on answering the following question: How can WQT programs be designed in ways that take into account factors that result in non-optimal contracting and what are the implications (if there are any) for determining trading ratios? Here, we find that apart from any implications for environmental risk or political-economic factors, there is an economic welfare justification for high trading ratios in certain situations with limited trading information and/or other barriers to trade. Limited information and other barriers to trade which inhibit the optimal contracting of trades introduces a random element to market participation, creating a risk that high-cost sellers (low-value buyers) will transact to displace low-cost sellers (high-value buyers) who could have traded for greater gain.

1. Introduction

With numerous water quality goals remaining unmet and many millions of dollars being spent on water quality improvement each year in the United States, there is an impetus to increase the economic efficiencies of pollution reduction (Peterson and Smith, 2012). Environmental economists have argued that pollution trading programs are an efficient means of improving environmental quality, as they give firms with the lowest pollution control costs the largest incentive to reduce pollution. Such low-cost firms are able to sell pollution credits to firms with higher control costs. Allowing firms with heterogeneous control costs the opportunity to cooperate displays the potential of reduced costs of pollution abatement. Such freedoms and flexibilities typically do not arise from traditional, uniform regulations.

Following on the highly successful trading programs for air emissions such as sulfur dioxide (NCEE, 2001), many states have recently adopted trading programs to improve water quality. There are at least 47 water quality trading (WQT) programs currently active or under development worldwide, with the overwhelming majority in the United States (Selman et al., 2009). In principle, such programs could be applied to any water-borne pollutant and allow trading among point sources, among nonpoint sources, or between point and nonpoint sources (the latter is known as 'point-nonpoint trading'). Most of the existing programs are designed with point-nonpoint trading to limit nutrient loading: point sources are allowed to meet their (reduced) nutrient emission limits by purchasing water quality credits from agricultural producers in the surrounding watershed. These producers are then obligated to implement a best management practice (BMP) that reduces expected nutrient loading by an amount commensurate with the number of credits sold. A regulatory agency lowering the acceptable limit of nutrient loading by point sources is the common "driver" necessary for the market to function.

From a conceptual standpoint, in a well-functioning market with perfect information and zero transaction costs, and where traders' decisions are motivated purely by the economic gain from trading, agents' propensity to trade is perfectly correlated with their relative positions along the demand and supply curves. Heterogeneity in point sources' willingness to pay (WTP) for credits brings about a downward sloping demand curve, where the sources with the highest WTP have the greatest likelihood of trading. Similarly, heterogeneity in nonpoint sources' costs or willingness to accept (WTA) payment for credits generates an upward sloping supply curve, where the sellers with the lowest WTA trade with the highest likelihood. In the case of a competitive, frictionless market, the equilibrium price is at the intersection of demand and supply and all buyers (sellers) with a WTP greater than (less than) or equal to this price will trade and all other potential traders will not. This outcome maximizes the social gain from trading, the aggregate cost savings from allowing point sources to buy credits instead of upgrading technology to meet their discharge limits.

Evidence exists that nonpoint sources can reduce nutrient loading at a much lower cost than point source polluters in many watersheds, suggesting substantial scope and gains (or cost savings) from point-nonpoint trading (e.g., Faeth, 2000; Fang et al., 2005; Selman et al., 2009). Despite the potential gains, perhaps the most commonly noted feature of existing programs is low trading volume; none of the programs have had extensive trading activity and many have had no trading at all (Hoag and Kughes-Popp, 1997; Selman et al., 2009). A widely cited and vivid example is the Fox River program in Wisconsin (Hahn, 1989), which had only one trade after its inception in 1981 even though an early study (O'Neil, 1983) found substantial potential gains from trading among all participating firms.

These outcomes suggest the presence of obstacles to trading that were not recognized in the design of existing programs. While these obstacles have not been studied in a systematic fashion, individual researchers have identified various trading barriers in different contexts. Some of the barriers discussed in the literature are limited trading information, transaction costs, search costs, risk preferences, and distortionary trading ratios. Barriers such as these (excluding trading ratios) in the marketplace can reduce the correlation between the relative WTP/WTA and the propensity to trade (Atkinson and Teitenberg, 1991; Netusil and Braden, 2001). In other words, non-optimal contracting (the participation of buyers and sellers) can take place.

The trading ratio in point-nonpoint programs is typically defined as the quantity of expected nonpoint loading reduction needed to offset one unit of point source loadings. Many existing programs set trading ratios substantially greater than one, ostensibly to adjust for the greater risk and uncertainty in nonpoint loading reduction (EPA, 1996). Other programs include a trading ratio greater than one to ensure that there are net water quality benefits beyond what can be achieved through regulation alone (Selman et al., 2009). These are sometimes referred to as "retirement ratios". As discussed in detail later, Horan (2001) and Horan and Shortle (2005) have shown that higher trading ratios don't necessarily reduce risk because they discourage nonpoint sources from trading and adopting (risk reducing) BMPs. Thus, social risk preferences must be eliminated as a general justification for high trading ratios. The only remaining justification is loading retirement. Regardless of the motives behind trading ratios greater than one, such ratios operate like a tax to dampen the benefits from trading, hence reducing trading volume and overall gains from trading (Malik et al., 1993; Horan, 2001; Horan and Shortle, 2005; Hennessy and Feng, 2008).

How can WQT programs be designed in ways that take into account factors that result in non-optimal contracting, and what are the implications (if there are any) for the determination of trading ratios? To examine the ways that these market imperfections may interact to affect the performance of a WQT market, a model is constructed which simulates a hypothetical point-nonpoint market. In particular, the market is modeled using a variant of the sequential, bilateral trading algorithm proposed by Atkinson and Tietenberg (1991).

2. Relevant literature

While WQT has been promoted by economists as a cost-effective means to achieve water quality goals, experience with actual WQT programs has yet to produce these results. Several theoretical studies have investigated the factors impeding trading (e.g., Malik et al., 1993; Horan, 2001; Hennessy and Feng, 2008; Stavins, 1995), but very few articles have simulated an environmental trading market in action and only a small number of these have focused on water quality trading. Two notable exceptions have utilized trading simulations and relate to this research. An often cited article in the environmental markets literature is Atkinson and Tietenberg (1991), who simulated a sulfur dioxide trading market. Netusil and Braden (2001) followed with a simulation of a water quality market with varying transaction costs. There also are several relevant articles that addressed the effects of a trading ratio, including Horan (2001) and Horan and Shortle (2005).

Atkinson and Tietenberg examined the bubble policy of the Emissions Trading Program. They attempted to explain the divergence in costs between the least cost solution and incentive-based emissions trading approaches in air quality. More specifically, the article examined the hypothesis that a sequential, bilateral process cannot achieve a cost-effective equilibrium in markets dealing with non-uniformly mixed pollutants (those which tend to pool around sources within the regulated area).

The authors concluded that the amount of information available and the sequencing of trades played a large role in the amount of cost savings realized. They thought that the most realistic scenario should be found somewhere between the complete information, sequential trading scenario and the random partial information scenario (thus achieving anywhere between 7% and 88% of the least-cost benchmark). They did admit, however, that their cost savings results may be too optimistic because they did not account for transaction costs. They also suggested that a market for uniformly mixed pollutants (those which become dispersed uniformly in the regulated area) may come closer to achieving the least-cost benchmark.

Netusil and Braden (2001) built upon Atkinson and Tietenberg (1991) and extended their previous work in the area of transferable discharge permits. This is one of only a few studies that simulated markets for water quality. The authors examined the effects of sequential bilateral trading under imperfect information in a hypothetical sediment loading market. Their model allowed market participants to make multiple trades, as opposed to a single trade. Their research also incorporated different levels of transaction costs into each trade.

The data used in this analysis came from a 1,064 acre watershed area in Macon County, Illinois. Modeling was performed using a gains-ranked (high information) and a random (zero information) contracting scenario. The results showed that under the gains-ranked scenario, the sediment load under all transaction cost levels were lower than the regulatory policy's requirement. Another important finding in this scenario was that the distribution of internal and external contracts changed as the transaction costs levels changed. High transaction costs resulted in a decrease in overall trading and caused a shift towards internal contracting. An interesting finding was that as transaction costs increased, the overall spending on abatement activities (inclusive of transaction costs) can sometimes decrease. The reasoning is that high transaction costs block low value contracts from occurring and allow the higher value trades to happen. Under random contracting (zero information), however, an increase in transaction costs always resulted in an increase in abatement and total costs.

Horan (2001) and Horan and Shortle (2005) analyzed different levels of trading ratios in the context of water quality trading. Horan (2001) presented trading ratios utilized in several existing, pilot, and planned point- and nonpoint-source trading markets. These ranged from 1.3:1 to 3:1. Horan and Shortle (2005) performed a numerical example of trading in Susquehanna River Basin and arrived at "optimal" trading ratios in the range of 0.89:1 to 3.3:1

Horan (2001) argued that from a welfare efficiency standpoint, the optimal trading ratio would necessarily be less than one when a WQT model is specified to have uniformly mixed pollutant loads, stochastic nonpoint loads, convex damages, and no transaction costs. This is because the variability in nonpoint loadings creates stochastic ambient pollution concentrations and stochastic damages from pollution. This leads to more social risk if damages are convex in ambient pollution and if increases in nonpoint loadings increase the variability of ambient pollution.[1] Social risk is costly, so there are more benefits to reducing the variable nonpoint source pollution. Higher trading ratios work against this objective because they reduce the trading revenue per unit of loading reduction for nonpoint sources, thereby attracting fewer nonpoint traders and a higher overall level of nonpoint pollution. Thus, smaller trading ratios are more economically efficient.

Horan (2001) suggested that it is realistic to assume policies are designed to allocate resources within the context of policy makers' preferences, not

[1] Social risk is defined as "real or perceived impacts on a broad range of issues related to human welfare – for example, environmental quality, health, or economic opportunity" (Bekefi et al., 2006).

to maximize aggregate economic surplus. Thus, trading ratios are designed to be politically optimal. He further argued that trading ratios in excess of one may be the rational public sector response to the risk associated with stochastic nonpoint pollution because political support groups are likely to focus on expected loading reductions as opposed to overall social risks. Thus, trading ratios must be greater than one for most trading programs to be politically palatable.

3. Simulation model

A model is created to simulate hypothetical pollution control trades (credits) between point and nonpoint sources. This trading simulation is one in which all point sources (hereafter, we also refer to point sources as "plants") are required to meet a lower limit of nutrient concentrations in their discharge stream. Plants can either upgrade their technology to meet this limit or keep their old technology and buy water quality credits from nonpoint sources (hereafter, also called "farms") to offset their excess discharges. Such a regulatory "driver" is necessary for the market to function. Farms who sell credits are then obligated to adopt land management practices to reduce expected loadings.

The model relies on pre-specified values of the WTP for purchasing credits by each plant and the WTA for selling credits by each farm who is a potential trader. A sequential, bilateral trading algorithm (Atkinson and Tietenberg, 1991) then simulates market outcomes from these base data. As described in the subsections below, the impact of contracting and trading ratios is captured either by varying the input data or by altering the assumptions in the trading algorithm that govern how buyers and sellers are paired together.

3.1. Market participants

The market participants in this model are point and nonpoint sources of water contaminants (e.g., nutrients). To "create" market participants for the model, costs and quantities are generated for each of I = 10 plants and J = 500 farms using random draws from independent lognormal distributions.[2] The lognormal distribution is chosen to allow for the well-documented skewness in the distribution of costs and environmental impacts across the population of polluters (Nowak et al., 2006). The parameter values of the lognormal distributions for both buyers and sellers are shown in Table 1. The distributional parameters and the population sizes are chosen to approximately reflect the data used by Smith (2004) to model phosphorus trading in the Middle Kansas River subbasin. To ensure that the final results are not sensitive to a particular set of random draws, all scenarios are repeated 10,000 times in Monte Carlo fashion, with a new set of prices and quantities assigned to all agents each time. The results reported are the means of the 10,000 iterations.

Table 1. Lognormal distribution parameters for buyers and sellers.

Item	Mean	Standard deviation
Buyer quantities	5,000	1,250
Buyer WTP ($/lbs)	20	15
Seller quantities	200	50
Seller WTA ($/lbs)	12	8

3.2. Trading mechanism

The 'trading mechanism' determines how buyers and sellers are paired together in the water quality trading market.

The marginal gains matrix and the trading ratio

In each iteration of the model, the WTP and WTA data were randomly generated from the distributions presented in Table 1. These data are used to form the core element of the simulation model, the marginal gains matrix. This matrix contains the potential gains from each possible pairing of the farms and plants. The rows of this matrix correspond to plants while its columns correspond to farms. In scenario s, the cell in row i and column j of this matrix is

$$MarGains_{s,i,j} = WTP_{s,i} - t_s WTA_{s,j} \qquad (1)$$

where t_s is the assumed trading ratio in scenario s (expressed as the number of credits a farm must sell to offset one unit of plant discharge) and *MarGains* is the mutual gain if plant i buys one more credit from farm j under the assumptions embedded in scenario s.

A related matrix, Q, has the same dimensions and tracks the quantity of credits available for trade between each trading partner. The quantity data are also generated from the distributions in Table 1. At the start of trading the (i,j)th element of Q is equal to

[2] There is no a priori expectation that low WTA sellers should be "small farms" with a small incremental quantity to sell, nor that high WTP buyers would be "small plants." Thus, independent lognormal distributions are used.

$Q_{ij} = \min(q_i, q_j)$, where q_i and q_j are the randomly generated quantity of credits demanded by plant i and quantity of credits to be supplied by farm j, respectively. As trading proceeds the values in this matrix are reduced by the quantity transacted by the respective trading partners. A trader is removed from the market when its available quantity reaches zero.

The trading algorithm and the contracting (or pairing) of traders

The effects of trading barriers like information levels, transaction costs, search costs, and risk preferences are captured by varying the assumptions in the sequential, bilateral trading algorithm that simulates individual transactions by pairing buyers and sellers together in a specific order. The pairing of buyers and sellers by this algorithm ultimately determines which traders participate in the market. Each of the barriers identified above can result in the non-optimal contracting of traders.[3] Four possible contracting scenarios are modeled, which are described in turn below.

Optimal contracting ('optimal' set of scenarios)

This scenario is the case of perfect correlation between a plant's WTP and its likelihood of being a buyer, as well as between a farmer's WTA and his/her likelihood of being a seller. In this situation, the most advantageous trades are executed first. Action begins by the plant with the highest WTP trading with the farm having the lowest WTA. This is determined by the element in the marginal gains matrix with the greatest positive value.

The plant purchases as many credits as it needed or until it buys out the farm, whichever occurs first. The quantity data and the marginal gains matrix are both updated accordingly when the trade is completed.

The second trade begins by finding the greatest positive number in the updated marginal gains matrix. This determines the next two trading partners. The aforementioned process is then repeated. This marginal gains-ranked process continues until there are no more gains to be made by trading. The 'Optimal' set of scenarios serves as one polar case to bracket the range of possible outcomes.

Random contracting ('random' set of scenarios)

The second scenario is zero correlation which implies that frictions such as low information, transaction costs, search costs, and risk preferences makes all traders equally likely to be chosen. Here, trades occur in a completely random order. The single restriction is that only trades resulting in positive gains are allowable. A single element from the marginal gains matrix is chosen at random and this determines the trading partners. The trade is then made and the marginal gains matrix and quantity data are updated. Subsequent trades operate in the same random fashion. Trading continues until no positive gains remain. The 'Random' set of scenarios serve as the other polar case to bracket the range of possible outcomes.

WTP correlated contracting ('correlated plants' scenarios)

The final two scenarios are necessary to decompose the effect of correlation on the demand side from the correlation on the supply side. The third scenario models the case where the plants' propensity to trade is still perfectly correlated with their WTP but farms participate randomly. The first trade is between plant with the highest WTP and a randomly selected farm. Plants in remaining trades are selected in descending order of their WTP, paired with a randomly chosen farm each time. Trading data are updated using the same process as the other scenarios.

WTA correlated contracting ('correlated farms' scenarios)

The fourth scenario is similar to the third but reverses the roles of the plants and farms. Here, the farms' propensity to trade is perfectly correlated with their WTA but plants participate randomly.

3.3. The simulation experiments

In total, there are 24 scenarios modeled. Each of the four alternative methods of contracting, or modeled scenarios, described above (hereafter, referred to as 'Optimal', 'Random', 'Correlated Plants', and 'Correlated Farms' scenarios) are simulated under six different trading ratios. The trading ratio is varied from 0.5 up to 3.0 in increments of 0.5.

To evaluate the performance of the trades in the WQT market, comparisons are made to a baseline situation in which treatment plants would be required to meet a nutrient reduction limit by upgrading technology. Based on the information about the plants' expected costs and quantities (Table 1), the limits require the plants to reduce their annual nutrient load by a combined (expected value of) 10 plants × 5,000 lbs/plant = 50,000 lbs. annually. The expected total annual cost of these technology upgrades would be \$20/pound × 50,000 lbs. = \$1.0

[3] "Non-optimal" to *society,* which includes plants (which are presumably taxpayer funded) and farmers.

million. These two values form a baseline for comparing market outcomes. As trades occur in a WQT market, the same loading reduction is achieved (assuming a 1.0 trading ratio) but an increasing share of loading reduction is obtained from farms instead of treatment plants.[4] Trading also reduces the overall cost of achieving the target. Therefore, cost savings can be expressed both in dollar terms and as a percentage of the baseline costs. Likewise, trading volume can be expressed as the number of credits traded (measured in the pounds of loading reduction borne by farms) or as a percentage of the loading reduction target.

Second, the gains from trading are equivalent to the cost savings to *society* from trading. A portion of these cost savings are a gain to the plants (which are presumably taxpayer funded), to the extent that their credit purchases are less costly than the technology upgrades are. The remaining portion is a benefit to farms, to the extent that credit revenue is larger than their costs of adopting land management practices. However, these simulations make no attempt to partition the total cost savings into the benefits to the two groups. The relative sizes of the gains depend on the actual credit prices, which vary across transactions and depend on the relative negotiating power of the two groups. Lacking any reliable means to estimate the relative bargaining power and contract prices, estimates of the gains to the two groups can only be obtained by making arbitrary assumptions.

4. Simulation results

Table 2 summarizes the results of the twenty-four scenarios resulting from the first 50 trades. While all of the scenarios ultimately resulted in more than 50 trades (ranging from 120-300 trades depending on the scenario), real-world evidence has shown that most programs result in very few transactions. Based on this, it was decided to primarily focus on the first 50 trades to provide a more realistic analysis setting. This offers one base of comparison which would apply if trading is limited. Appendix A displays the results for each scenario when all possible trades are completed.

The first and second columns of Table 2 list the assumptions for each scenario. The third through sixth columns report trading volume and loading reductions by type and source.

The next two columns report the cost savings, in total dollars and as a percentage of the baseline total costs ($1.0 million from above description). Simulated cost savings varied widely, ranging from approximately $24,000 to $413,000 or from 2.4% to 41.3% of baseline costs.

The last two columns report the final (post-trading) costs. Due to the different trading ratios, some of the scenarios (those with a 1.0 trading ratio) exactly achieved the loading reduction target while others were either below (those with <1.0 trading ratio) or above the target level (those with >1.0 trading ratio). The next-to-last column was computed simply as the baseline (pre-trading) costs less the cost savings from trading (e.g., in the 'Optimal, 0.5 trading ratio' scenario: $1,000,000 - $412,685 = $587,315), while the last column expresses the final cost in average terms – i.e., costs per unit of loading reduction achieved (in the 'Optimal, 0.5 trading ratio' scenario: $587,315/40,867 lbs. = $14.37/lb. of loading reduction). The last column provides a useful comparison of the cost-effectiveness across scenarios. With no trading, the cost per unit of loading reduction is $1,000,000/50,000 lbs. = $20.00/lb. With trading, this cost ranged from $14.37/lb. to $18.92/lb, so, as expected, trading will reduce per-unit control costs.

4.1. Contracting of traders

The effect of random contracting on overall cost savings is unambiguously negative. This can be illustrated by comparing the 'Optimal, 0.5 trading ratio' scenario, which resulted in net cost savings of $412,685, to the 'Random, 0.5 trading ratio scenario', which resulted in savings of only $226,862. This relationship between optimal and random contracting held for every scenario modeled regardless of trading ratios. These results were expected and are similar to the findings of Atkinson and Tietenberg (1991). Intuitively, random contracting reduces cost savings because it creates some risk that "high cost" sellers – those with high WTA values – will displace some low-cost sellers that could have traded for a larger gain. Similarly, the "low paying" buyers with low WTP values may displace some of the higher paying buyers. The market transactions that maximize cost savings would include the low-cost sellers paired with the high-value buyers, but in the limiting case of random contracting all buyers and sellers are equally likely to participate.

[4]A trading ratio of greater than 1.0, on average, results in additional loading reduction whereas a trading ratio of less than 1.0 results in lesser amounts of loading reduction than would be achieved in the absence of WQT and reliance on only technology upgrades.

Table 2. Simulation results for twenty-four trading scenarios.

		Volume Traded				Cost Savings		Final Costs	
Contracting	Trading Ratio	Base Loading Reduction by Farms (lbs.)	Loading Reduction by Plants (lbs.)	Additional Loading Reduction by Farms (lbs.)	Total Loading Reduction (lbs.)	Total ($)	Percent (%)	Total ($)	Avg. ($/lb.)
Optimal	0.5	9,133	31,735	-	40,867	412,685	41.3	587,315	14.37
Optimal	1.0	9,476	40,524	-	50,000	228,499	22.8	771,501	15.43
Optimal	1.5	6,351	43,649	3,175	53,175	147,751	14.8	852,249	16.03
Optimal	2.0	4,816	45,184	4,816	54,816	106,804	10.7	893,196	16.29
Optimal	2.5	3,888	46,112	5,832	55,832	76,717	7.7	923,283	16.54
Optimal	3.0	3,239	46,761	6,479	56,479	56,569	5.7	943,431	16.70
Random	0.5	9,139	31,722	-	40,861	226,862	22.7	773,138	18.92
Random	1.0	9,492	40,508	-	50,000	85,333	8.5	914,667	18.29
Random	1.5	6,368	43,632	3,184	53,184	50,567	5.1	949,433	17.85
Random	2.0	4,822	45,178	4,822	54,822	37,452	3.7	962,548	17.56
Random	2.5	3,887	46,113	5,831	55,831	29,546	3.0	970,454	17.38
Random	3.0	3,240	46,760	6,480	56,480	24,331	2.4	975,669	17.27
Corr. Plants	0.5	9,134	31,733	-	40,866	363,109	36.3	636,891	15.58
Corr. Plants	1.0	9,476	40,524	-	50,000	177,677	17.8	822,323	16.45
Corr. Plants	1.5	6,354	43,646	3,177	53,177	101,392	10.1	898,608	16.90
Corr. Plants	2.0	4,820	45,180	4,820	54,820	66,671	6.7	933,329	17.03
Corr. Plants	2.5	3,888	46,112	5,832	55,832	43,917	4.4	956,083	17.12
Corr. Plants	3.0	3,240	46,760	6,480	56,480	31,088	3.1	968,912	17.16
Corr. Farms	0.5	9,134	31,733	-	40,866	275,477	27.5	724,523	17.73
Corr. Farms	1.0	9,476	40,524	-	50,000	117,971	11.8	882,029	17.64
Corr. Farms	1.5	6,351	43,649	3,175	53,175	68,249	6.8	931,751	17.52
Corr. Farms	2.0	4,816	45,184	4,816	54,816	49,469	4.9	950,531	17.34
Corr. Farms	2.5	3,888	46,112	5,832	55,832	42,166	4.2	957,834	17.16
Corr. Farms	3.0	3,240	46,760	6,479	56,479	38,569	3.9	961,431	17.02

When the gains per trade are depicted graphically, the effects of the contracting of traders on market performance become more pronounced. Figure 1 illustrates the gains per trade under alternative contracting methods with a 1.0 trading ratio assuming all trades are completed. The ‘Optimal’ scenario ends at $497,161 of total gains. This level of gains is reached after 227 trades have been completed. The ‘Random’ scenario, on the other hand, reaches a maximum of $392,259, but does so after 255 trades; an additional 28 trades. The ‘Optimal’ scenario could have ceased after 118 trades and more gains would have been realized ($393,724) than the total for the ‘Random’ scenario. If trading were halted after 118 trades in the ‘Random’ scenario, only $188,623 (48% of its final value) of gains would have been realized.

Figure 1 also reveals the effects of different types of non-optimal contracting. When traders are informed of buyers’ prices (‘Correlated Plants’ scenario), the cumulative cost savings curve behaves very similarly to the ‘Optimal’ contracting case across the early trades, while the ‘Correlated Farms’ scenario (WTA Known) behaves similarly to the random contracting case. The ‘Correlated Plants’ scenario results in more cost savings than the ‘Correlated Farms’ scenario across the first 65% of trades. Analyzing only the first 50 trades (Figure 2), shows the importance of correlation on the demand side (i.e., between plant’s WTP and likelihood of being a buyer) relative to the sellers’ side (i.e., between farm’s

WTA and likelihood of being a seller) when only a limited number of trades occur. These results imply that frictions on the demand side of the market are more detrimental to overall cost saving than frictions on the supply side when a limited number of trades are completed. Thus, WQT program designers should weigh the benefits of reducing frictions to the associated costs of providing adequate information to market participants and/or reducing other trade barriers that contribute to non-optimal contracting.

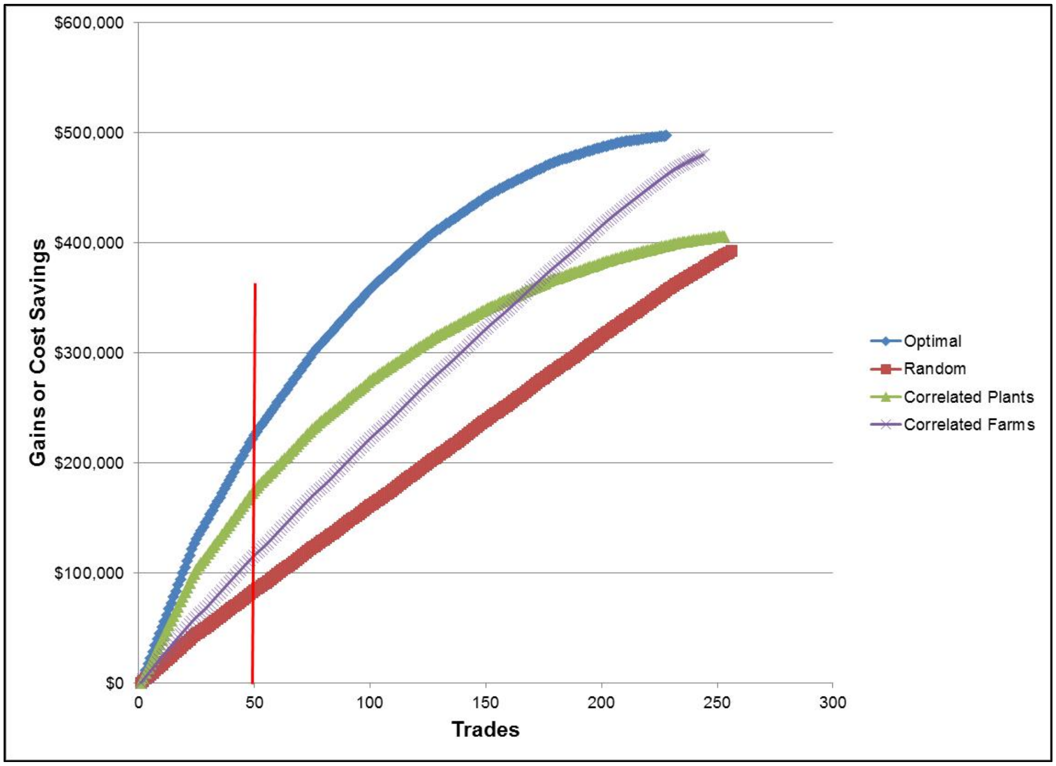

Figure 1. Effects of marketplace contracting on cost savings with a 1:1 trading ratio (vertical line indicates results after only 50 trades).

4.2. Trading ratio

As expected, there is a negative relationship between the trading ratio and potential gains from trading. Focusing on the 'Optimal' scenarios, the cost savings decrease from over $412,000 to $56,000 as the trading ratio increases from 0.5:1 to 3:1. However, this can be somewhat misleading because each of these scenarios results in a different amount of nutrient loading reduction. In the case of a 0.5:1 trading ratio, the nutrient reduction target of 50,000 lbs. is not met. And in the case of a 3:1 trading ratio, there are an additional 6,479 lbs. of nutrient reduction beyond the target.

As stated earlier, the purpose of a trading ratio greater than one is to account for nutrient reduction uncertainty and ensure that there is an overall increase in water quality (beyond that which would occur in the absence of WQT and reliance on only technology upgrades). According to the simulation results, this is generally the case. Figure 3 illustrates the trading volume and net environmental gains in the different scenarios. The height of the red bars represents the amount of loading reduction transferred from the plants to the farms through trading. The green bars represent the amount of loading reduction achieved from necessary upgrading of wastewater treatment plants. In cases of a trading ratio greater than 1:1, there are additional loading reductions achieved beyond the target, represented by the height of the blue bars. With a 2:1 trading ratio for example, each unit of increased plant loadings is offset by a two pound reduction in expected loading by farms, resulting in (on average) net environmental gains. The 'Optimal, 2.0 trading ratio' scenario results in 4,816 credits traded. Because of the 2:1 trading ratio, farms reduce expected loading by a total of 9,632 lbs, (2*4,816), so combining this with the 45,184 lbs. of reduction achieved from wastewater treatment plant upgrades the total expected loading reduction amounts to 54,816 lbs. So, the introduction of a trading ratio greater than 1:1 results in an environmental improvement – the 50,000 lbs. loading reduction target is exceeded by 4,816 lbs.

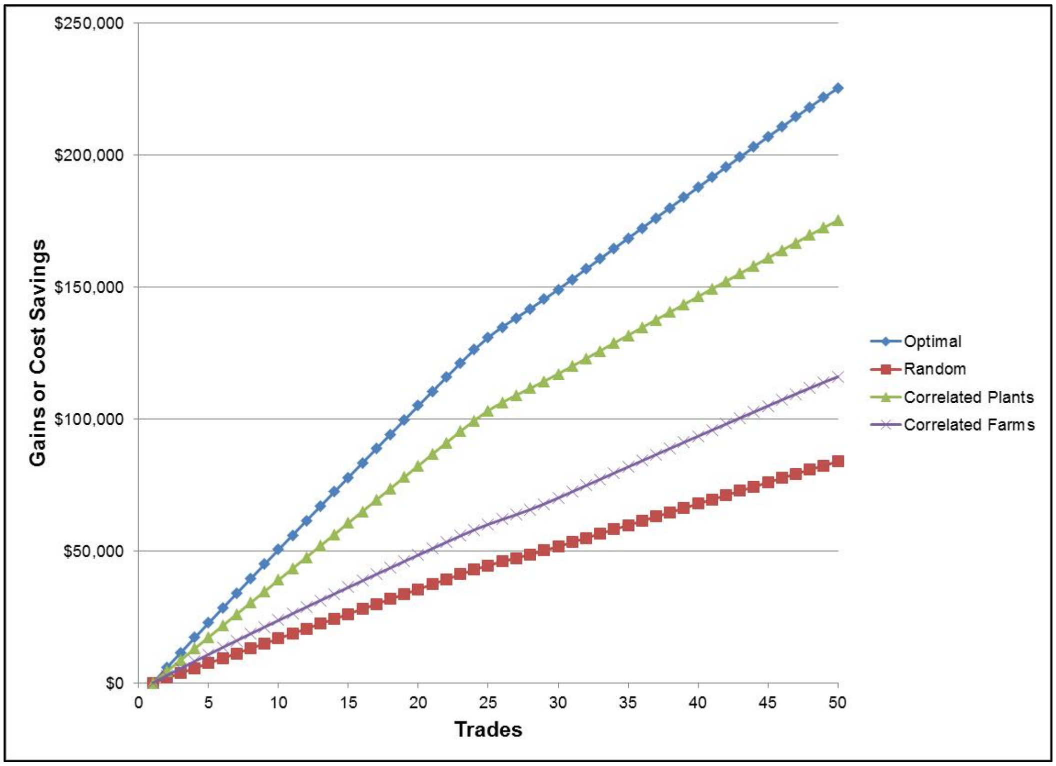

Figure 2. Effects of marketplace contracting on cost savings with a 1:1 trading ratio (first 50 trades).

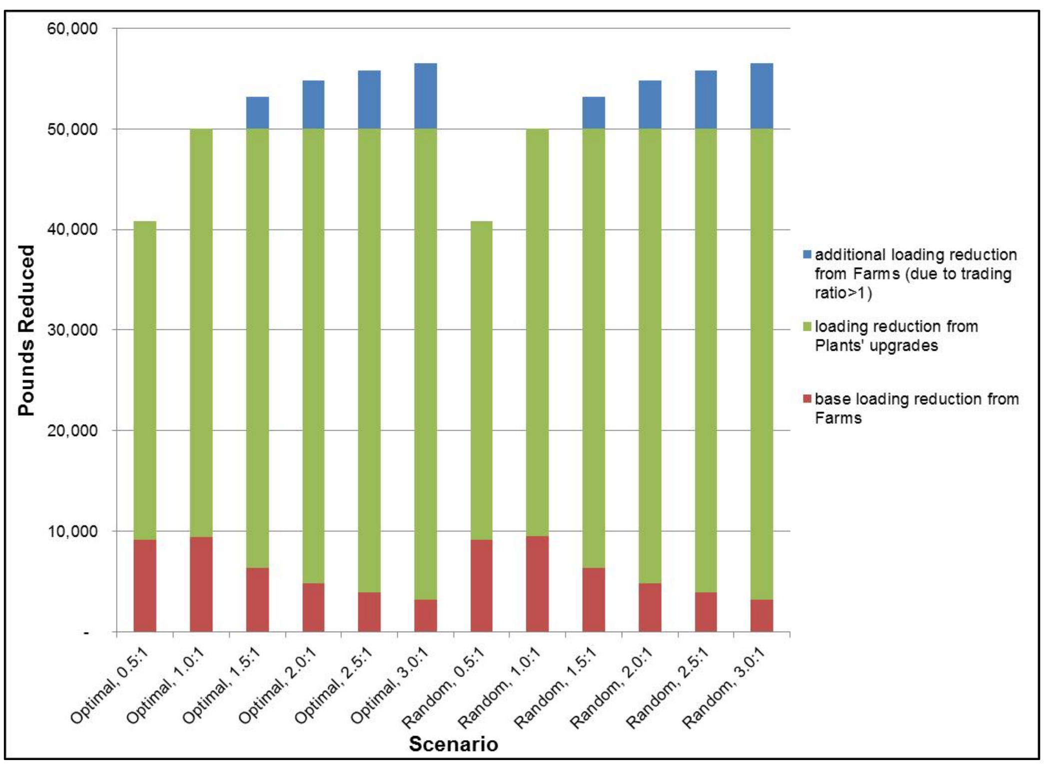

Figure 3. Trading volume and additional loading reduction by scenario (first 50 trades).

4.3. Co-effects of contracting of traders and trading ratios

Because of reasons stated earlier, the most useful metric for evaluation and comparison across scenarios may be the average cost of nutrient reductions. The effect of the trading ratio on cost-effectiveness is not independent of the different methods of contracting. This is demonstrated graphically by comparing Figure 4 and Figure 5. Under optimal contracting, an increase in the trading ratio raises average costs throughout the period of trading (Figure 4). Increasing the trading ratio from 1:1 to 2:1 increases final average costs from \$15.43 to \$16.29, an increase of 5.6%. Increasing the ratio from 1:1 to 3:1 increases final average costs by 8.2%. Further, with optimal contracting reducing the trading ratio from 1:1 to 0.5:1 results in an increase in final average costs.

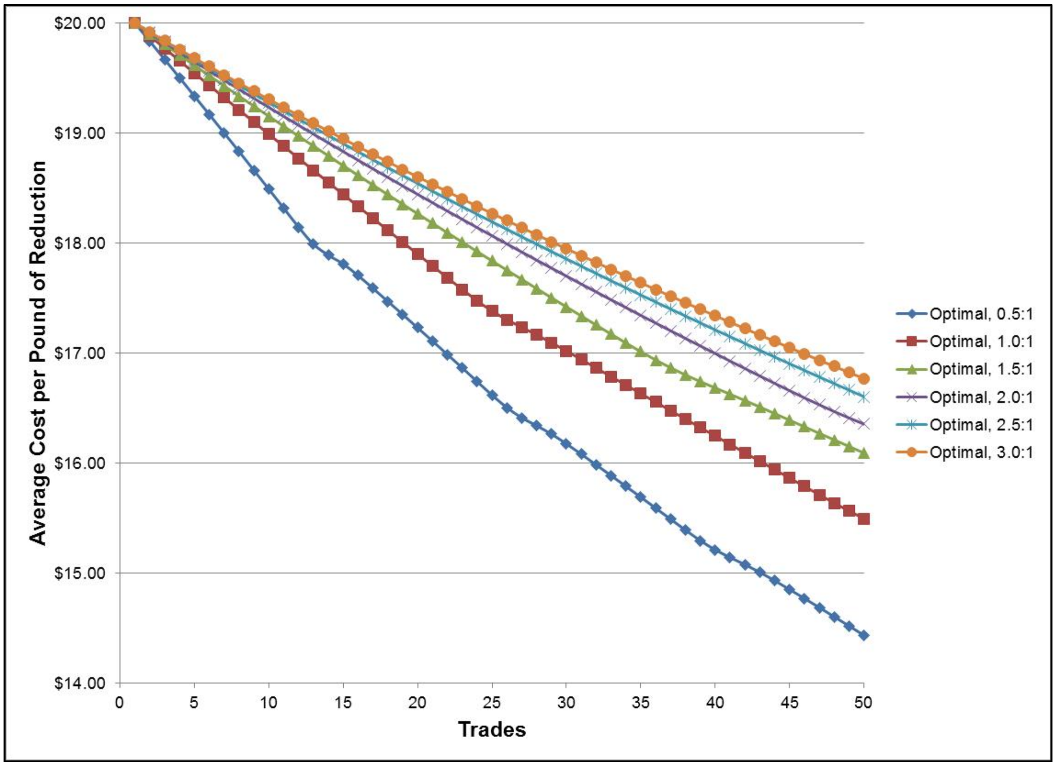

Figure 4. Effects of a trading ratio under optimal contracting

The results are different for random contracting. Here, the 0.5:1 trading ratio is the least cost-effective (highest average costs) across the first 50 trades (Figure 5). Under random contracting, we find that the trading ratio has an unambiguously positive effect on cost-effectiveness. One reason this occurs is that high trading ratios help to eliminate the highest-cost sellers by pricing them out of the market.[5] As noted above, random contracting creates a risk that high-cost sellers make transactions that displace their low-cost peers. However, this occurs only to the extent that high-cost sellers can find buyers with high enough WTP to generate gainful transactions. An increase in the trading ratio can be interpreted as a proportional increase in each seller's effective WTA (e.g., a 2:1 trading ratio doubles each sellers' WTA). As such, the sellers with initial WTAs near the maximum WTP will not be able to find a gainful trading partner if the trading ratio is increased.

Table 3 shows the effects of contracting on cost-effectiveness across different trading ratios. Specifically, the 'Optimal' scenarios are compared to the 'Random' scenarios. The results show that as the trading ratio increases, the optimal contracting of traders become less important. A high trading ratio may actually increase market performance in cases where buyers and sellers are not paired optimally, because it makes it harder for high-cost sellers to find a gainful trading partner. At extremely high

[5] It should be noted that in reality, some high cost sellers may be the most dependable and least risky when controlling pollution. Their costs may be higher because they do a better job. Our model assumes that all credit generation is uniform and dependable.

trading ratios, the difference in average cost-effectiveness between optimal and random contracting approaches zero. However, this difference will never become positive. In other words, optimal contracting is always preferred to random contracting, but it becomes less important as the trading ratio increases.

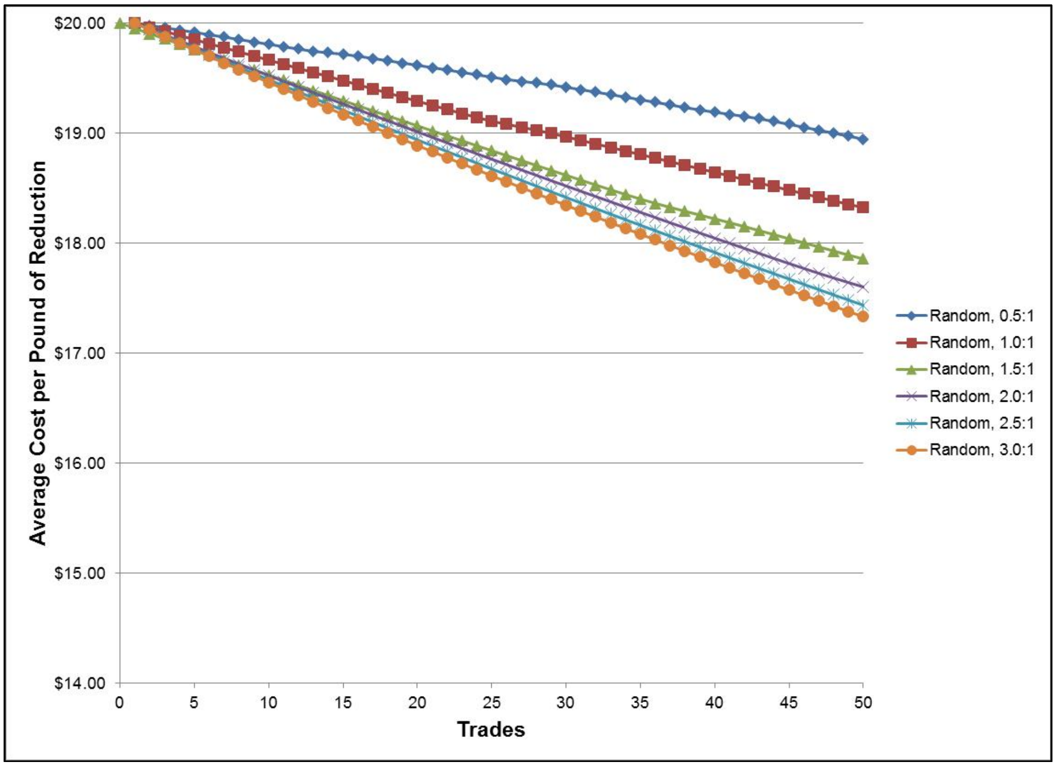

Figure 5. Effects of a trading ratio under random contracting.

Table 3. Effects of contracting on cost-effectiveness across different trading ratios.

Scenarios for Comparison	Trading Ratio	Difference in Average Cost-Effectiveness ($/lb.)	More Cost-Effective Scenario?	Conclusions
Optimal vs. Random	0.5:1	-4.55	Optimal	As trading ratio increases, optimal contracting of traders becomes less important.
Optimal vs. Random	1:1	-2.86	Optimal	
Optimal vs. Random	1.5:1	-1.82	Optimal	
Optimal vs. Random	2:1	-1.26	Optimal	
Optimal vs. Random	2.5:1	-0.85	Optimal	
Optimal vs. Random	3:1	-0.57	Optimal	

4.4. Simulation of real-world WQT markets

Although the constructed data was used in the model, there is no reason why these same market simulation algorithms cannot simulate markets using observed data from actual specific locations. Because WQT programs, by nature, involve complex interactions between economics and the biophysical world, accurately simulating a WQT market requires detailed point and nonpoint source control cost and watershed modeling data.

There are two types of cost data needed. Upgrade costs and annual operation maintenance costs of meeting more stringent nutrient standards are needed for wastewater treatment plants in the study watershed. These data either can be attained from surveys or by using general industry cost functions (e.g., Greenhalgh and Sauer, 2003). In either case, the one-time and annual costs along with the appropriate time horizon should be used to calculate the annualized costs, which consider the time value of money by including a discount rate.

Expected costs for BMPs used on farms also are needed. These costs can be collected from surveys or from previous research. University Extension fact sheets provide general estimates for this type of data (e.g., Devlin et al., 2003). One-time and annual costs should be converted to an annualized basis in analogous fashion to the plants' data.

Further, traders may perceive "intangible" costs that are weighed against any potential gains. That is, the assumption that only monetary trading gains enter traders' utility functions does not consider other factors such as perceived risk, public perceptions, and the fear of increased regulatory scrutiny. A growing literature documents that the behavior of participants in an institution is influenced by institutional processes and rules, independent of the participants' fiscal outcomes (Berg et al., 2005; Johnston and Duke, 2007). Obtaining the information necessary to estimate intangible costs that may exist is crucial for simulating a real-world WQT market. Since these data are subjective by nature, they can be obtained accurately through interaction with potential market participants via experiments, interviews, or surveys.

Along with the economic data, biophysical watershed data are needed. Watershed models play a central role in the simulation and execution of real-world WQT markets. Watershed models represent a scientific understanding of how land characteristics, BMPs, and other factors relate to pollutant loading into surface water bodies (Nejadhashemi et al., 2009). There are many types of models ranging from very simple to very advanced (see Nejadhashemi et al., 2009, for guidance in choosing a model). Regardless of the type of model used, the minimum output from the model should be: the baseline nutrient loading from each subwatershed, reduction in loading from each subwatershed after BMPs are implemented, and relevant delivery ratios. The risk and uncertainty around pollutant loading and/or modeling error also could be included. Combining all of this information will allow the researcher to generate the necessary WTP and WTA curves discussed previously in this paper.

5. Conclusions

While there is evidence that nonpoint sources have lower nutrient reduction costs than point sources, experience with WQT reveals a common theme: little or no trading activity. The success of WQT seems, in part, to depend on the structure of the market created to bring buyers and sellers together to transact. These outcomes suggest the presence of barriers to trading that were not recognized in the design of existing programs.

While the 'Optimal' scenario modeled here serves as a useful benchmark, most existing WQT markets are decentralized in nature, so that limited information and other barriers to trade can cause traders to be matched in a less efficient sequence. A variety of trading scenarios are possible. For example, one side of the market may have more information or higher search costs than the other, or neither side may have adequate knowledge of the other side's bid or offer prices. High-cost sellers and low-value buyers may simply "sneak" into actual trades because they happen to find a trading partner such that there are mutual bilateral gains. Each of these scenarios leads to a different sequencing of trades, and thus different levels of cost savings and cost-effectiveness. The model used here shows some of the possible consequences of non-optimal contracting.

Several notable results are found regarding barriers to trade. The results imply that frictions on the demand side of the market are more detrimental to overall cost saving than frictions on the supply side when a limited number of trades are completed. Thus, WQT program designers should weigh the benefits of reducing frictions against the associated costs of providing adequate information to market participants and/or reducing other trade barriers that contribute to non-optimal contracting. Overall, optimal contracting of traders is always better, but it becomes less important with higher trading ratios.

Trading ratios are a common component of many existing WQT programs. A typical trading ratio of 2:1 requires a nonpoint source to reduce two pounds of expected nutrient loading in order to receive one pound of trading credit. These ratios are purported to serve as a "safety factor" and are incorporated to account for the uncertainty in the measurement and monitoring of nonpoint source loading. Because nonpoint traders must reduce loading by two pounds for every one pound emitted by point source traders, there will be a net reduction of one pound of expected loading for each trade. So, while inhibiting some trades from ever occurring, trading ratios also have the potential to improve water quality beyond trading with a 1:1 trading ratio.

Previous studies (Malik et al, 1993; Horan, 2001; Horan and Shortle, 2005) have shown that under plausible conditions a trading ratio greater than 1:1 is likely to increase the risk of environmental damage because it dampens the incentive for nonpoint sources to trade and results in a greater share of overall loading attributed to (risky) nonpoint sources. This result is at odds with the trading ratios chosen in existing programs, nearly all of which are greater than 1:1. Horan (2001) offers one potential explanation for this discrepancy – certain groups of political stakeholders lobby for higher trading ratios because their goal is to raise overall loading reductions. Here, we find that apart from any implications on environmental risk or political-economic factors, there is an economic welfare (overall cost savings to society) justification for high trading ratios in certain situations with limited trading information and/or other barriers to trade. Limited information and other barriers to trade which inhibit the optimal contracting of trades introduces a random element to market participation, creating a risk that high-cost sellers (low-value buyers) will transact to displace low-cost sellers (high-value buyers) who could have traded for greater gain. To the extent that high trading ratios price the highest-cost sellers and lowest-value buyers out of the market, it reduces this risk and lowers average costs.

A limitation of this study is that the simulations did not explicitly consider the risk and variability associated with nonpoint source loading. Mean loading values were used. In the real world, there will most definitely be some years in which the BMPs put in place by nonpoint sources will overperform and significantly reduce nutrient runoff and in other years the BMPs may significantly underperform. Incorporating this stochastic process into the model would illuminate the effect of social environmental risk – which previous research has shown will tend to decrease the welfare-maximizing trading ratio – against the non-optimal contracting of traders considered in the present study. A stochastic model also would be capable of predicting policy-relevant measures such as the percentage of time nutrient reduction targets would be exceeded and by how much.

Based on the findings of this paper and the previous research that helped formulate this study, there appears to be a need for the comprehensive simulation of a WQT market in a real-world watershed to provide a further examination of potential market impediments. Along with this, more research is warranted to more fully understand those factors which result in the non-optimal contracting of market participants. The data requirements for a study such as this would be substantial but necessary for describing the "true" story that has and continues to be played out in past, current, and future WQT markets.

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Appendix A - Simulation results considering all trades are consummated.

Scenario	Trading Ratio	Volume Traded: # of Trades	Volume Traded: Base Loading Reduction by Farms (lbs.)	Volume Traded: Loading Reduction by Plants (lbs.)	Volume Traded: Additional Loading Reduction by Farms (lbs.)	Volume Traded: Total Loading Reduction (lbs.)	Cost Savings: Total ($)	Cost Savings: Percent (%)	Final Costs: Total ($)	Final Costs: Avg. ($/lb.)
Optimal	0.5	134	24,088	1,823	-	25,912	701,703	70.2	298,297	11.51
Optimal	1.0	227	40,816	9,184	-	50,000	497,161	49.7	502,839	10.06
Optimal	1.5	224	26,396	23,604	13,198	63,198	319,788	32.0	680,212	10.76
Optimal	2.0	188	16,210	33,790	16,210	66,210	205,138	20.5	794,862	12.01
Optimal	2.5	151	9,993	40,007	14,990	64,990	134,540	13.5	865,460	13.32
Optimal	3.0	121	6,386	43,614	12,772	62,772	90,824	9.1	909,176	14.48
Random	0.5	134	24,112	1,777	-	25,888	597,226	59.7	402,774	15.56
Random	1.0	255	47,156	2,844	-	50,000	392,259	39.2	607,741	12.15
Random	1.5	301	36,035	13,965	18,017	68,017	234,861	23.5	765,139	11.25
Random	2.0	258	22,515	27,485	22,515	72,515	142,475	14.2	857,525	11.83
Random	2.5	203	13,613	36,387	20,419	70,419	90,259	9.0	909,741	12.92
Random	3.0	154	8,356	41,644	16,712	66,712	59,869	6.0	940,131	14.09
Corr. Plants	0.5	134	24,108	1,785	-	25,892	602,482	60.2	397,518	15.35
Corr. Plants	1.0	252	46,330	3,670	-	50,000	406,054	40.6	593,946	11.88
Corr. Plants	1.5	273	32,630	17,370	16,315	66,315	262,055	26.2	737,945	11.13
Corr. Plants	2.0	228	19,860	30,140	19,860	69,860	161,605	16.2	838,395	12.00
Corr. Plants	2.5	181	12,261	37,739	18,392	68,392	101,590	10.2	898,410	13.14
Corr. Plants	3.0	141	7,700	42,300	15,401	65,401	65,051	6.5	934,949	14.30
Corr. Farms	0.5	134	24,098	1,804	-	25,902	699,950	70.0	300,050	11.58
Corr. Farms	1.0	243	43,916	6,084	-	50,000	479,847	48.0	520,153	10.40
Corr. Farms	1.5	266	31,444	18,556	15,722	65,722	293,180	29.3	706,820	10.75
Corr. Farms	2.0	232	19,951	30,049	19,951	69,951	180,392	18.0	819,608	11.72
Corr. Farms	2.5	185	12,388	37,612	18,581	68,581	116,491	11.6	883,509	12.88
Corr. Farms	3.0	147	7,988	42,012	15,976	65,976	81,077	8.1	918,923	13.93