Does adopting a nitrogen best management practice reduce nitrogen fertilizer rates?

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Abstract: Technical best management practices are the dominant approach promoted to mitigate agriculture's significant contributions to environmental degradation. Yet very few social science studies have examined how farmers actually use these practices. This study focuses on the outcomes of farmers' technical best management practice adoption related to synthetic nitrogen fertilizer management in the context of Midwestern corn agriculture in the United States. Moving beyond predicting the adoption of nitrogen best management practices, I use structural equation modeling and data from a sample of over 2,500 farmers to analyze how the number of growing season applications a farmer uses influences the rate at which synthetic nitrogen is applied at the field-level. I find that each additional application of N during the growing season is associated with an average increase of 2.4 kg/ha in farmers' average N application rate. This result counters expectation for the outcome of this practice and may suggest that structural pressures are leading farmers to use additional growing season applications to ensure sufficiently high N rates, rather than allowing them to reduce rates. I conclude by discussing the implication of this study for future research and policy.

Keywords: Best management practices; Farmer decision-making; Nitrogen fertilizer; Midwest; Political Economy

Abbreviations: BMP = Best Management Practice; N = Nitrogen; SEMLV = Structural Equation Modeling with Latent Variables; FIML = Full Information Maximum Likelihood

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1. Introduction

A dominant response to agricultural nutrient pollution in the United States (US) has been the promotion of *technical best management practices* (BMPs)—practices that use fertilizer-based, technical means to increase crop uptake of N and reduce nutrient loss potential (Drinkwater and Snapp 2007; Blesh and Drinkwater 2013). These practices include devices, tests, or equipment that enable farmers to more efficiently manage their inputs and thereby significantly reduce unnecessary contributions to environmental harms. But do farmers actually use these technical BMPs to conserve resources and reduce chemical input use?

Despite ample evidence from natural science studies measuring the potential environmental benefits of technical BMPs (e.g., Gardner and Drinkwater 2009) and decades of social research on what drives farmers' adoption of BMPs (Prokopy et al. 2019; Ranjan et al. 2019), very few studies have investigated the on-farm outcomes of BMP adoption. In a review of 174 BMP adoption studies from the social sciences, only around 10% explored the outcomes of adopted practices (Yoder et al. 2019). In other words, little research has examined how farmers actually use the BMPs they adopt and specifically whether they use these practices toward conserving resources and reducing the potential for environmental harm.

There is, rather, evidence to suggest efficient or "green" technologies like BMPs are often employed in ways that lead to more resource use or environmental harm (York 2012; York and McGee 2016). For instance, Sanderson and Hughes (2019) found that when farmers adopted more water-efficient irrigation technology, they tended to use more irrigation water. This, the authors argued, was a result of system-level political-economic pressures, where farmers needed to expand production to pay-off the cost of the more efficient equipment. This result reflects a growing body of research that emphasizes how the political economy of agriculture constrains farmers' management choices to necessarily prioritize production and profit (e.g., Levins and Cochrane 1996; Stuart & Schewe 2017). Given structural pressures, it is possible that technical BMPs are often not being used to achieve their intended outcomes and are rather applied to ensure profitability and in consequence accelerate resource use. Should this be the case, it would further point to the limited potential for within-system, incremental technical approaches to singularly address agricultural nutrient pollution and instead suggest the need for solutions aimed at altering the structural social, and ecological conditions of the modern agricultural system (Drinkwater and Snapp 2007; Gardner and Drinkwater 2009; Joyce et al. 2013; Prokopy et al. 2020).

To help address this research gap, this study focuses specifically on the outcomes of BMP adoption related to synthetic nitrogen (N) fertilizer use. Like the broader BMP literature, past research specific to N use has primarily examined what leads farmers to adopt a variety of technical N BMPs, including N soil tests, the use of variable rate/precision application and split- (i.e., multiple) and spring N applications (Khanna 2001; McBride and Daberkow 2003; Lambert et al. 2007; Lemke et al. 2010; Weber and McCann 2015). Moving beyond predicting the adoption of N BMPs, I use quantitative data from a sample of over 2,500 Midwestern row-crop farmers in the United States (US) to analyze how the *number of applications during the growing season*—with multiple applications being a widely recommended N BMP—relates to farmers' *N application rate* at the field scale. Though technical BMPs like growing season application of N can reduce the potential for N loss, this benefit is maximized when farmers capitalize on greater crop uptake of N by lowering their total N application rate (Mackown & Sutton 1997; Tran et al., 1997; Drinkwater and Snapp 2007). Reducing N rates is therefore a key practice outcome of technical N BMPs. This study explores whether this outcome goal is realized as farmers use additional growing season applications of N. I begin by discussing the context of N use and related BMP adoption and outcome research.

2. Background

2.1 N use and loss

Nitrogen (N) fertilizer is currently an integral agricultural input (Robertson and Vitousek 2009), contributing to crop yield increases that supply an estimated 40% of the global population with its caloric needs (Smil 2002). However, when N fertilizer is applied in amounts greater than what a crop can use quickly, it is a primary cause of excess environmental N (Vitousek et al. 1997). In the US, corn production in the Midwest region is a key site of N use and loss (Ribaudo et al. 2011; Basso et al. 2019). Midwestern states are the primary corn-growing areas in the nation, and about 50 percent of all N applied in the US is applied to corn (ERS 2017). Of all the N applied to corn, approximately 50 percent is typically lost to the environment (Cassman et al. 2002). Reflecting the prevalence of corn production and the crop's relationship with N use, nitrous oxide (N_2O) emissions are the primary greenhouse gas from the agricultural sector in the US Midwest (Larsen et al. 2007). N loss from row-crop agriculture in the region is also the primary driver of the Gulf of Mexico's hypoxic "dead zone" (David et al. 2010). Despite years of scientific and political efforts, recent evidence suggests that N loss from Midwestern states, such as Iowa, has only increased over the last two decades (Jones et al. 2018).

2.2 Best management practices and multiple applications during the growing season

A variety of factors shape farmers' N decision-making and contribute to N loss generally (see Stuart et al. [2015] for a more comprehensive review). Related to farmers' management, these include using higher than necessary N application rates as a "risk reduction" strategy (Sheriff 2005), collective action dilemmas (e.g., Yoder 2019), and political-economic factors that constrain farmers' choices, leading them to prioritize expanding production over efficient N use (e.g., Stuart and Schewe 2016). But the question of why farmers voluntarily adopt (or do not adopt) BMPs has been given the majority of academic attention, being thoroughly examined for over 30 years (see Prokopy et al. [2019] for a review). This degree of focus is in large part a reflection of US agricultural policy, which is almost entirely focused on encouraging voluntary adoption of N BMPs via financial incentives or technical assistance (Ribaudo 2015). While measures that directly reduce N use, such as taxing N fertilizer or capping total N application rate, have been shown to be very effective in other national contexts (Hamblin 2009), these mandatory approaches would likely receive significant pushback from politicians, farmers, and agribusinesses in the US (Hauter 2012). Consequently, to date, achieving improved environmental outcomes has largely depended on farmers choosing to adopt new management practices. Even among voluntary N BMPs, technical BMPs have received the lion's share of attention, rather than ecological-based management approaches (e.g., cover crops, diversified rotations, conservation tillage) (Blesh and Drinkwater 2013). This is likely a reflection of a general technology fetish in agricultural production that privileges high tech solutions to agricultural issues (Altieri 1989; Montenegro de Wit and Iles 2016) and a result of these practices being pushed by agribusinesses and the fertilizer industry (Weber and Stern 2015; see TFI, n.d.).

The use of more frequent *growing season applications of N* or using "split applications" is one of the technical N BMPs which has received the most attention to date (Caswell et al. 2001; Robertson and Vitousek 2009; Lemke et al. 2010). Corn crops rely on sufficient N for optimal growth (Robertson 1997). Too little N will stunt the crop's yield, while too much will contribute to environmental harm and waste N. Both harm farmers' profits. Toward ensuring the most efficient N management, farmers make key choices about when to apply N. Rather than applying seasonal N needs at one point in time—such as in the fall—farmers can increase the number of times they apply throughout the growing season. By more frequently applying N (at planting; after planting but before crop emergence; after crop emergence; or late season), farmers can more closely match N supply with corn's seasonal demand. In this way, more frequent growing season N applications can increase *N use efficiency*, or the proportion of applied N that is captured by the crops (Mackown and Sutton 1997; Tran et al. 1997; Robertson et al. 2013).

2.3 Why using more growing season applications should lead to lower N rates

By increasing N use efficiency, using more frequent N applications during the growing season can enable farmers to use lower overall rates of N without harming yields, which should translate into lower input costs and eventually net gains in profits (Robertson and Vitousek 2009; Flis 2017). Importantly, farmers' N rates are shaped by several auxiliary factors. Farmers using a corn-corn rotation require higher N rates, as a corn-soy rotation supplies an organically fixed source of N (Lasley et al. 1990; Puntel et al. 2016). Similarly, corn yields and N rates should be roughly positively related, so farmers expecting lower yields will likely apply less N per hectare (Caswell et al. 2001). However, after accounting for these factors, using more growing season applications still has the potential to enable farmers to reduce their N rates. Robertson and colleagues (2013: 55) reflect this integral nature of lowering N rates as a practice outcome in saying: "In many cases timing [i.e. growing season applications), placement, and formulation [other types of N BMPs] provide their benefit by effectively reducing fertilizer N in soil. In this sense, fertilizer rate is a good integrator of multiple practices." Practices like more frequent growing season applications provide some direct benefits in terms of reducing N loss potential. Yet, farmers ultimately should use additional growing season applications to lower their total N rate, capitalizing on their greater N use efficiency, as we can expect efficiency gains in N use for each application. For instance, compared to conventional application timings, some studies have suggested that in-season application techniques such as sidedress can enable farmers to lower their N application rates by around 40% without harming yields (Gehl et al. 2005; Zhang et al. 2015).

To date, there is little evidence to show farmers are using N BMPs, like additional growing season applications, to reduce N rates. Achieving this practice outcome is particularly important because, while N rate does not absolutely determine the amount of N lost to the environment, it is one of the key factors shaping the potential for N loss (Gardner and Drinkwater 2007; Ribaudo et al. 2011).

2.4 Predicting growing season applications and N rate

Like other work on N BMPs, most research related to growing season applications has focused on what predicts farmers' use of the practice (Caswell et al. 2001; Lemke et al. 2010). This research and related work point to key motivating factors related to farmers' use of growing season applications and N rate decisions. Using a greater number of N applications requires more time spent in the field, along with knowledge of specialized equipment/technologies such as a sidedress applicator "toolbar." Farmers who seek out more agricultural information, as well as those who are more highly educated are more likely to use more growing seasons N applications (Caswell et al. 2001; Daberkow and McBride 2003; Lemke et al. 2010). More highly educated farmers and those utilizing more information may then also be likely to use lower N rates, as some research has found that in-field training can reduce farmers' N rates (Huang et al. 2015). Older farmers are generally less progressive in terms of their practice use (Khanna, 2001; McBride and Daberkow, 2003). Consequently, older farmers will likely use fewer growing season applications but may be more likely to adhere to now out-of-date and generous application rate "rules of thumb" (Reimer et al. 2020). Therefore, age may positively predict N rate. Farmers must also be able to test for current N availability, as growing season applications are intended to match applied N with crop N needs. Using N testing methods, such as pre-sidedress nitrate tests (PSNT), is associated with greater use of growing season applications (Weber and McCann 2015) and should also lead to more conservative N rates. Further, while multiple applications can reduce N related costs for farmers, it will likely take years of reduced N use to offset the up-front costs of growing season application technology. Consequently, farmers who hold pro-environmental attitudes or values are more likely to use multiple growing season applications (Lambert et al. 2007). Relatedly, farm size often positively predicts BMP adoption as larger farmers can better offset the costs of equipment due to their economies of scale (Denny et al. 2019; Prokopy et al. 2019). Farmers operating on more land are likely to use more growing season applications. However, some work suggests that the size of these farms promotes a "one size fits all" approach to N rates across the farm, where too much is better than too little (Reimer et al. 2020). Larger farmers may use greater amounts of N.

It is also common for farmers to hire local chemical businesses to provide N rate recommendations and to do the applications for them (Stuart et al. 2018). Using hired services then may increase the use of growing season applications but could also be associated with higher overall N use as these firms tend to recommend higher N rates because they also often sell fertilizer (Ibid). Fall application of N is widely considered one of the least efficient times to apply N fertilizer, as the land is typically barren until the following spring leaving N highly susceptible to loss (David and Gentry 2000). Farmers using fall application to any extent are likely to use fewer growing season applications having applied at least a portion of their N pre-season. Fall applicators will also likely use higher N rates to accommodate for lower use efficiency. Crop/field characteristics will also play a role. In addition to farmers in a corn-corn rotation likely using higher N rates, they may also be more likely to use more growing applications given their greater dependence on synthetic N inputs (Caswell et al. 2001).

Evidence specific to the outcomes of using growing season applications is especially limited. However, in a recent qualitative study, many of the Midwest corn farmers Houser and Stuart (2020) interviewed used additional growing season applications as a means to increase N rates in response to N loss from heavy rainfall events. Rather than achieving lower rates, farmers in their study commonly saw growing season applications as a means to ensure they had sufficiently high N rates to maximize yield, even if some N was wasted. This decision was reported to be in part a constrained choice, shaped by political-economic pressures to achieve maximized yields and profitability. Other studies have similarly shown these conditions are present and constrain farmers' capacity to pursue conservation efforts (Schewe and Stuart 2017; Sanderson and Hughes 2019; Borlu and Glenna 2020; Cilia 2020). If this applies broadly, each additional growing season application would be associated with *higher* N rates.

Given the need to reduce agriculture's environmental impact and the current reliance on voluntary, technical approaches, we must develop a greater understanding of the outcomes of farmers' BMP use. To address this need, I examine how additional growing season applications of N are related to farmers' N fertilizer application rate.

3. Data and methods

3.1 Data

Data for this analysis comes from a 2017 survey of Midwestern row-crop farmers across four states: Illinois, Indiana, Michigan, and Ohio. The survey focused on gathering information on farmers' N fertilizer use, among other dimensions of crop management during the previous growing season in 2016. The four states were selected to represent a range of social, economic, and biophysical factors dispersed across the Midwestern 'corn belt' states. Together, planted hectares of corn in these states made up 26% of the total hectares planted in the US in 2016[1] (NASS 2016), and these states are located in the agricultural region of the US where the greatest amount of N is applied (Ribaudo et al. 2011).

To reach corn-soy farmers in these states, a list of 10,582 farmer addresses was purchased from a private firm that specializes in agricultural marketing. The percentage of farmers' addresses purchased for each state varied according to the state's total row-crop farming

[1] Percentage of US total hectares in each state is as follows: Michigan (2.5%); Indiana (6.5%); Illinois (13.2%); Ohio (3.8%) (NASS 2016).

population. In this way, the sample better reflects the regional population. A stratified random sample design was then used to ensure adequate representation of large farms. Two categories were used, farms of less than 202 hectares and farms of more than 202 hectares. In mailing surveys to farmers in these states, a modified Dillman approach was used, with two mailing waves beginning in February 2017 (Dillman et al. 2014). To ensure questions were readable and relevant, local farmers and an Extension educator provided feedback on the survey's questionnaire via two focus group discussions before mailing.

A usable response rate of approximately 26% was achieved. This response rate accords well with other recent mail surveys of Midwestern corn farmers (e.g., Stuart et al. 2012; Arbuckle et al. 2013). Over-sampling of large farms led to a high percentage of respondents operating over 404 hectares (39%). In consequence, this sample may over-represent large farmers in these states (see appendix for more details). Given the ongoing trend of farm consolidation (MacDonald 2020) and that I am primarily concerned about farmers' environmental impact, a sample that overly represents those with the largest potential environmental footprints is a desirable bias.

To focus on synthetic N management, I excluded all farmers in the sample who utilized manure (n=185), leaving a usable sample of 2,573 farmers. Related to management, the analysis draws on results from questions regarding farmers' N fertilizer use and best N management practice use on the largest field on which they grew corn in the 2016 growing season. Following the practice of USDA's Agricultural Resource Management Survey (ARMS)[2], these questions about nutrient use and practice adoption were asked regarding a specific field with two primary benefits: focusing on a specific management area increases the ease of responding for farmers and, given that this is the largest field, it is likely representative of the practice's farmers use across the majority of their tillable land.

3.2 Conceptual and analytical approach

For this analysis, I conceptualize growing season application and N application rate as linked in a causal path, where farmers' N rate (the practice outcome) is related to their use of growing

[2] See the ARMS survey at: https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/

season applications (the BMP), along with the relevant decision-making and field-specific management factors. To account for this conceptual relationship, I use structural equation modeling with latent variables (SEMLV) to accurately account for direct and indirect paths as specified in the model shown in *Figure 1* below (Bollen 1989; Hoyle 2012).

SEMLV is a multi-equation regression technique that accommodates relations between multiple exogenous and endogenous variables simultaneously and includes both latent and observed variables. SEMLV can simultaneously analyze multiple relationships between exogenous and endogenous variables. I use SEMLV techniques to conduct a path model that predicts N application rate, working through the number of growing season applications. Consequently, my analysis predicting total N application rate accounts for the indirect effects of variables predicting practice adoption and the direct effect of practice adoption on farmers' N application rate, along with other relevant control variables. This technique ensures the practice of growing season applications remains exogenous to N rate, helping to avoid potential endogeneity issues in the final model.

A latent construct, also called a latent variable, is an unobserved variable that captures the relations between the multiple observed variables being used to measure it (Bollen 1989). As is standard practice in SEMLV, I evaluate the fit of each of the two latent variables used as predictors in my model via measurement models (or confirmatory factor analysis (CFA)). I use STATA 15, and AMOS 27 for my analyses (Long and Freese 2006; Arbuckle 2010). Missing data was present.[3] Following recommendations (Cham et al. 2017), SEM's full information maximum likelihood estimation (FIML), with the means and intercepts option in AMOS, was used in estimation to address missing data.[4]

[3] The average item missingness was approximately 36%. Total N application rate and total number of growing season applications had the highest at approximately 47% & 43% missing respectively. Question length likely explains higher rates of missingness. These two variables were asked as part of a detailed, page-length table on nutrient management. Future work should simplify these questions to single items to encourage higher response rates.

[4] FIML has been shown to produce relatively unbiased estimates at 75% missing data even in small sample sizes (e.g., n=300 complete cases) and it is often compared favorably to other missing data techniques, including multiple imputations (Allison 2012; Enders et al. 2001; Newman 2003). While FIML is appropriate for this analysis, for reliability's sake the model was examined using three missing data techniques: FIML, multiple imputations (w/ OLS regression), and listwise deletion. Results suggest the FIML analysis presented here is robust: in every case, the

CFA results provide fit statistics for each measure or component included in the latent variable and the overall fit or quality of the latent construct, both of which need to be examined to comprehensively assess the fit of the latent constructs and evaluate their appropriateness for use in the analysis. The component fit of an acceptable latent variable has standardized and unstandardized factor loadings close to one another (the former above .40 and the latter around 1.00), which taken together with other aspects of component fit show that the included measures are valid and reliable measures of the latent construct. Overall model fit statistics for such a latent variable include a non-significant chi-square value (indicating that the estimated model is not significantly different from the data), fit indices like the Comparative Fit Index (CFI), and a Root Mean Square Error of Approximation (RMSEA) (West et al. 2012). CFIs compare the fit of a target model to the fit of an independent, or null, model. Good models achieve CFI's that are approximately 0.95 or above. RMSEA's is an absolute measure of fit based on the non-centrality parameter. RMSEA's that are below 0.05 are considered good fitting models (see West et al. 2012 for more detail). These fit statistics will also be used the assess the overall model fit.

<Figure 1 about here>

3.3 Variables and models

Variables in this model reflect the above depicted conceptual categories and relationships (Figure 1; see appendix for a description in Table A5). Two models are simultaneously examined in this analysis. The "first" model's outcome is *the number of growing season application*s. This is treated as a continuous variable, which measures the total number of growing season applications of N undertaken by the farmer, including applying N: (1) before planting, (2) at planting, (3) and post-crop emergence, which includes both sidedress and after sidedress/late season. For analysis, the range of this variable was expanded for better prediction (1=3.333; 2=6.666; 3=10). Higher values equate to a greater number of applications. *The number of growing season applications* applies specifically to a farmer's largest field.

relationship between growing season applications and N rate was significant, positive, and had approximately the same coefficient shown in this paper.

The second outcome, and the one of primary interest, is *N application rate*. Following the past literature, N application is measured at the field scale, in kg/ha (e.g., Hoben et al. 2011) and is specific to a farmer's largest field. N rate per hectare is calculated by aggregating the kg/ha application rate of all N products used by respondents. Some farmers reported the amount of N product they applied (e.g., lbs of urea). These figures were converted to reflect the kilograms of actual N applied using standard measures for the percent of N within each product. After visual inspection of the distribution of the N application rate variable, three outlying responses were dropped.[5] Each additional growing season application of N should be associated with lower N rates if farmers are using the practice as expected.

3.4 Predictors of farmers' N management

The model also includes several auxiliary variables that may shape farmers' decision-making related to N rate, as well as drive the number of growing season applications (see appendix for a descriptive table). Based on the past literature discussed above and a meta-analysis of the BMP adoption literature (Prokopy et al. 2019), I include measures for *farmers' value orientations, information use, field characteristics, operation characteristics*, and *farmer characteristics*.

Farmers' values are measured by two latent constructs. *Environmental values* and *economic values a*re latent constructs that each include four variables gauging values related to how important the items were to being a farmer and managing their operation. These are measured on a scale from 1=low importance to 5=high importance. The indicator variables and CFA results and fit statistics for each latent construct are shown in Table 1. Results indicate a good (environmental values) to very good fit (economic values) (West et al. 2012).

Information use is captured by two variables. First, *PSNT use* (a test used to determine current N availability in soil) is a binary variable, with use being defined by the regular or occasional use of *a PSNT* in corn years (use=1). Second, *information source use index,* which measures farmers' total use of agricultural information sources, with higher values being associated with higher total use frequency in the following information sources: (1) campus-based extension faculty, (2) county-based extension educators, (3) chemical dealers, (4)

[5] The decisions were ultimately based on the author's existing knowledge of farmers' N management.

seed dealers, (5) independent agronomists, (6) other farmers and family, (7) agricultural magazines, (8) agricultural websites and smart-phone apps, (9) grower associations, and (10) any other agricultural information sources used. Response options ranged from the farmer using the source "Never" (=1) to "Daily" (=5). The information source use index variable ranges from 9-35.

Field characteristics includes three variables. These are intended to control for factors that would influence farmers' N rate. *Custom fertilizer use* is a binary, dummy variable. *Custom fertilizer use* measures whether the farmer reported any custom blends of fertilizer (1=custom blend used). Given the difficulty of accurately assessing actual N rates in these blends, this was converted to a binary variable to control for potential N supplied, or other benefits farmers' may anticipate from their custom blends. If used (1=custom blend used), it should reduce N rate from primary sources. Custom blends are typically granular forms of N, and thus less applicable post-crop emergence. Using a custom blend may therefore reduce the total number of applications used. *Crop rotation* on the largest field was included as three dummy variables: *corn-corn* rotation, *other crop-corn*, and *corn-soy*. Corn-soy is used as the reference category as it is the rotation used by the majority of survey respondents. Finally, the 2014 corn *yield goal* is also included as a continuous variable to capture the effect of yield goal on N application rate.[6] As most farmers were in corn-soy rotation, the 2014 corn yield represents the majority of sampled farmers who had most recently grown corn on their largest field.[7] All variables are specific to the largest-field and thus accord with the measure of N application rate and growing season application.

Operation characteristics includes the variables *fall application, farm size, hired fertilizer sampling and recommendation,* and *hired fertilizer application. Fall application* is a dichotomous variable, measuring the effect of whether a farmer applies N in the fall or not (1=yes). *Farm size* is a continuous variable, measuring farmers' total hectares operated. *Hired fertilizer sampling and recommendation* (1=hired) and *hired fertilizer application* (1=hired) are both binary, dummy variables. These variables capture whether or not a farmer did fertilizer

[6] Visual inspection of a dot plot of the yield variable was used to detect and drop outliers. A total of 8 cases were dropped.
[7] For those in rotations other than corn-soy (i.e., they did not grow corn and thus didn't have corn yields to provide) 2016 corn yields were imputed when possible.

sampling and applications themselves or hired another individual or private contracting company to do them.

Farmer characteristics includes three variables. *Education* comes from a question asking respondents to select their highest level of education. It is treated as a continuous measure, where higher scores equate to higher levels of education. Farmers' *age* is measured as a continuous variable, with higher scores indicating older ages. Finally, the state in which the farm was located was also included, with *Ohio*, *Michigan*, *Indiana,* and *Illinois* (reference) compared as dummy variables.[8] Illinois represented the majority of sampled farmers and for this reason, it was used as a reference group.

<Table 1 about here>

<Table 2 about here>

4. Results

Descriptive results for the variables used in the analysis are presented in Table 2. Table 3 contains results from my SEMLV model predicting (1) *number of growing season application*s and (2) *farmers' N application rate*. Again, these outcomes were modeled simultaneously, but results are presented in two columns in Table 3 for readability.

<Table 3 about here>

In predicting the number of growing season applications, a variety of predictors were significant at the 0.05 level (see Table 3). The information source use index variable was significantly and positively related to growing season applications, where an increase in information source use led to a 0.05 increase in the number of applications. Farmers using custom fertilizers (compared to those not using them) used significantly fewer growing season applications (-0.594). Farmers who practiced a corn-corn rotation on their largest field used more applications compared to those who had a corn-soy rotation (0.428). Farm size positively

[8] Intraclass correlation coefficient (ICC) test showed that 2.3% and 5.5% of the variability in farmers' N rate and number of growing season applications was attributed to the state-level, respectively.

predicted the number of applications, where a per acre increase in farm size was associated with a <0.0001 increase in the number of applications. Compared to farmers who only applied N during the growing season, those who applied at least some N in the fall used significantly fewer applications during the growing seasons (-0.46). Finally, state of residence also mattered. Farmers in Indiana (1.200), Michigan (0.624), and Ohio (1.461) all were significantly more likely to use a greater number of N applications than Illinois farmers. These variables predict around 12% of the variation in total number of growing season applications on the largest field.

Controlling for these relationships, the model shows several significant predictors of N application rate at the 0.05 level. Most notably, the total number of growing season applications positively and significantly predicted per hectare N rate, with each increase in the number of applications leading to a 2.4 kg/ha increase in the amount of N applied. Turning to values, farmers' economic value orientations, measured as a latent construct, positively and significantly predicted N application rate (4.477). Farmers applying custom fertilizer blends applied significantly lower N rates (-8.093) compared to those who did not, while farmers using a corn-corn (9.085) and other rotation (10.708) used significantly more N than those using a corn-soy rotation on their largest fields. Increases in corn yield expectations led to a 0.292 increase in N application rate. Farm size (0.004) also significantly and positively predicted N application rate. Farmers who applied N in the fall to any extent, compared to those who did not, also used significantly more N (10.205). Michigan (-7.884) farmers had significantly lower total N rates than Illinois farmers, where Indiana (9.277) and Ohio (8.676) farmers used significantly more N on their largest fields than Illinois farmers. These variables predict just over 15% of the variation in N application rate on the largest field. Overall model fit is reasonable. The chi-square value is significant ($p = 0.000$), though this is expected given the number of cases in the model (West et al. 2012). The CFI is 0.932 and the RMSEA is 0.045 (CI=0.042, 0.048), both suggesting good overall model fit (West et al. 2012).

5. Discussion

Few studies to date have examined how farmers use the BMPs they adopt (Yoder et al. 2019). My analysis shows that each additional growing season application is associated with higher application rates of synthetic N fertilizer, controlling for a range of other variables. Each additional application of N is associated with an approximately 2.4 kg/ha increase in synthetic N application rate. The average N application rate across the sample was approximately 205 kg/ha. Consequently, per application increases were relatively small. Yet, if applied consistently across an entire farm, they represent significant increases in total N applied. Importantly, using a greater number of growing season applications, along with other technical N BMPs, has been shown to increase N use efficiency, meaning that using this practice will mitigate N pollution at least to a degree even without reducing N rates (Mackown and Sutton 1997; Tran et al. 1997). However, the ecological benefits of using more growing season applications are most realized if N rates are also reduced (Gardner and Drinkwater 2009). N rates are often positively associated with N loss, especially N_2O emissions (Millar et al. 2010). Consequently, because additional growing season applications of N were associated with higher N rates, this result suggests that the BMP is not being used to achieve its full potential in terms of reducing agricultural N pollution levels.

This result engages with and builds on recent work in the agricultural BMP literature. Like past work showing that adopted practices may not be used in their intended manner (Genskow 2012; Osmond et al. 2014; Ulrich-Schad et al. 2017; Sanderson and Hughes 2019), my findings suggest farmers may adopt N BMPs, but use them in ways that increase, rather than decrease, N rate. Though initially counterintuitive, this relationship reflects the general perspective of a significant vein of the environmental sociology literature, which shows that "green" or more efficient technologies are often used in ways that lead to greater resource use (York and McGee 2016). This effect is argued to be a result of social context, primarily political-economic forces, which encourage continual increases in production, meaning that more environmentally efficient technologies are often deployed to increase production, rather than conserve resources (York 2012). More specifically, this finding relates to Houser and Stuart's (2020) recent study. They found that farmers used additional growing season applications to increase their N rates to ensure they maximized corn yields, rather than as an attempt to minimize N rate and pollution. The current analysis suggests many Midwest farmers may similarly use their growing season applications. Like the environmental sociology research on green technologies, Houser and Stuart (2020) along with others (Ashwood et al. 2014; Roesch-McNally et al. 2018; Hendrickson et al. 2019) emphasize that farmers' capacity to prioritize conservation over profitability is highly constrained by structural, political-economic pressures.

The systematic pressure to ensure profitability and high yields may then be driving the positive relationship between growing season applications and increased N rate.

That said, alternative or complementary explanations for this relationship are certainly possible. Rebound effects—where the benefits of a more efficient practice are reduced, or offset given how the practice is used—are widely noted in conservation literature and this effect can be explained by rather small benefits that emerge from complex feedbacks (Sorrell and Dimitropoulos 2008). For instance, it could be that farmers who use more growing season applications have unique access to lower-priced fertilizer products. By applying N throughout the season, these farmers may be able to avoid the "spring rush" on N and therefore purchase at least some of their product at a lower price. Capitalizing on their lower prices, these farmers may also apply more N in the hopes of achieving higher yields. Alternatively, it could be a case of complex information feedbacks. For instance, where a farmer takes soil or leaf samples before each additional application and, seeing lower residual N than they expect or are accustomed to, they add a little more N as a security measure. Given the limited cost of applying extra N and the pressures to ensure profitability, farmers are likely generally inclined to apply an excess of N, rather than minimal (Pannell 2017). Again, these possible explanations are not necessarily alternatives to the structural one proposed here. The systematic pressures to achieve profitability would help explain why farmers would act on these "benefits" by applying more N.

In any case, the results of this analysis further point to the limited potential of addressing modern agriculture's environmental issues through voluntary, technical solutions alone (Drinkwater and Snapp 2009; York and Clark 2010). Technical N BMPs, like growing season N applications, are an incremental attempt to improve the corn-soy industrial agricultural system—i.e., they do not fundamentally change the system's current social, economic, and ecological relations. If the structure of modern agriculture is the key factor limiting farmers' capacity or willingness to use N BMPs to lower their N rates, it suggests that the problem with agriculture is not primarily a technical one, but rather a structural one and thus we need to pursue solutions which change the structure of the agricultural system itself. Calls for structural solutions have already widely emerged, with scholars promoting the need for system transformation toward a bio-diverse, low-input agroecological system that relies on ecologically-based management approaches (e.g. conservation tillage, diversified rotations) (Drinkwater and Snapp 2007; Altieri and Nicholls 2012; Ponisio et al. 2015; DeLonge and Basche 2017). Agroecological approaches such as these are not only more effective at reducing N loss than technical approaches alone (Gardner and Drinkwater 2009) they would also likely improve farmers' profitability (Prokopy et al. 2020) and promote climate resilience (Frison 2016). Recent work has begun to focus on what leads or prevents Midwestern farmers from individually undertaking these more fundamental management shifts (Blesh and Wolf 2014; Roesch-McNally et al. 2018; Houser et al. 2020) and the results from this study suggest the need for greater attention to this topic. Should future studies continue to confirm that farmers use technical N BMPs in ways that do not maximize their potential to reduce N loss, it will further suggest the need for a more effective policy that can motivate or enable farmers to transition row-crop agriculture toward an agroecological approach.

While the relationship between N rate and growing season applications is the main focus of this study, several auxiliary variables also deem brief mention. Few studies have explored the empirical drivers of N application rate at the individual level (Arbuckle and Rosman 2014; c.f., Lasley et al. 1990), especially using inferential, quantitative methods (c.f., Schewe and Stuart 2017). First, my results suggest significant variations in average N rates and the number of growing season applications by farmer's state of residence. Because this study is focused on regional level trends, dummy variables were used to account for the fact that there are differences across states within this region. This approach, however, cannot tell us why these variations occur. N rate and practice use may vary across states for a variety of reasons that are unaccounted for in this model, including distinct biophysical conditions such as growing season length, soil characteristics, and differences in corn varieties that may be associated with these differences, though evidence suggests biophysical factors are not the major factor in N management outcomes (Drinkwater and Snapp 2007). State-level differences in policy or variability in access to, use of, or recommendations about N use information may also be important. Intraclass correlation coefficients (ICC) show (results not shown) that approximately 2% of the variance in total N rate and 5% of the variance in growing season application use were attributable to state-level factors. While this is a small amount of variability, future studies—using a sampling approach designed to include a sufficient number of level 2 cases (units into which farmers can be clustered. E.g., watersheds, states, counties)—should employ a multi-level modeling approach to examine the state- and individual-level drivers of N rate variations across the region (Raudenbush and Bryk 2002).

Additionally, while farm size is often found to positively predict BMP use (Prokopy et al. 2019), here farm size significantly and positively predicted N rate. Larger farms may be associated with higher average N rates because farmers who manage more hectares are less able to precisely manage inputs, and as a means to reduce the decision-making burden, they use higher rates to simplify their decision and ensure they have enough N (Reimer et al. 2020). That farmers with greater economic-value orientations use significantly higher amounts of N suggest that this is a profit-seeking behavior, as others have shown (Stuart and Houser 2018; Stuart et al. 2012). This finding further builds the case for the importance of farmers' values in shaping management decisions, outcomes, and general views (Lambert et al. 2007; Reimer et al. 2012; Sanderson et al. 2018; Denny et al. 2019). Finally, it is also clear that some N BMPs are being used as expected. Due to the conceptual focus of this study, whether a farmer applied N in the fall was largely treated as a control variable. However, it is widely considered an important N BMP, as fall application of N is highly inefficient (David and Gentry 2000). Not surprisingly then, farmers who applied at least some of their N in the fall tended to use more total N per hectare. This points to the importance of continuing to discourage this practice.

My analysis focuses on the N BMP of the number of growing season applications, and neglects to consider other important N BMPs including the use of N stabilizers, the placement of the fertilizer (e.g., broadcast versus injected under the soil surface), and the use of non-technical practices, such as cover crops (Gardner and Drinkwater 2009; Robertson et al. 2013). All of these may be important factors that also shape farmers' N rates, and potentially interact with or even outweigh the influence of multiple growing season applications. Future work should build on this study by examining the outcomes of the adoption of different and multiple N BMPs (Adrian et al. 2005; Price and Leviston 2014; Denny et al. 2019). Similarly, in modeling, I treated the number of growing season N applications as a continuous variable, examining the effect of each additional application. This may miss key categorical differences, such as between farmers who apply only at planting compared to those who applying N post crop emergence (i.e., sidedress). Alternative estimating and modeling procedures than those used here, like generalized SEM, can handle binary or ordinal outcomes while still be able to simultaneously estimate multiple equations (Rabe-Hesketh et al. 2004). Future research may consider employing these methods to examine the outcomes of new combinations and comparisons of N BMPs. Finally, other work may further refine the dependent variable used as the practice outcome measure. I focused on the outcome of N application rate. While lowering N application rate is a key outcome goal of N BMPs, future studies would benefit from incorporating measures of N use efficiency (e.g., partial factor productivity), which could serve as a more direct proxy of N pollution levels (McLellan et al. 2018). Including additional independent variables—potentially N price—may also increase the explanatory power of these models. While this study leaves much room for refinement and future analysis, in being one of the first social studies to explore the on-farm outcome of BMP adoption, it offers key guiding insights for this coming work.

6. Conclusion

To date, little research has explored how farmers actually use the BMP that they adopt (Yoder et al. 2019). Focusing on the context of N fertilizer loss, I began to address this research gap by examining if Midwest corn farmers who used more applications of N fertilizer during the growing season had lower total N application rates at the field scale. Applying N more frequently during the growing season increases N use efficiency and thereby enables farmers to reduce their overall N application rate, which would reduce costs and mitigate the potential for fertilizer loss to the environment (Mackown and Sutton 1997; Tran et al. 1997; Robertson et al. 2013). Though past qualitative work has indicated that farmers may be using growing season applications of N to increase N rates (Houser and Stuart 2020), this study is among the first to use quantitative methods to investigate the relationship between this BMP and farmers' N application rate. Using SEM to analyze the data from over 2,500 Midwest row-crop farmers, this study indicated that each additional application of N during the growing season was associated with an average increase of 2.4 kg/ha of N.

Ultimately, my results counter optimistic expectations for the outcome of this practice. Instead, like Houser and Stuart's (2020) results, the outcome here suggests that Midwest corn farmers may be using growing season applications to ensure sufficiently high, rather than minimal, N rates. This positive association between use and N rate undercuts this BMP's full potential to mitigate N loss to the environment. Maybe more than anything, this result continues to point to the need for further research into the outcomes of N BMP adoption (Urlich-Schad et al. 2017). Without doing this type of work, technical BMP-focused policy and outreach efforts run the risk of promoting technical solutions that are not in themselves sufficient to address their intended problems. If future research continues to suggest technical N BMPs are not being used by farmers to conserve resources and maximize their potential to reduce N loss given structural conditions, then there is an even greater and more urgent need to direct our research and policy efforts toward understanding and encouraging system-level shifts in the US agricultural system, like agroecological approaches to crop and nutrient management (Delonge and Basche 2017; Prokopy et al. 2020).

7. Appendix 1

<Table A4 about here>

<Table A5 about here>

8. References

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Table 1: Measurement model and component fit statistics for latent variables

Latent variable	Variables (factors)	Unstandardized factor loadings	Reliability estimates	Composite reliability
Environmental values	Looking after the environment	0.49	0.85	0.79
	Concern about agricultural contributions to hypoxia	0.86	0.70	
	Concern about agricultural contributions to ground water contamination	0.83	0.71	
	Concern about agricultural contributions to algal blooms	0.90	0.64	
Economic values	Importance of being among the best in the industry	0.71	0.74	0.74
	Importance of building up wealth and family assets	0.77	0.66	
	Importance of profit maximization	0.72	0.68	
	Importance of earning a high income	0.81	0.62	

Measurement model fit	Chi-Square:	CFI	TLF	RMSEA (CI)
Environmental values	p = 0.02	0.995	0.986	.060 (90% CI=0.020-.11)
Economic values	p = 0.204	0.998	0.995	0.027 (90% CI=0.0-0.08)

Table 2: Descriptive results

Variables	*Mean*	*Standard Dev.*	*Range*
Outcome variables			
Per acre N application rate (kg/ha)	205	36.2	51-300
Number of growing-season applications	3.970	2.15	3.333-10
Values			
Environmental values	3.6	.82	1-5
Economic values	3.97	.66	1-5
Information Use			
Information use index	20.2	4.55s	9-35
PSNT use	.175	.387	0-1
Field Characteristics			
Custom fertilizer use	.16	.21	0-1
Corn-corn rotation	.125	.32	0-1
Other crop-corn rotation	.108	.30	0-1
Soy-corn rotation	.74	.41	0-1
Yield goals (Mg/ha)	11.4	2.11	5.65-17.35
Operation Characteristics			
Farm size (ha)	205.5	289	1-17,000
Hired fertilizer sampling and recommendation	.492	.50	0-1
Hired fertilizer application	.51	.50	0-1
Fall application	.19	.389	0-1
Farmer Characteristics			
Age (years)	63.77	11.51	24-100
Education (level)	2.76	.84	0-4
Indiana farmers	.23	.38	0-1
Michigan farmers	.19	.36	0-1
Ohio farmers	.27	.46	0-1
Illinois farmers	.31	.48	0-1
Total n	2,572	--	--

Table 3: Unstandardized effects for SEMLV model		
Unstandardized effects for path analysis	***Number of* growing *season application*s**	***Per acre N application rate (kg/ha)***
Number of growing *season application*s	--	2.4***
		(0.497)
Values		
Environmental values	-0.028	0.111
	(0.058)	(1.055)
Economic values	-0.119	4.477*
	(0.097)	(1.772)
Information Use		
Information source use index	0.050***	0.295
	(0.014)	(0.265)
PSNT-use	0.251	-4.866
	(0.154)	(2.804)
Field Characteristics		
Custom fertilizer use	-0.594***	-8.093**
	(0.156)	(2.870)
Corn-corn rotation	0.428*	9.085*
	(0.184)	(3.368)
Other crop-corn rotation	-0.216	10.708**
	(0.201)	(3.667)
Soy-corn rotation (ref)	--	--
Yield goal (Mg/ha)	0.002	0.292***
	(0.002)	(0.033)
Operation Characteristics		
Farm size (acres)	0.000*	0.004*
	(0.000)	(0.002)
Hired fertilizer sampling and recommendations	-0.276	1.231
	(0.154)	(2.826)
Hired fertilizer application	0.011	2.69
	(0.151)	(2.782)
Fall application	-0.460**	10.205***
	(0.155)	(2.849)
Farmer Characteristics		
Age (years)	-0.008	-0.036
	(0.005)	(0.091)
Education (level)	0.094	1.927
	(0.068)	(1.254)
Indiana farmer	1.200***	9.277**
	(0.157)	(2.950)
Michigan farmer	0.624***	-7.884*
	(0.180)	(3.325)

Ohio farmer	1.461***	8.676**
	(0.162)	(3.070)
Illinois farmer (ref)	--	--
Squared Multiple Correlations	.122	.154
Significance levels key: *=.05; **=.01 *=.001; Standard errors in parentheses.**		

Table A4: Sample versus population characteristics

Characteristics	*Survey (row-crop farmers)*	*Census (2017/all farmers)*	*ERS (2016)*
Farmers' average age	63.55	56.475	NA
Farm size (ha)	213.8	103.8	NA
Yield (Mg/ha)	11.4	10.6	NA
N rate on corn (kg/ha)	205	NA	174
****All table figures are specific to the sample states of IL, IN, MI, OH.***			

Table A5: Model variables and descriptions

Variable category	*Variable*	*Description*
Values	Environmental values	Importance of environmental outcomes in farm management
	Economic values	Importance of economic outcomes in farm management
Information Use	Information Use Index	farmers' total use of agricultural information sources
	PSNT use	Use of pre-sidedress nitrate test (yes = 1; no = 0)
Field Characteristics	Custom fertilizer use	Use a custom blend of fertilizer on largest field (yes = 1; no = 0)
	Corn-corn rotation	Use a corn-corn rotation on largest field (yes = 1; no = 0)
	Other crop-corn rotation	Use an "other" crop-corn rotation on largest field (yes = 1; no = 0)
	Soy-corn rotation (ref)	Use a soy-corn rotation on largest field (yes = 1; no = 0). Base reference category for rotation variables.
	Yield goals	Corn yield goals, from 2014 season, for largest field in bushels per acre.

Operation Characteristics	Farm size	Total farm size, in aces
	Fall application	Does a farmer apply N, to any extent, in the fall (yes=1; no=0)
	Hired fertilizer sampling and recommendation	Use a hired fertilizer sampling and recommendation service (yes = 1; no = 0)
	Hired fertilizer application	Use a hired fertilizer application service (yes = 1; no = 0)
Farmer Characteristics	Age	Farmers' age in years
	Education	Level of education farmer achieve
	Indiana farmers	Farm located in Indiana (yes = 1; no = 0)
	Michigan farmer	Farm located in Michigan (yes = 1; no = 0)
	Ohio farmer	Farm located in Ohio (yes = 1; no = 0)
	Illinois farmer	Farm located in Illinois (yes = 1; no = 0). Base reference category for state variables.

Figure 1: Hypothesized Conceptual Realtionship