CAFOs and surface water quality: Evidence from Wisconsin

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Abstract

Concentrated Animal Feeding Operations (CAFOs) – animal feeding operations with over 1,000 animal units in confined spaces – have proliferated over the past 30 years in the United States. CAFOs provide operational cost savings, but higher animal concentrations in confined spaces can generate external costs, e.g., non-point source water pollution. In this study, we improve on previous research designs to estimate the relationship between the growth in CAFOs and surface water quality using longitudinal data on a large spatial scale. We use a panel dataset from 1995-2017 that links CAFO intensity with nearby surface water quality readings in Wisconsin to perform our analysis. Leveraging variation in CAFO intensity within hydrological regions over time, we find that increasing CAFO intensity increases the levels of nutrients, specifically total phosphorus and ammonia, in surface water; adding one CAFO to a Hydrologic Unit Code-8 (HUC8) region leads to a 1.7% increase in total phosphorus levels and a 2.7% increase in ammonia levels relative to sample mean levels. These effects imply that, in our sample, the average total phosphorus reading is 10.9% higher and the average ammonia reading is 16.5% higher than they would be in a counterfactual world without CAFOs. Using these values, we find that CAFOs in Wisconsin account for losses in non-market surface water quality benefits of approximately \$35-\$51 per household per year (\$82-\$119 million per year for the entire state).

Over the past several decades, technological change and economies of scale have led to significant changes in livestock operations in the United States (Osterberg and Wallinga 2004; Sneeringer 2009). The industry has steadily moved from small, individual operations to larger and more concentrated operations. U.S. Environmental Protection Agency (EPA) estimates show that the number of animal feeding operations (AFOs) has declined considerably over this time period, while the number of animals at each operation has increased (EPA 2001; Copeland 2010). In U.S. dairy production for example, the midpoint herd size – where half of all cows are in larger herds and half are in smaller herds – increased from 101 cows in 1992 to 900 cows by 2012 (MacDonald and Newton 2014).

Concentrated Animal Feeding Operations (CAFOs) are large AFOs that do not store or grow crops on any part of the lot/facility and have over 1,000 animal units[1] onsite which are covered for at least 45 days per year (EPA 2004). However, CAFOs can impose more substantial external costs on outside parties than small-scale AFOs (EPA 2002a,b; Copeland 2010). Specifically, CAFOs produce large amounts of animal waste in confined spaces (Hribar 2010), which must be stored onsite or spread onto agricultural fields. The waste can then leach into groundwater or, when precipitation events occur, run off the land into surface waterbodies (EPA 2004; Burkholder et al. 2006). Importantly, the runoff is considered a non-point source pollutant, which is largely exempt from Clean Water Act (CWA) regulation (Olmstead 2009). Indeed, existing ecological studies document a correlation between CAFOs and lower ambient water quality at the individual waterbody level. For example, water samples near CAFOs are often found to contain elevated levels of pollutants such as fecal coliform and nutrients such as nitrates (Weldon and Hornbuckle 2006; Mallin et al. 2015). However, previous studies have not established or quantified a link between CAFOs and surface water pollution on a large spatial scale; nearly all studies

examine water quality near individual CAFOs without a suitable comparison group. Additionally, government reports that link CAFOs and surface water quality (e.g., EPA 2000; EPA 2002a,b) rely on ecological modeling to predict these effects, rather than observational data to examine the effects, *ex post*.

In this paper, we improve upon and add to previous analyses by identifying a link between the size and scope of CAFOs and ambient surface water quality on a large spatial scale. To identify this link, we use longitudinal data on of the size and location of the universe of permitted CAFOs in Wisconsin and proximate water quality data. Specifically, we use a difference-in-differences (DD) framework to examine the effects of CAFOs on nearby ambient concentrations of total phosphorus and ammonia (jointly hereafter "nutrients").[2] This approach allows us to compare changes in nutrient concentrations among watersheds with large expansions in CAFOs with changes in nutrient concentrations in control watersheds with no or low expansion in CAFOs.[3] We also monetize these effects to calculate the loss in non-market water quality benefits associated with CAFOs.

The connection between CAFOs and water quality has been well-studied, particularly in the ecological literature. The animal waste produced by CAFOs is not treated like that of humans (EPA 2001), so the excessive nutrients present in animal waste can increase eutrophication in surface waterbodies via discharge events (Hooda et al. 2000; Weldon and Hornbuckle 2006). As a result, EPA regulates CAFOs under the CWA more strictly than other AFOs. There is evidence that regulation decreases surface water pollution from CAFOs (Chen et al. 2019), but may lead to regulatory avoidance by AFOs, i.e., bunching at the size threshold (Sneeringer and Key 2011). Manure from CAFOs also contains pathogens that can be harmful to humans, e.g., E. coli; these pathogens can live in surface water and impair its quality (Spellman and Whiting 2007; Heaney et

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al. 2015). Hormones and heavy metals injected into animals at CAFOs and present in manure can also impair water quality (Barker and Zublena 1995; Boxall et al. 2003). Hooda et al. (2000) and Hu et al. (2017) provide thorough reviews of the literature connecting CAFOs and water pollution.

Another relevant literature focuses on other external costs associated with CAFOs. First, the large amounts of animal waste in confined spaces at large AFOs produce sulfur-related air pollution (Sneeringer 2010). Next, a sizable epidemiological literature shows that proximity to large AFOs negatively affects human health, both of the employees at AFOs and of the general public (e.g., Greger and Koneswaran 2010).[4] In the economics literature, Sneeringer (2009) uses longitudinal data to find a causal relationship between human health and animal concentrations. The author finds that larger concentrations of animals at feeding operations increase infant mortality. Finally, CAFOs are associated with external costs in the housing market through property value decreases (Ready and Abdalla 2005; Isakson and Ecker 2008). Importantly, the literature lacks any study that uses longitudinal data to identify the effects of the growth of CAFOs on surface water quality on a large spatial scale.

This study adds to these literatures in several ways. First, we provide more credible *ex post* estimates of the effects of CAFOs on ambient surface water quality than previous studies. The literature, including several EPA reports, lacks identified econometric studies that connect CAFOs and surface water quality on a large spatial scale. Instead, prior research uses ecological modeling and case studies to document this association. We rely on plausibly exogenous variation in the timing of CAFO expansion within a watershed to address these potential differences between nutrient levels in areas with differing CAFO intensity. We then use EPA methodology to monetize these effects. Second, we add to a growing literature that examines non-point source pollution using a rich water quality dataset on a large spatial scale (Grenestam and Nordin 2018; Meyer

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2018; Paudel and Crago 2018; Behrer et al. 2019; Chen et al. 2019; Grant and Langpap 2019; Keiser and Shapiro 2019).[5] The literature is rife with studies that examine point source pollution,[6] i.e., discharges directly from a "pipe", as discharge data are easier to identify from point sources than non-point sources. However, quantifying non-point discharges is extremely difficult and the literature on the longitudinal effects of various sources of non-point source pollution is scarce. Our use of water quality measures as an outcome helps to close this gap in the literature. Third, our study is important from an economic perspective. Elevated levels of nutrients in surface waterbodies can lead to eutrophication and algal blooms, which are costly.[7] The total annual costs associated with damages from freshwater eutrophication in the United States are estimated to be $2.2 billion (Dodds et al. 2009). Additionally, algal blooms are becoming more prevalent with climate change (Wells et al. 2015) so this issue is likely to be even more important in the future.[8] Our study improves understanding of the non-market surface water quality damages associated with CAFOs, which is useful for policymakers.

To address our research question, we create a panel dataset that links CAFO presence and intensity with nearby surface water quality readings of total phosphorus and ammonia for the state of Wisconsin between 1995 and 2017. We use Wisconsin's hydrological network to identify the level of CAFO exposure at each water quality monitoring location. The USGS methodology that identifies hydrological networks divides and sub-divides the United States into successively smaller networks nested within larger networks. Each area is given a hydrological unit code (HUC) with two (largest areas) to twelve (smallest sub-basins) digits. For our analysis, we use the eight-digit HUCs (HUC8), which are called "cataloging units" or "watersheds" and correspond to a drainage basin or distinct hydrologic feature; HUC8s also follow natural boundaries for surface water flow (Seaber et al. 1987).[9] Our primary empirical strategy leverages within HUC8 variation

in CAFO presence and intensity over time to estimate the effects on surface water quality from these operations. We find that increasing CAFO presence and intensity leads to significantly higher levels of nutrients in surface water readings. Estimation results show that adding one CAFO to a HUC8 region leads to a 1.7% increase in average total phosphorus levels and a 2.7% increase in average ammonia levels, while controlling for several time-varying characteristics such as precipitation, land use patterns, and land cover. We monetize these effects using EPA methodology and find that the average Wisconsin household's willingness to pay (WTP) to eliminate the water quality damages produced by CAFOs is roughly $35-$51 per year. Collectively, the water pollution externality produced by CAFOs in Wisconsin during our sample period is valued at $1.9-$2.7 billion. To put this value into perspective, the direct sales of dairy CAFOs in Wisconsin (which account for more than 90% of the state's CAFOs) in 2017 were $5.5 billion. The non-market water quality damages from CAFOs during our sample period therefore compare to approximately 5-8% of the sales from CAFOs during this time. Policymakers can use this information about lost non-market water quality benefits to quantify how much external damage should be priced into production decisions.

The paper proceeds as follows. The next section provides background information on CAFOs and non-point source pollution. We then describe the data, including statistical summaries. The following section provides the empirical analysis, which discusses the empirical results and provides robustness checks. The final section concludes.

Background

In this section, we first discuss the specifics of CAFOs, water pollution stemming from CAFOs, and the regulatory efforts aimed at preventing this externality. We then discuss our selection of research site.

CAFOs and water pollution

The distribution of animals on AFOs has trended away from traditional, small-scale AFOs over the past several decades; this is evidenced by the decline in the number of livestock farms at a time when livestock inventory has remained constant (Sneeringer 2009; Copeland 2010). In Wisconsin, this trend has resulted in the rapid growth in the number of CAFOs in the state. Figure 1 shows Wisconsin CAFO locations in 1994 and 2017, respectively, which confirms this growth. CAFOs still comprise a relatively small percentage of the total AFOs in Wisconsin, but a growing percentage of livestock are located on CAFOs. In 2019, about 3.5% of all dairy operations in Wisconsin were CAFOs but nearly 25% of dairy cows were located on CAFOs (Cushman 2019).

Growth in CAFOs can pose a threat to human health and the environment because of the extreme concentration of animal waste at CAFOs. In 1997, over 291 billion pounds of wet manure[10] were produced by CAFOs in the United States (EPA 2001). According to the U.S. Government Accountability Office (GAO), a dairy farm with 1,200 dairy cows could produce almost 30,500 tons of manure a year. This amount of animal waste is roughly equivalent to the amount of annual human sanitary waste produced by a U.S. city with 46,000 people (GAO 2008). Manure is most often dealt with at CAFOs in one of two ways. First, manure can be stored onsite, typically within surface "lagoons", in large piles, or under buildings or tarps. Second, manure can be spread onto farmland, often at agronomically inappropriate rates (Osterberg and Wallinga 2004; Hu et al. 2017). The potential for water pollution is significant for either storage method. Regarding the former, manure lagoons are typically insecure and do not contain linings or retaining walls (Hribar 2010). Thus, manure can leach into groundwater or leak from piles and lagoons, especially during precipitation events. Regarding the latter, when manure is overspread on surrounding farmland the

ground is unable to fully absorb the excessive nutrients present in manure (EPA 2001). When this occurs, precipitation events and melting snow carry the manure to surface waterbodies. This form of water pollution is referred to as non-point source pollution and is largely exempt from CWA regulation.[11] There is considerable heterogeneity in the regulation of non-point source pollution at the state level. In Wisconsin for example, all agricultural operators are subjected to broad non-point source policies, which include the adoption of a nutrient management plan. However, non-point source pollution remains difficult to regulate and most states focus on the adoption of Best Management Practices (BMP) or Total Maximum Daily Loads for nutrient loadings into surface waterbodies.

CAFOs can also manage animal waste through its direct discharge into surface waterbodies. In 2003, EPA updated the permitting program of the CWA, the National Pollutant Discharge Elimination System (NPDES), to require CAFOs to obtain permits to operate and to develop nutrient management plans to control animal waste (Sneeringer and Key 2011; Chen et al. 2019).[12] Permitted CAFOs are then considered point source dischargers and are subjected to discharge limits (EPA 2004). The implementation of the NPDES program and the issuance of permits are administered by individual states that have been granted primary authority to operate the NPDES program, which include 46 of the 50 states.[13] In Wisconsin, two administrative codes were also implemented during our sample period that govern agricultural water quality performance standards. Administrative code NR151 sets agricultural performance standards for the state and administrative code ATCP50 guides how livestock operators meet the performance standards, e.g., nutrient management plans, which all CAFOs must submit.

Regardless of this regulatory environment, the control of wastewater discharges and non-point source pollution from CAFOs remains insufficient. First, almost all CAFOs are considered

"minor" dischargers (EPA 2020), which are not required to systematically report discharges to EPA or authorized state agencies (Raff and Earnhart 2019). Indeed, direct discharge data from CAFOs are virtually non-existent in EPA's point source discharge data system, the DMR Pollutant Loading Tool (EPA 2020). It is therefore difficult to determine the NPDES compliance status of CAFOs. Second, there is considerable heterogeneity between states in the regulation of direct discharges from CAFOs. Many states, e.g., North Carolina, Arkansas, have large numbers of unpermitted CAFOs, which is likely the result of the differences in NPDES implementation and the definition of potential dischargers among states (GAO 2003) and regulatory avoidance by large AFOs (Sneeringer and Key 2011). Third, NPDES permits do not regulate the amount of animal waste from CAFOs that is spread onto fields. Non-point source pollution is still possible even if the proper NPDES permits are secured. And finally, nutrient management plans are often insufficient for the control of animal waste produced at CAFOs. The nutrient management requirements of EPA's 2003 CAFO rule did not significantly affect surface water quality in Iowa after the rule's implementation (Chen et al. 2019). Collectively, there exist shortcomings in the regulation of point source and non-point source pollution from CAFOs in the United States. Water pollution from these sources remains a large concern for policymakers.

Selection of research site

A nationwide study of the impact of CAFOs on surface water quality is not feasible because data on the numbers and locations of CAFOs are sparse. EPA has reported national summaries of the total number of estimated CAFOs and permitted facilities by state since 2011. The EPA summaries show that many states have permitted only a small percentage of CAFOs, which results in little information available about CAFO location and size for these states. For example, the 2017

summary document indicates that Idaho has issued permits for 0 of the state's 365 CAFOs, Illinois has issued permits for 32 of its 297 CAFOs, and New York has issued permits for just 21 of its 571 CAFOs.[14] Earlier data on CAFOs are more difficult to locate. A 2008 GAO report states that "no federal agency collects accurate and consistent data on the number, size, and location of CAFOs" (GAO 2008).

As a result, we focus our analysis on one state: Wisconsin. Our focus on a single state is like other studies that examine non-point source pollution (e.g., Meyer 2018; Chen et al. 2019) and is typical of policy analyses in other literatures. Wisconsin represents a useful state to study for several reasons. First, Wisconsin has collected much better data on CAFO size and location over time than other states. The 2017 EPA summary document shows that Wisconsin has permitted 295 of its 315 CAFOs. More historically, EPA estimated in 2000 the number of CAFOs in each state as part of its proposed NPDES permitting rule (EPA 2000). The report estimated that there were 141 CAFOs located in Wisconsin at that time. In the same year, the Wisconsin Department of Natural Resources (WDNR) had 110 CAFO locations permitted. Thus, we are confident that the historical data that we have acquired represent the majority of the CAFO universe in Wisconsin during our sample period.

In addition to implementing the NPDES rule at nearly all CAFOs, Wisconsin is also a leader in the control of wastewater from CAFOs in other ways. The NR151 and ATCP50 rules in the state place further restrictions on CAFOs, which do not exist in many states. Additionally, data on CWA Section 319 grants administered to the state indicate that most non-point source pollution grants from the program are targeted to BMPs for confined livestock waste control (GRTS 2020). As a result, the estimated effects of CAFOs on surface water quality in Wisconsin can be reasonably considered a conservative baseline comparison for states with little CAFO regulation.

Second, Wisconsin contains a tremendous amount of fresh, surface water (WDNR 2011). Importantly, the large amounts of surface water in our sample are also monitored at levels well above the national average, which increases the statistical power of our analysis. We use the Water Quality Portal to determine the count of surface waterbody locations that are sampled in each state in 2017.[15] Wisconsin sampled 6.72 surface waterbody locations per 100 square miles in 2017. For the rest of the country, the average state sampled 1.35 surface waterbody locations per 100 square miles.[16]

Third, Wisconsin is typical of other corn belt states that contain considerable CAFO presence (EPA reports that the corn belt contains 8,083 of the country's 19,961 CAFOs, or over 40%), which lends support to the external validity of this study to states in this region.[17] The assimilative capacity for manure phosphorus and nitrogen of Wisconsin's soil is like that of other corn belt states. According to the U.S. Department of Agriculture (USDA), nearly all counties in Wisconsin and other states in this region have cropland and pastureland with the assimilative capacity to process manure phosphorus and nitrogen of 5 to 10 million pounds per county and 25 to 40 million pounds per county, respectively (USDA 2000). The types of livestock at Wisconsin CAFOs are also like those of other corn belt states. In Wisconsin, 97% of CAFOs contain cattle or swine, while only 3% are poultry operations. This composition is mirrored in the rest of the corn belt, which contains only 7% of the poultry CAFOs in the country (USDA 2002). The similarity in operations is important because poultry waste contains 3 to 5 times more phosphate per pound than waste from dairy and beef cows and swine (Madison et al. 1995). Collectively, livestock manure that is discharged from CAFOs or spread onto fields in Wisconsin creates point source and non-point source pollution similarly to water pollution from CAFOs in other corn belt states.

The preceding points notwithstanding, we acknowledge that a study of only one state may

not generalize to other regions of the country. However, our results can be useful for policymakers in other states outside of the corn belt. For example, the southeastern portion of the United States contains a large share of poultry CAFOs and has soil with very poor assimilative capacity for manure phosphorus and nitrogen (USDA 2000). Counties in this section of the country are therefore more conducive to non-point source pollution from CAFOs that spread waste with higher phosphate concentrations than Wisconsin and other corn belt states.

Data

This section describes the data used in our empirical analysis. We first provide an overview of the process we use to geographically and temporally match CAFO location and size with water quality measures. We then describe our data sources in detail, discuss summary statistics, and examine trends in CAFOs and surface water nutrient concentrations over the study period.

Construction of panel

To construct our panel, we must first spatially link water quality data and CAFO intensity data. For our purposes, there exists a tradeoff when deciding which HUC level to use in the analysis. We want to use a small enough geographic area so that CAFOs could feasibly affect water quality readings. But using too small of a geographic area can be problematic because animal waste could potentially be spread outside of the small area.

We use HUC8 level spatial delimiters in our analysis for two reasons. First, it is imperative for our analysis that the manure from CAFOs remains in the same HUC region as the CAFO itself; thus, using too small a HUC region is problematic for our identification. When CAFOs store waste onsite, geolocating the manure from a CAFO to a HUC8 region is straightforward. However, manure from CAFOs is often spread onto nearby fields. It is therefore important to understand

whether this manure spreading is likely occurring in the same HUC8 region as the CAFO itself. We do not have data on where the CAFOs in our sample spread their manure. Existing literature suggests that manure is typically transported short distances. Ali et al. (2012) provide evidence that farmers in two similar states to Wisconsin (Iowa and Missouri) transport manure short distances. The authors find that the average maximum manure transport distance is 2.35 miles for dairy cows, 2.78 miles for beef cows, 2.95 miles for swine less than 55 pounds, 4.25 miles for swine greater than 55 pounds, 14.78 miles for broilers, and 13.66 miles for turkeys.[18] The vast majority of CAFOs in our sample (greater than 90%) are dairy cows so the manure for most sample CAFOs is most likely spread within a few miles of their location. Thus, we are confident that the manure from CAFOs in our sample is spread inside the geolocated HUC8 region. Second, the growing literature on non-point source pollution primarily uses HUC8 level measures (Grant and Grooms 2017; Paudel and Crago 2018; Grant and Langpap 2019). We follow the lead of these studies and use HUC8 level measures as well.[19]

We therefore construct our panel by matching the HUC8 region of each water quality monitoring location to HUC8 level CAFO intensity measures. As a specific example, the nutrient readings from a monitoring location of a surface waterbody in a specific HUC8 on April 15 of 2001 are paired with the CAFO intensity measures from that same HUC8 region on April 15 of 2001. Thus, the CAFO variable measures the level of CAFO exposure for a given water quality monitor on a given day.[20]

We then merge time-varying controls to our panel. For several controls, the data are only available at the county-year level. We spatially transform these county level measures to HUC8 level measures because multiple HUC8s can span a single county. To do so, we weight each county level measure by the area of the county that lies within each HUC8 region. We then aggregate the

oftentimes multiple weighted measures to create a single HUC8 level measure for these control variables. Finally, we standardize these values to account for HUC8 regions that span into other states. We temporally convert the control measures to daily or monthly observations via linear extrapolation and interpolation.

CAFO intensity

We obtain CAFO data through an open records request with the WDNR, which results in information on the historical population of CAFO permits in Wisconsin dating back to 1990. Figure 2 shows the variation over time in the number of CAFOs in Wisconsin from the beginning of 1995 to 2017. Prior to 1995, there were only six permitted CAFOs throughout the state.[21] CAFO presence in Wisconsin has steadily increased during our sample period; there were 274 permitted CAFOs in Wisconsin by 2017.[22] Figure 2 also shows that the number of total animal units at CAFOs has closely trended with the number of CAFOs in the state, suggesting that the average CAFO size has not changed significantly since 1995.[23] However, CAFO growth has not been uniform throughout Wisconsin. Figure 1 shows the geographic distribution of CAFOs in Wisconsin in 1994 and 2017, respectively. Some HUC8 regions have seen significant CAFO growth over time, some experienced little CAFO growth, and some HUC8s have zero CAFOs for the entirety of our panel.

Water quality

We collect water quality data from three primary sources: U.S. Geological Survey (USGS) National Water Information System (NWIS), EPA Storage and Retrieval (STORET), and USGS Biodata.[24] In our sample, roughly 70% of observations come from STORET. We are interested in

non-point source pollution of excess nutrients from CAFOs for our primary analysis, so we collect data for total phosphorus and ammonia readings. We also collect data on pesticides and metal concentrations for placebo tests. We focus on nutrients because these are two of the most common pollutants resulting from animal waste, as highlighted by EPA and WDNR (EPA 2000; EPA 2002a,b; WDNR 2011). Finally, we only collect water quality readings for surface waterbodies, e.g., lakes, rivers; we do not collect data for non-surface waterbodies, e.g., wells, ditches.

Each water quality observation represents a given monitoring location, in a HUC8 region, on a specific day. We retain all observations on nutrient levels that match to a HUC8 region in Wisconsin. There exist some extremely high readings on nutrient levels for a very small subset of the water quality data. Therefore, we follow Keiser and Shapiro (2019) and winsorize data at the 99% (and 1%) level.

These water quality measures have been used previously in the ecological literature to examine individual surface waterbodies (e.g., Landon et al. 2014). We are aware of only two published studies in the economics literature that use these water quality measures to answer economic questions over a large spatial scale (Grant and Langpap 2019; Keiser and Shapiro 2019). However, there exist several working papers that use these data in this way (Paudel and Crago 2018; Chen et al. 2019; Behrer et al. 2019). Thus, our study and use of these data serve as a contribution to the growing economic literature on non-point source water pollution.

Control variables

Various time-varying factors may affect the concentrations of nutrients in surface waterbodies. Adding these factors to our regression specifications can help reduce residual variation and increase the precision of our estimated coefficients of interest. First, we use weather and precipitation

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data from Schlenker and Roberts (2009; 2020). The authors use PRISM climate data and weather monitoring station locations to develop daily weather and precipitation data for 2.5 by 2.5-mile grids throughout the contiguous United States from 1900-2020.[25] We geocode each water quality monitoring location to the nearest PRISM grid centroid. In our analysis, we use daily measures of total precipitation and maximum temperature at each monitoring location.

We also control for variation in macroeconomic conditions during our sample period. We control for median household income in our analysis, which is provided at the county-year level from the U.S. Census Bureau's American Community Survey (ACS). We also use unemployment statistics from the Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) program. The LAUS provides unemployment percentages for each county in the United States every month.

Finally, we control for land usage patterns and land cover. We gather these measures from two data sources. First, we collect our measures of land usage – the county level number of farm acres and number of acres with commercial fertilizer applied – from the USDA Agricultural Census, which is administered every five years.[26] Second, the National Land Cover Database (NLCD) provides the most comprehensive and most frequently updated land cover maps for the United States. The NLCD classifies land cover at 30m resolution for the years of 2001, 2003, 2006, 2008, 2011, 2013, and 2016. For each of these years, we overlay the NLCD maps on HUC8 regions and calculate the percentage of each HUC8 that is developed, forested, and planted.

Sample summary statistics and trends

We construct two final analysis samples: one for total phosphorus readings and another for ammonia readings. Table 1 provides summary statistics for each sample. The mean total phosphorus

and ammonia readings at the monitoring location level are 0.258 mg/L and 0.227 mg/L, respectively.[27] Heterogeneity in these measures by CAFO exposure is presented in Online Appendix Table A1. Table 1 also presents summary statistics for our measure of CAFO intensity, which represents treatment. The mean monitoring location (of both nutrient types) is exposed to over six HUC8 level CAFOs between 1995 and 2017. During our sample period some HUC8s do not contain any CAFOs, while the maximum CAFO count is 41.[28]

We next discuss the trends in our CAFO and nutrient concentration measures. Figure 3 shows how average nutrient concentrations and exposure to CAFOs have trended over time across all monitoring locations. Panel A shows trends for total phosphorus and Panel B shows trends for ammonia. Both panels reveal increases in the number of CAFOs to which an average water quality monitor was exposed coincident with the increases in nutrient concentrations, especially during the latter portion of our study period. Online Appendix figures A1 and A2 present analogous figures where we separate water quality monitors into three groups based on ultimate levels of CAFO intensity. These figures reinforce the correlation between CAFO intensity and nutrient concentrations in surface waterbodies. Although these patterns are suggestive, time-invariant factors across HUC8 regions or secular trends throughout Wisconsin in CAFO intensity and nutrient levels could drive the correlations seen in these figures. We address both potential confounders in the empirical analysis of the following section.

Empirical analysis

In this section, we describe our empirics. We first discuss the baseline estimation and describe our identification strategy. Next, we provide the primary DD estimation results and evidence supporting our identifying assumptions. We then monetize the water pollution externality associated with CAFOs using EPA methodology to value non-market water quality benefits. Third, we address

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several threats to our identification. Finally, we examine the sensitivity of our results to the choice of regression specification and analysis sample.

Estimating equation and identification

We are interested in the effect of CAFO presence and expansion on a HUC8 region's surface water quality. We begin by estimating the following DD specification:

$$Y_{ijdmt} = \beta_1 CAFO_{jdmt} + \beta_2 M_{ijdmt} + \beta_3 X_{jdmt} + \gamma_j + \psi_m + \lambda_t + \varepsilon_{ijdmt}, \tag{1}$$

where Y_{ijdmt} is the concentration (in mg/L) of total phosphorus or ammonia at monitoring location i in HUC8 region j on day d in month m of year t. We code $CAFO_{jdmt}$ as the count of CAFOs present in the HUC8 region each day. In the online appendix, we also estimate specifications where $CAFO_{jdmt}$ represents the number of animal units at CAFOs within each HUC8.

M_{ijdmt} and X_{jdmt} are vectors of time-varying controls at the monitoring location- and HUC8-day levels, respectively. The components of each vector likely impact the nutrient concentrations in surface waterbodies and thus, inclusion of these control factors can reduce the variance of the error term and improve the precision of our estimates. M_{ijdmt} is a vector of climatological controls at the monitoring location-day level: precipitation (including its square) and maximum temperature. We control for daily total precipitation at each monitoring location because snow and rain events affect how much non-point source runoff occurs, which impacts surface water quality. We include the square of total precipitation because dilution occurs during the runoff process, which may affect the level of pollutants that reach each waterbody. We also include a measure for the maximum daily temperature because temperature affects nutrient concentrations, primarily through the release of legacy pollutants from sediment (Jensen and Andersen 1992; Genkai-Kato and Carpenter 2005).

Next, X_{jdmt} includes several time-varying controls at the HUC8-day level. First, X_{jdmt} contains macroeconomic indicators. We include as controls median household income and unemployment rates, both of which may affect surface water quality for several reasons. If macroeconomic conditions signify a poor economy, then citizen pressure for environmental protection is likely to fall as the concern most important to policymakers is not the environment but the economy (Earnhart 2004). Also, unemployment can affect pro-environmental behavior and attitudes (Meyer 2016). Moreover, these measures could proxy other economic activities that plausibly affect surface water quality. If changes in non-CAFO economic activity are correlated with CAFO expansion, we could misattribute general economic effects to CAFOs. Third, X_{jdmt} contains land usage and land cover measures. For land usage, we include in our specification controls for the number of farm acres and the number of farm acres that are applied with commercial fertilizer; each of these measures contributes to non-point source pollution. Finally, X_{jdmt} includes NLCD land cover classifications in percentages, e.g., percent of the HUC8 that is forested. These land cover measures control for how likely it is that other non-CAFO non-point source pollution occurs in each HUC8. In addition, these measures capture the likelihood of urban runoff, which can affect nutrient concentrations in surface waterbodies. Alternatively, more developed land may be associated with decreased non-point source nutrient runoff if there is no agriculture in the region. X_{jdmt} contains measures for the percentage of land in each HUC8 that is forested, planted, or developed; our omitted category is the percentage of wetlands.

Equation (1) also contains a series of fixed effects. γ_j are HUC8 fixed effects that control for time-invariant HUC8 level characteristics that affect surface water quality. HUC8 fixed effects control for factors such as the size of the HUC8, land slope, and soil type, the last of which affects the ability of non-point source pollution to absorb into the ground before reaching surface

waterbodies. ψ_m are month fixed effects that control for the seasonality of the pollutant concentration readings and λ_t are year fixed effects that control for unobservable factors common to the entire state that change over time, e.g., state or national policies to control non-point source pollution.[29,30] Finally, we cluster standard errors in the baseline regressions at the HUC8 level, which is our level of identifying variation, to allow for within hydrological region correlation in the error term (spatial and serial correlation). We also show results for our main specification where we use two-way clustering of standard errors (HUC8 and year).

Identification of our coefficient of interest, β_1, comes from changes in water quality within HUC8 regions coincident with plausibly exogenous variation in CAFO presence and intensity. Our identifying assumption, which is standard in DD models, is the parallel trends assumption; in the absence of any CAFO expansion, average nutrient concentrations in surface waterbodies would have trended the same way in HUC8 regions with varying intensities of treatment from CAFOs. Although this assumption is fundamentally untestable, examining the trends in nutrient concentrations in the years leading up to CAFO treatment can be informative. We examine pre-treatment trends and other threats to identification in a subsequent sub-section.

Primary estimation results

Results for the estimation of equation (1) are tabulated in Table 2.[31] The first three columns show results for total phosphorus and the second three columns present results for ammonia. Columns 1 and 4 show regression results with no time-varying controls and all other columns present results including monitor level and HUC8 level time-varying covariates. Including these controls does not change the qualitative results but does add precision to our estimates. Exclusion of these factors could incorrectly attribute all changes in nutrient readings solely to CAFO exposure if the controls

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are correlated with CAFO exposure. The addition of one CAFO to a HUC8 region leads to an increase in average total phosphorus levels of 0.00436 mg/L. Relative to the mean total phosphorus reading from our sample of 0.258 mg/L, this represents a 1.7% increase in total phosphorus levels in surface waterbodies. And relative to the median of 0.07 mg/L, an additional CAFO increases total phosphorus levels by 6.2%. The magnitude of the effect is somewhat larger for ammonia. One additional CAFO in a HUC8 region increases average ammonia concentrations by 0.00614 mg/L. This is a 2.7% increase relative to the mean and a 12.1% increase relative to the median. To further put the magnitude of the results into context, note that the average water quality reading in our total phosphorus (ammonia) sample is exposed to 6.4 (6.1) CAFOs. Thus, the average total phosphorus (ammonia) reading in Wisconsin is approximately 10.9% (16.5%) higher than it would be in a counterfactual world without any CAFOs. As seen in columns 3 and 6, our main coefficients of interest remain statistically significant at conventional levels when we implement two-way clustering at the HUC8 and year levels.[32]

Next, we assess our key identifying assumption of parallel trends in potential outcomes. This assumption is fundamentally untestable, but we examine the trends in nutrient concentrations in the years leading up to CAFO treatment to provide empirical support to the assumption. To empirically examine the pre-treatment trends, we modify our primary specification (1) to include pre-treatment indicators in the spirit of an event study. The estimating equation becomes:

$$Y_{ijdmt} = \sum_{k=-4}^{-1} \tau_k I_j(t - c_j = k) + \beta_1 CAFO_{jdmt} + \beta_2 M_{ijdmt} + \beta_3 X_{jdmt} + \gamma_j + \psi_m + \lambda_t +$$

$$\varepsilon_{ijdmt}, \qquad (2)$$

where notation is the same as described for equation (1). In this specification, c_j denotes the year that the first CAFO was permitted in monitor i's HUC8 region j. Thus, $I_j(t - c_j = k)$ are event indicators, equal to 1 when the year of observation is k years before the first permitted CAFO

begins operation in HUC8 region j. We group years more than 4 years before the first permitted CAFO into the k=-4 indicator.[33] The coefficients, τ_k, represent the evolution in nutrient concentrations at eventually treated monitors before the first CAFO arrived relative to changes in untreated monitors net adjustments in model covariates.

Table 3 shows that the pre-treatment indicators are never statistically significant for either outcome. Furthermore, the point estimates on these pre-treatment indicators do not reveal systematic patterns in pre-treatment trends and are close to zero. The point estimate for the coefficient on CAFO is also similar to the baseline estimate in Table 2 and remains statistically significant. This specification demonstrates that there are no noticeable pre-trends in nutrient concentrations before the arrival of CAFOs to surface waterbody monitoring locations.

Economic impacts

It is important to quantify the increased nutrient concentrations associated with CAFO expansion to understand the implications for ecological health and compliance with environmental regulations, e.g., surface water quality standards. However, society loses non-market benefits when surface water pollution increases so we also need an estimate of the extent of economic damage. Our model predicts improved surface water quality in the counterfactual world where Wisconsin did not experience CAFO expansion. Improved water quality enhances aquatic ecosystems and provides benefits to humans outside of market transactions. For example, enhanced fish populations increase the scope and quality of recreational fishing opportunities and decreased eutrophication enhances swimming and boating experiences. Outings that occur near surface waters such as hiking, biking, or wildlife viewing also benefit from improved water quality.

We implement a modification of the 2009 EPA methodology for estimating non-market

benefits from improved water quality. This methodology is based on a benefit transfer approach, using a meta-analysis of surface water valuation studies. Benefit transfer is a standard non-market valuation method used to estimate the welfare change from a policy or scenario using value estimates from past research. EPA (2009) provides the complete technical details of the meta-analysis estimation used to generate the benefit transfer function.[34] We highlight some of the most important details:

1. The analysis uses a water quality index (WQI) approach, which translates water quality measurements into a single index. The WQI is measured on a scale of 0 to 100, with 0 representing the worst water quality and 100 representing the best water quality. The EPA (2009) WQI adapts McClelland's (1974) and Cude's (2001) WQI methods to the national scale. This method takes water quality measurements from each parameter included in the WQI, transforms the measurements into sub-index values on a 0-100 scale, and aggregates the sub-indices into the overall WQI. Walsh and Wheeler (2013) provide justification that WQI aggregation is appropriate for estimating benefits and costs of water quality changes.

2. EPA (2009) uses a WQI with six sub-indices based on six water quality parameters. Of these six water quality parameters, we have estimated impacts on phosphorus and nitrogen (from ammonia). Phosphorus and nitrogen are equally weighted in the EPA (2009) WQI so we create a WQI that equally weights phosphorus and nitrogen. As in EPA (2009), we use the weighted geometric mean of the sub-indices.

3. EPA's (2009) meta-analysis generates a benefit transfer function that translates predicted changes in the WQI into household level WTP. We assign independent variables as described in EPA (2009) in the benefit transfer function.

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We estimate the loss in non-market water quality benefits from CAFO expansion by feeding estimated changes in water quality from our empirical model of equation (1) to the EPA benefit transfer function. To illustrate methods, we focus on the example of total phosphorus. We begin by applying the equation from EPA (2009) that links total phosphorus concentrations to the total phosphorus sub-index (0-100 scale) to each water quality monitor in our sample. We then use our empirical model to simulate total phosphorus levels at each water quality monitor in the counterfactual world of zero CAFOs, and again use EPA (2009) equations to link total phosphorus levels to a WQI index. Next, we calculate the annual mean of the total phosphorus index for observed and counterfactual scenarios. We complete the same process for nitrogen and then generate the annual average WQI. The mean annual WQI for the observed historical CAFO expansion is 66.96 and the mean annual WQI for the counterfactual scenario with zero CAFOs is 72.52.[35] For reference, Vaughan (1986) classifies water quality based on its suitability for potential uses: 25=boating, 45=rough fishing, 50=game fishing, 70=swimming, and 95=drinking without treatment. Therefore, Wisconsin's average water quality during our sample period is suitable for game fishing and the average water quality in the counterfactual scenario with zero CAFOs would move up to suitable for swimming. However, there is substantial heterogeneity amongst surface waterbodies even in the counterfactual "no CAFO" scenario, with 6% of locations suitable only for rough fishing or boating and 17% suitable for no use.[36] We input the change in the annual average WQI into the EPA (2009) benefit transfer function, which generates mean annual household WTP values in 2008 dollars. We then apply an annual discount rate of 3% to the mean annual WTP values and sum the WTP into a present value of the 23 years of benefits that were lost associated with CAFO expansion. Finally, we convert the present value of the 23 years of benefits to 2017 dollars.

The WTP value is a nonlinear function of the WQI, which is a nonlinear function of the

coefficient on CAFOs from our regression model. These nonlinearities imply that procedures to estimate WTP, such as the delta method, are inappropriate because they produce symmetric confidence intervals. Therefore, we empirically bootstrap the distribution of WTP using a Krinsky and Robb (1986) procedure. We assume that the coefficient on CAFOs is normally distributed with mean and standard deviation taken from our baseline estimation of equation (1). We randomly draw from the coefficient distribution to calculate new parameter estimates for the effects of CAFOs on total phosphorus and ammonia concentrations, and then follow the above described procedure for calculating the simulated WQI and associated WTP for the counterfactual of no CAFOs. We repeat this for 10,000 random draws and then obtain a 95% confidence interval around the median by dropping the highest and lowest 2.5% of the simulated WTP values.

We find that the average household would be willing to pay a present discounted value between $801.19 and $1,163.79 (central estimate of $1,026.60) [in 2017 dollars] for the non-market benefits from improved water quality they would have experienced in the absence of CAFOs from 1995-2017.[37] Averaged over the 23 years of our sample, this implies annual average forgone non-market water quality benefits of $34.83-$50.60. According to the U.S. Census Bureau ACS 5-year estimates, there were 2,343,129 households in Wisconsin from 2014-2018 (U.S. Census Bureau 2019). Therefore, the present discounted value of a policy that would have prevented any CAFOs in Wisconsin from 1995-2017 would be around $1.9-$2.7 billion dollars (in 2017 dollars). On an annual basis, this is approximately $81.6-$118.6 million (in 2017 dollars). To put these values into context, Wisconsin's GDP was approximately $322 billion in 2017. And for further context, a 2019 University of Wisconsin report estimates that dairy farming directly contributed around $5.5 billion of sales revenue to Wisconsin's economy in 2017 (Deller 2019). In 2019, "CAFOs represent about 3.5% of the state's dairy farms but are home to nearly 25% of its dairy

cows" (Cushman 2019). And, over 90% of CAFOs in the state are dairy operations. Thus, annual lost non-market water quality benefits represent approximately 5-8% of total sales from Wisconsin dairy CAFOs.

Threats to identification

In this sub-section, we lend support to our identification and to the validity of our results in several ways. We consider the possibility of endogenous water quality sampling, examine the effects of CAFOs on several placebo outcomes, and address possible endogenous CAFO location and expansion decisions.

The water quality readings that we use as outcomes are measured intermittently in time and space. It is therefore possible that government agencies and citizen volunteers are more likely to sample water quality under certain conditions. And, these conditions could be correlated with nutrient concentrations. For example, it is well known that precipitation events create runoff from agricultural fields, which increases nutrient concentrations in sampled waterbodies. It is plausible that concerned agencies or individuals would then be more likely to sample water quality on the day of the precipitation event, or possibly a day or two after the event. Because we control for precipitation in our DD framework, the biggest threat to our identification would be if the probability of sampling increased differentially in watersheds with more CAFOs. Empirically, a statistically significant and economically meaningful positive effect of the interaction between total precipitation and CAFO intensity would likely indicate that sampling is endogenous and our estimates biased. We test for differential sampling by examining the effects of CAFOs and total precipitation levels on the probability of sampling at a given water quality monitoring location on a given day. To perform this exercise, we create a daily panel dataset of all the monitoring locations

in each analysis sample. We then link these panels with daily CAFO exposure (at the HUC8 level) and daily total precipitation. Using these panels, we estimate the following specification using ordinary least squares:

$$Sampled_{ijdmt} = \beta_1 CAFO_{jdmt} + \beta_2 Prec_{ijdmt} + \beta_3 CAFO_{jdmt} \times Prec_{ijdmt} + \gamma_j + \psi_m +$$

$$\lambda_t + \varepsilon_{ijdmt}, \qquad (3)$$

where the notation is identical to that used in equation (1). There exist three key differences between equations (1) and (3). First, the outcome, $Sampled_{ijdmt}$, in equation (3) is now a dummy that indicates the presence of a water quality sample (including non-detects) of total phosphorus or ammonia, at a given monitoring location, on a given day. Second, we include as a stand-alone regressor $Prec_{ijdmt}$, which measures: 1) daily precipitation at each monitor or 2) a three-day average of precipitation at each monitor that includes precipitation of the day itself and the two days prior. Third, we include the interaction of our CAFO measure and the precipitation measures to examine the differential probability of sampling based on precipitation amounts and treatment intensity. As before, standard errors are clustered at the HUC8 level.

Table 4 presents results for the estimation of equation (3). We highlight two conclusions from these results. First, the interaction between $CAFO_{jdmt}$ and $Prec_{ijdmt}$ is statistically insignificant and very close to zero. Second, the precipitation coefficients are also statistically insignificant and practically zero. Collectively then, precipitation events (and those of the recent past) do not affect the probability that a given water quality monitoring location is sampled when there is zero CAFO exposure at that location. Importantly, as CAFO intensity increases, the probability of a sample on these days with precipitation events does not change. Thus, we are confident that the intermittent nature of water quality readings does not bias our primary estimates.

Although we provide evidence that sampling does not appear to be endogenous, doubts

about the timing of sampling surrounding precipitation events could remain. To assuage this concern, we also estimate equation (1) at the aggregated HUC8-month level. The estimating equation then becomes:

$$Y_{jmt} = \beta_1 CAFO_{jmt} + \beta_2 X_{jmt} + \gamma_j + \psi_m + \lambda_t + \varepsilon_{jmt}, \qquad (4)$$

where Y_{jmt} is the monthly average nutrient reading of all samples taken from all monitoring locations in HUC8 region j. Some HUC8 regions have many more underlying water quality readings available in a month than others and thus provide a more reliable measure of true water quality. We therefore use the number of dependent variable readings in a HUC8 region in a month as analytic weights in all regressions at the HUC8 level.[38] As shown in Table 5, estimates are similar to our baseline results.

Next, we lend support to our identification by estimating our primary regression specification with placebo outcomes. If CAFO presence and intensity significantly affects surface waterbody concentrations of pollutants unrelated to CAFOs, then our model is likely misspecified. There are several types of surface waterbody pollutants that are ubiquitous throughout the United States but should not be associated with CAFOs. First, non-point source pollution can consist of pesticides used on planted acres; concentrations of these chemicals in surface waterbodies likely indicate agricultural activity within the watershed. However, CAFOs do not grow crops on any part of the lot/facility and operators therefore do not apply pesticides at CAFOs. We estimate equation (1) using two measures of pesticide presence in surface waterbodies as outcomes. We first use the concentration of pesticides present at surface waterbodies as our outcome. We collect pesticide measurements from the water quality portal's "Organics, Pesticide" pollutant group and operationalize this measure in a way identical to that of our primary nutrient readings.[39] We also estimate a specification where the placebo outcome is a dummy variable that indicates a reading that does

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not detect a positive concentration of pesticides, i.e., non-detect. We examine non-detected measurements because pesticide concentrations during our sample period are low and thus, results for pesticide concentrations may be sensitive to small changes in the outcome. In fact, 85% of pesticide measurements in our sample are coded as non-detects. Results for the estimation of these falsification tests are presented in Table 6. As expected, the number of CAFOs at the HUC8 level does not affect pesticide concentrations or the detection of non-zero pesticide levels at surface waterbodies in Wisconsin; coefficient estimates for the CAFO measures in these falsified specifications are statistically insignificant and close to zero.

Next, industrial activity oftentimes results in point source discharges of heavy and light metals.[40] This industrial activity occurs in Wisconsin and most other states and results in elevated concentrations of metals in surface waterbodies. CAFOs however, do not directly discharge metals and as a result, our CAFO measures should not be associated with changes in surface water concentrations of industrial metals. We conduct a second falsification test by estimating equation (1) with the concentrations of both heavy and light metals as outcomes. We choose three metals as placebo outcomes and operationalize these measures in the same way as our other water quality measures: (1) cadmium (heavy metal), (2) nickel (light metal), and (3) silver (light metal). [41] We tabulate the results for these falsification tests in Table 7. The number of CAFOs at the HUC8 level does not affect surface waterbody concentrations of cadmium, nickel, or silver. For all outcomes, the coefficient estimates for the falsification tests are statistically insignificant and close to zero. Collectively, these falsification tests lend support to our identification and to the validity of our primary estimates.

Finally, we address the possibility of endogenous CAFO location and expansion. For our estimates to be unbiased, the CAFO intensity measures should be uncorrelated with the error term

in equation (1) conditional on time-invariant unobservables, aggregate time effects, and time-varying controls. It is possible that CAFO permittees endogenously choose to locate in a HUC8 region concurrently with changes in other unobserved determinants of nutrient concentrations. Another potential endogeneity issue is raised by Sneeringer and Kay (2011), who find bunching in the distribution of operations just below the size threshold for CAFOs. Operations that cross the threshold to become CAFOs may be different in ways that are systematically related to water pollution and correlated with location selection and expansion timing, creating a selection into treatment on unobservables problem. The ideal solution to these sources of potential omitted variable bias is to find a time-varying instrument for CAFO expansion within a HUC8. The instrument must influence location decisions of CAFOs without directly affecting surface water quality; such an instrument is difficult to find in the real world. In Online Appendix D, we show an alternative long-difference estimation strategy in which we instrument for CAFO expansion with freeway access. Here, we show how Oster (2019) bounding methods can inform on the direction and magnitude of bias from potential omitted variables.

Oster (2019) shows that one can establish the robustness of an estimate to omitted variable bias by examining coefficient and R-squared stability. Under two assumptions, one can estimate a consistent bias-adjusted treatment effect (Oster 2019). The first necessary assumption is the relative selection of unobservable and observable factors that are related to treatment; Oster denotes this ratio as δ. Oster argues that $\delta = 1$ is an appropriate assumption for generating a bounding set on the treatment effect. Intuitively, this assumes that treatment selection is equally driven by observable and unobservable characteristics. The second assumption involves the theoretical maximum value of R-squared, denoted R^2_{max}. Here, Oster suggests that R^2_{max} will typically be smaller than 1 because of measurement error in Y or because other factors affect Y after the assignment of

treatment. In our context, there is reason to suspect measurement error in surface waterbody nutrient concentrations. Furthermore, decisions to expand CAFOs are made well before the realization of many other factors that affect pollution levels. Oster's analysis of randomized data suggests setting R^2_{max} to 1.3 times the r-squared of the regression including controls. In the notation of Oster (2019), this means that $R^2_{max} = 1.3\tilde{R}$ Then, under these assumptions, the bounding set for the treatment effect of interest is $\Delta = [\tilde{\beta} \ \beta^*(1.3\tilde{R} \ 1)]$. For each estimated treatment effect, we report the bounding set and indicate whether this set includes 0.

Table 8 summarizes the bounding sets for our treatment effects of interest. For both dependent variables, we show the bounding sets for the coefficient on the number of CAFOs. In each case, the bounding set excludes 0; correcting for selection on unobservables moves the estimated treatment effect further away from 0. Table 8 suggests that CAFOs may affect water quality more than we are reporting in our baseline estimates on the monitor-level sample. The bias-corrected effect sizes are especially large for total phosphorus when we set $R^2_{max} = 1.3\tilde{R}$ For comparison purposes, we also show bias-corrected effects when assuming the theoretically max R-squared is 1.15 times the R-squared of the regressions including controls. Bias-corrected effects are still larger than the baseline estimates but get closer to the magnitude of the baseline estimates. Table 8 also shows a similar pattern in bounding sets for estimates from our HUC8 aggregated analysis. The takeaway message from this robustness exercise is that our baseline estimates likely represent a lower bound on the true treatment effects of interest. Selection on unobservables may lead us to understate the extent that CAFOs affect surface water quality.

Sensitivity analysis

In this sub-section, we test the sensitivity of our primary estimation results to changes in the

regression specification and the analysis sample. First, we add to equation (1) a HUC8 level measure for the number of animals at livestock operations net of those on our sampled CAFOs. We include this control to better account for the non-point source pollution that can occur from livestock operations, regardless of their size. For example, there exists bunching at the CAFO size threshold (Sneeringer and Key 2011) so AFOs with hundreds of animal units may affect surface water nutrient concentrations in ways like CAFOs. We therefore gather the livestock count within each county from the Agricultural Census. We then transform this measure to the HUC8-day level like our other Agricultural Census measures and subtract the HUC8 level count of CAFO animal units. The first and second columns of Table 9 present estimation results for this exercise and show that our treatment measure is robust to the inclusion of non-CAFO animals as a control.

Second, we add to our primary regression specification controls for the legacy concentrations of nutrients. Past period CAFO exposure or other agricultural or urban activity can lead to the build-up of nutrients in surface waterbodies. Thus, inclusion of these controls allows us to model both the stock and flow of nutrients in surface waterbodies and to isolate the effects on nutrient concentrations from current CAFO exposure. Because nutrient concentrations are measured intermittently, we construct two variables, one for each outcome, that measure the average nutrient concentrations of each HUC8 over the past five years to account for the stock of pollutants in surface waterbodies. The third and fourth columns of Table 9 present results for the estimation of equation (1) with these measures included. Inclusion of these controls does not substantially alter the estimates of our primary specification presented in Table 2. We also provide several sets of estimation results in the online appendix that further model the stock and flow of pollutants. Online Appendix Table A6 tabulates estimation results where we control for the previous nutrient concentration level at each monitoring location (Paudel and Crago 2018) and where we control for

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CAFO exposure one through five years before each pollutant concentration reading. Our primary estimation results are robust both qualitatively and quantitatively to the inclusion of these additional controls.

We also test the robustness of the results to several alternative specifications. We provide complete details, justification, and results for these robustness tests in Online Appendix E. Additional specifications include: 1) adding year-by-HUC2 fixed effects (rather than only year fixed effects), 2) using HUC10 level fixed effects (rather than HUC8 fixed effects), 3) adding a variable to control for HUC8 level land in the Conservation Reserve Program (CRP), 4) examining the effects of upstream CAFO presence and intensity, and 5) allowing for differential trends before and after CAFOs enter a HUC8 watershed. For changes to the analysis sample, we: 1) limit the sample to HUC8 regions with a CAFO presence throughout our sample period, 2) limit the sample to the growing season months of April-October, and 3) limit the sample to exclude observations from HUC8 regions with poultry CAFO presence. Collectively, empirical results are robust to changes in model specification and analysis sample.

Conclusion

Previous studies suggest a negative correlation between CAFO presence and surface water quality in nearby areas, but prior evidence using longitudinal data on a large spatial scale is lacking. To address this gap in the literature, we assemble a panel that links essentially the entire history of CAFO expansion in Wisconsin with readings on total phosphorus and ammonia levels at surface water monitoring locations in corresponding HUC8 regions. Our identification strategy leverages plausibly exogenous within-HUC8 level variation in the timing and extent of CAFO expansion to identify an effect. We find that adding an additional CAFO to a HUC8 region increases average total phosphorus (ammonia) levels in surface waterbodies by approximately 1.7% (2.7%), relative

to sample means.

We then use EPA methodology to convert increased nutrient concentrations associated with CAFO expansion to losses in non-market surface water quality benefits. This methodology estimates changes in a water quality index and monetizes the changes with a benefit transfer function. We estimate that the present value of lost non-market water quality benefits is approximately $801-$1164 per household; this implies an annualized WTP of about $35-$51 per household to avoid any CAFOs in Wisconsin. Aggregated to the entire state, Wisconsin loses approximately $81.6-$118.6 million in annual non-market water quality benefits from the water quality changes associated with CAFO expansion. A complete enumeration of the costs of CAFOs would likely include several other categories beyond the scope of this study including commercial fishing impacts, increased contamination of private wells, increased contamination of animal water supplies, and increased water treatment costs (EPA 2002b). EPA (2002b) estimates that non-market surface water quality benefits comprise around 75-95% of the benefits of revised CAFO regulations so our estimate of $35-$51 per household likely captures most external costs. The other sizable category from EPA (2002b) is contamination of private wells, so a similar analysis to estimate changes in private well water quality associated with CAFO expansion would be an important extension of our work.

There are important policy implications of our findings. As livestock operations continue to shift toward more concentrated operations, policymakers and regulatory agencies should be aware of the potential external costs of production. We find that one external cost of CAFO production is heightened nutrient levels in surface waterbodies. Excess nutrients degrade water quality and cause algae growth which can harm aquatic life and even be toxic to humans. Ours and previous studies show that degraded water quality leads to lost recreational activities, lowered property

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values, and human health costs. These economic costs should be part of a benefit-cost analysis to guide public policy regarding the regulation of CAFOs.

Finally, we note that there is still much to learn concerning the effects of CAFOs on various outcomes. We have documented the first large scale link that CAFO growth leads to worsening water quality in Wisconsin. This link establishes one mechanism for other potential impacts such as changes in recreational fishing patterns, changes in property values, or changes in human health. The next step should be analyses to discern whether these outcomes of interest are affected by CAFOs, and if so, to what extent. Furthermore, our study has focused exclusively on one midwestern U.S. state, Wisconsin. Although Wisconsin has significant CAFO presence, there are nine other states with higher numbers of total animal units and almost every state has some CAFO presence. Additional studies to identify water quality impacts in other states would help create a more comprehensive picture. Lastly, one limitation of this research is that we cannot identify the specific avenue by which nutrients enter surface waterbodies. From a policy perspective, we would like to know if most of the runoff is occurring from the CAFO site itself or if spreading animal waste onto agricultural fields is the more problematic practice. The answer to this question is important for formulating an effective policy to reduce nutrient levels but one would need data on specific operations of CAFOs to provide an answer.

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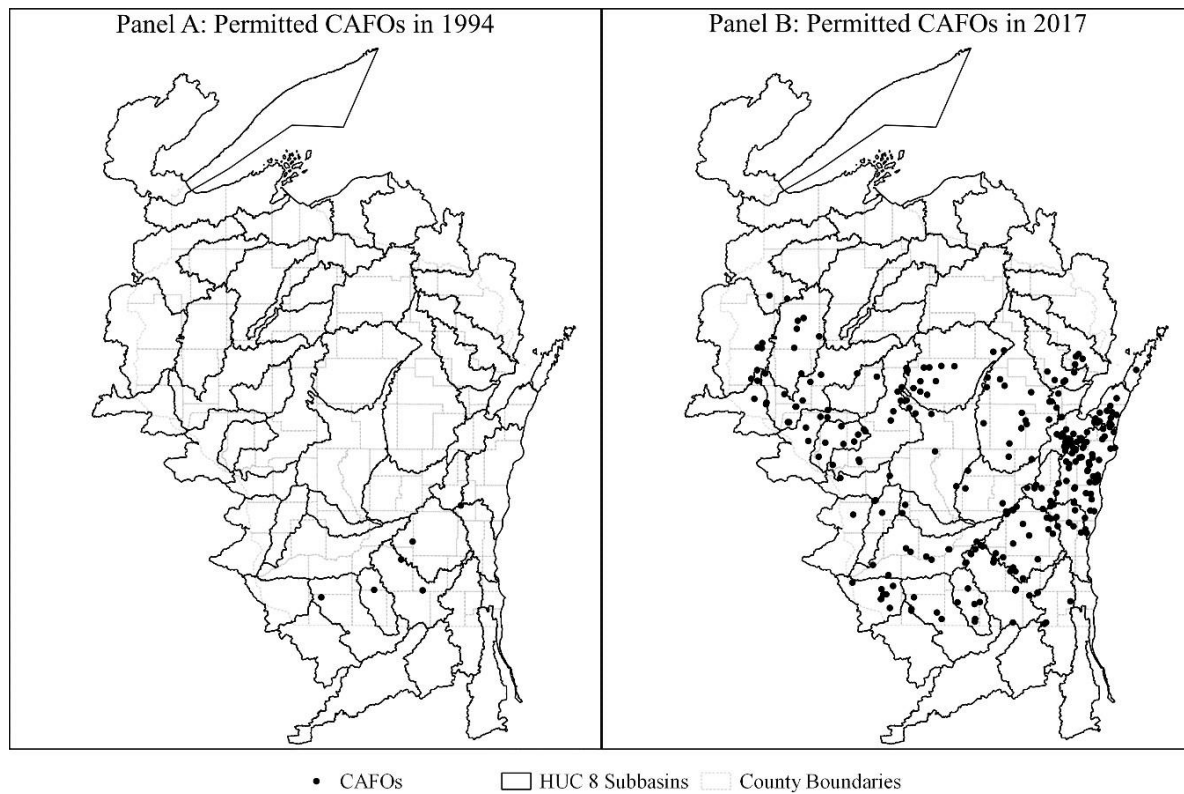
Figure 1. Map of Wisconsin CAFOs in 1994 and 2017

Notes: The panels of this figure show the HUC8 regions of Wisconsin (dark lines) overlaying maps of county borders (faded lines). Each black dot represents a permitted CAFO. Panel A shows permitted CAFOs that were operating in 1994 (the year prior to our sample period) and Panel B shows permitted CAFOs that were operating in 2017.
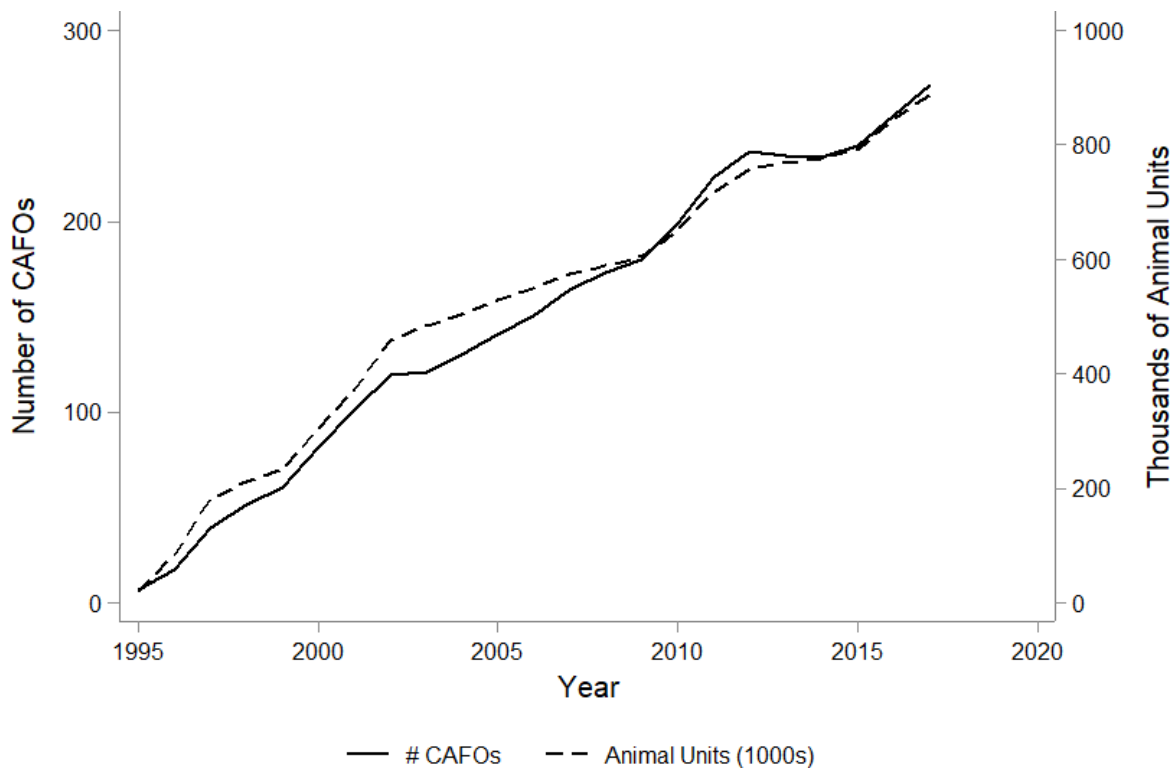
Figure 2. CAFO expansion in Wisconsin

Notes: This figure shows the total number of CAFOs and the total number of animal units in CAFOs for the state of Wisconsin from 1995 to 2017.

Figure 3. Average total phosphorus and ammonia vs. CAFO exposure, 1995-2017

<u>Notes:</u> The two panels of this figure show median annual total phosphorus (Panel A) and ammonia (Panel B) readings and the average number of CAFOs in the HUC8 region of a water quality monitor in our sample for the years 1995-2017.

Table 1. Summary statistics for analysis samples

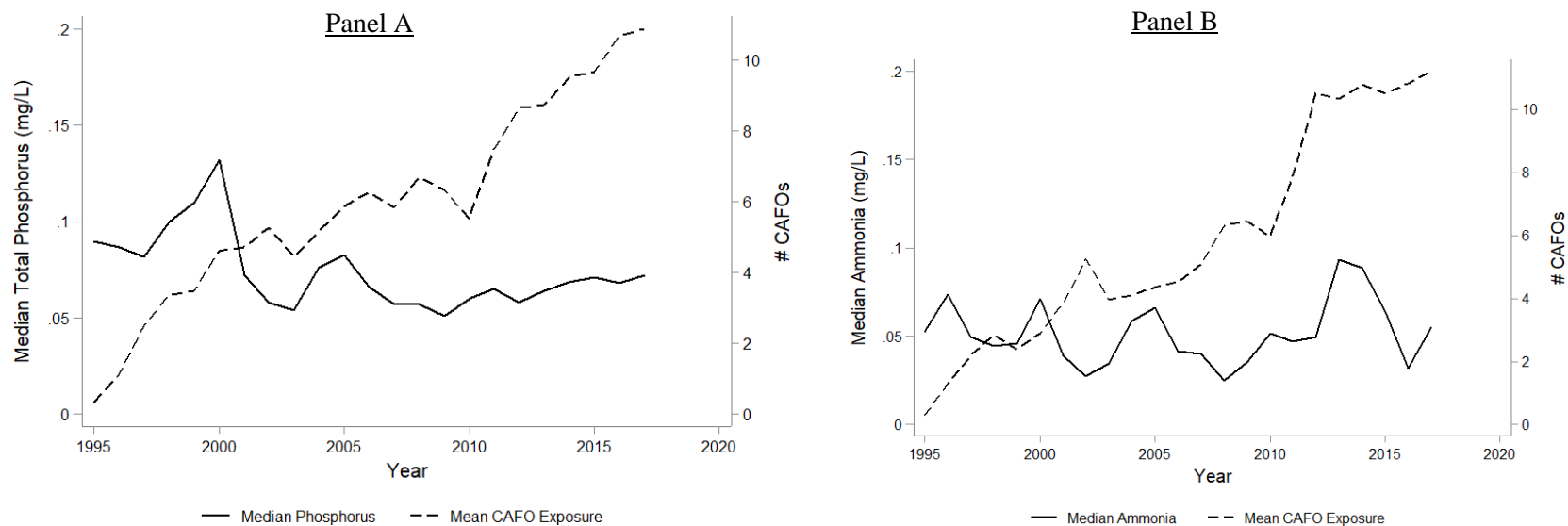| Variable	Total phosphorus		Ammonia	
	Mean	SD	Mean	SD
Pollutant concentration (mg/L)	0.258	0.720	0.227	0.591
CAFOs	6.387	6.942	6.075	6.745
Total precipitation (cm)	0.548	1.061	0.609	1.123
Maximum daily temperature (°C)	19.17	9.334	17.30	10.08
Median income ($)	48,197	8,806	48,075	8,835
Unemployment rate	5.538	1.932	5.361	1.891
Farm acres	221,002	110,020	234,096	105,038
Acres spread with commercial fertilizer	114,050	67,256	116,766	60,195
Developed land (%)	12.48	10.51	13.47	11.17
Forested land (%)	23.37	16.88	22.38	16.59
Planted land (%)	42.29	20.60	44.53	17.96
Observations	237,528		108,577	

Notes: Summary statistics for the pollutant concentration, total precipitation, and temperature measures are at the individual reading level, i.e., monitor-day level. All other measures are at the HUC8-day level. HUC8 level measures are standardized to account for multi-state HUC8s.

Table 2. Effects of CAFOs on surface water nutrient levels

Variable	Panel A: Total phosphorus			Panel B: Ammonia		
	(1)	(2)	(3)	(4)	(5)	(6)
CAFOs	0.00523**	0.00436***	0.00436***	0.00637**	0.00614**	0.00614**
	(0.00232)	(0.00135)	$(0.0097)^+$	(0.00261)	(0.00246)	$(0.0131)^+$
Time varying controls		X	X		X	X
Observations	237,528	237,528	237,528	108,577	108,577	108,577
Clustering	HUC8	HUC8	HUC8 and year	HUC8	HUC8	HUC8 and year
R-squared	0.111	0.141	0.141	0.145	0.146	0.146

Notes: Each column presents regression results from a separate specification of equation (1). Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level for columns 1, 2, 4, and 5. [+] Wild cluster bootstrapped p-value in parentheses are for two-way clustering on HUC8 and year in columns 3 and 6. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3: Testing for pre-trends

Variable	Total phosphorus		Ammonia	
	(1)	(2)	(3)	(4)
CAFOs	0.00488**	0.00457***	0.00618**	0.00636**
	(0.00227)	(0.00152)	(0.00274)	(0.00267)
τ_{-4}	-0.0409	-0.0313	0.0311	-0.0271
	(0.0625)	(0.0591)	(0.0823)	(0.0851)
τ_{-3}	-0.0340	-0.0309	-0.0505	-0.0970
	(0.0627)	(0.0626)	(0.0611)	(0.0653)
τ_{-2}	0.0347	0.0402	-0.0309	-0.0657
	(0.0886)	(0.0876)	(0.0428)	(0.0566)
τ_{-1}	-0.0277	-0.0204	0.0135	-0.000483
	(0.0529)	(0.0566)	(0.0620)	(0.0637)
Time varying controls		X		X
Observations	237,528	237,528	108,577	108,577

Notes: Each column presents regression results from a separate specification of equation (2). Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. Tau variables represent indicators for 1 through 4+ years before each HUC8 experienced any CAFO expansion. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4. Effect of CAFOs and precipitation on water quality sampling

Variable	Total phos-phorus (1)	Ammonia (2)	Total phos-phorus (3)	Ammonia (4)
CAFOs	-0.000019 (0.000031)	-0.000045 (0.000047)	-0.000036 (0.000032)	-0.000052 (0.000045)
Total day of sample precipitation (cm)	0.000210 (0.000145)	0.000211 (0.000138)		
Total precipitation, 3-day average (cm)			0.000029 (0.000021)	0.000244 (0.000185)
CAFOs × total day of sample precipitation (cm)	0.000076 (0.000049)	0.000031 (0.000024)		
CAFOs × total precipitation, 3-day average (cm)			0.000144 (0.000086)	0.000058 (0.000043)
Observations	90,596,384	57,933,296	90,596,384	57,933,296

Notes: Each column presents OLS regression results from a separate specification of equation (3). Column headings represent the type of pollutant sample examined. The dependent variable is a dummy indicating the presence of a water quality sample of total phosphorus or ammonia (including non-detects) at a given monitoring location on a given day. Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. The total precipitation, three-day average variable measures the mean of precipitation of the day itself and the two preceding days at each monitoring location. Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5. Data aggregated to HUC8-month level

Variable	Panel A: Total phosphorus		Panel B: Ammonia	
	(1)	(2)	(3)	(4)
CAFOs	0.00488**	0.00433***	0.00638**	0.00627**
	(0.00187)	(0.00128)	(0.00262)	(0.00243)
Time varying controls		X		X
Observations	10,199	10,199	8,673	8,673

Notes: Each column presents regression results from a separate specification of equation (4) where data are aggregated to the HUC8-month level and the number of water quality readings are used as analytic weights. Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6. Placebo test: Pesticides

Variable	Concentrations (1)	Non-detect (2)
CAFOs	0.00423 (0.00617)	-0.00179 (0.00468)
Time varying controls	X	X
Observations	131,831	131,831

Notes: Each column presents regression results from a separate specification of equation (1) with a placebo outcome. The outcome in column 1 is the monitor-day surface water concentration of pesticides (measured in mg/L). The outcome in column 2 is a dummy indicating a sample that does not measure a positive concentration of pesticides. Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7. Placebo test: Heavy and light metals

Variable	Cadmium (1)	Nickel (2)	Silver (3)
CAFOs	0.00264 (0.00682)	-0.07577 (0.14967)	-0.01758 (0.02103)
Time varying controls	X	X	X
Observations	9,216	7,663	6,726

Notes: Each column presents regression results from a separate specification of equation (1) with a placebo outcome. The outcomes include heavy (Cadmium) and light (Nickel, Silver) metals. Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Bounding set for estimates

			$(R^2_{max} = 1.3\tilde{R})$		$(R^2_{max} = 1.15\tilde{R})$	
Dep. variable	Analysis level	β	Bias-adjusted $\beta^*(1.3\tilde{R},1)$	Robust to excluding 0	Bias-adjusted $\beta^*(1.15\tilde{R},1)$	Robust to excluding 0
Total phosphorus	Monitor reading	0.00436***	0.403	X	0.0131	X
Total phosphorus	HUC8-month	0.00439***	0.0592	X	0.00858	X
Ammonia	Monitor reading	0.00614**	0.147	X	0.0150	X
Ammonia	HUC8-month	0.00627**	0.0187	X	0.00921	X

Notes: This table presents bounding sets for the coefficients on CAFOs from the estimation of equations (1) and (4). The column denoted β shows the original estimates from the full models (columns 2 and 4 from Tables 2 and 5). The bias-adjusted estimates adjust for selection on unobservables using the methods of Oster (2019). We indicate whether the bounding set excludes 0 for each bias-adjusted estimate.

Table 9. Primary sensitivity analyses

Variable	Total Phosphorus (1)	Ammonia (2)	Total phosphorus (3)	Ammonia (4)
CAFOs	0.00345**	0.00524**	0.00358**	0.00601**
	(0.00134)	(0.00234)	(0.00148)	(0.00266)
Time varying controls	X	X	X	X
Non-CAFO animals	X	X		
Legacy total phosphorus levels			X	
Legacy ammonia levels				X
Observations	237,528	108,577	237,503	108,531

Notes: Each column presents regression results from a separate specification of equation (1) with additional controls included. Each specification includes year, month, and HUC8 fixed effects. CAFOs is the treatment variable and measures the number of CAFOs within each HUC8. The non-CAFO animals measure represents the count of all animals at livestock operations net of those located on the CAFOs in our sample at the HUC8-day level. The legacy total phosphorus and ammonia level measures are the average HUC-year concentrations of each respective pollutant over the previous five years. Time varying controls include monitor-day level maximum temperature, total precipitation, and total precipitation squared, and HUC8-day level median income, unemployment rate, farm acres, acres of commercial fertilizer application, and NCLD land cover (percent planted, developed, forested). Robust standard errors are in parentheses and are clustered at the HUC8 level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

[1] An "animal unit" is the equivalent of 1,000 pounds live weight of animals.

[2] Phosphorus and ammonia (nitrogen) are two of the most prevalent pollutants found in animal waste (EPA 2000; EPA 2002a,b; EPA 2004). Total phosphorus is a measure of all forms of phosphorus in surface waterbodies (e.g., ortho-phosphate, organic phosphate) and is reported as such by the Wisconsin Department of Natural Resources. Ammonia concentrations, however, are reported in two forms: (1) ammonia (NH3) and (2) ammonia as nitrogen (NH3-N). Like other studies (e.g., Chen et al. 2019), we convert ammonia to ammonia as nitrogen using the following weight conversion: NH3=NH3-N*1.12589.

[3] Surface waterbody concentrations of nutrients such as phosphorus and ammonia can be linked to physical and economic impacts in several ways. We illustrate these physical linkages in the "Economic impacts" sub-section, using a water quality index approach, and in Online Appendix C, using a trophic state index.

[4] O'Connor et al. (2010) systematically review this literature.

[5] Most similar to our study, Chen et al. (2019) examine water pollution from CAFOs before and after the implementation of an EPA regulation that requires CAFO permitting under the CWA. Our study differs from Chen et al. (2019) in several ways. First, we estimate the effect on water quality of CAFOs themselves, specifically the increase in the number of CAFOs (a trend that is likely to continue), while Chen et al. (2019) perform a policy analysis of an EPA rule implemented to curb water pollution from CAFOs. This is a critical difference because the intensity of CAFOs has increased substantially since the 2003 rule. Thus, our study reveals the effects of increasing CAFO intensity even in the presence of permitting requirements. Second, we monetize the changes in water quality that result from CAFO exposure, whereas Chen et al. (2019) look exclusively at the water quality impacts of the policy. Finally, Chen et al. (2019) examine ammonia as the outcome of interest and we examine ammonia and total phosphorus as outcomes.

[6] See Gray and Shimshack (2011) for a thorough review of the environmental compliance literature, which studies point source water pollution in depth.

[7] Algal blooms lead to reduced recreation (Zhang and Sohngen 2018), low fish yields (Anderson et al. 2000), decreased property values (Wolf and Klaiber 2017), and potential adverse health effects (Townsend et al. 2003).

[8] Several popular press outlets have covered the prevalence of algal blooms in the presence of climate change in detail, see, e.g., https://www.nytimes.com/2018/07/09/us/algae-blooms-florida-nyt.html.

[9] There are 2,264 HUC8 regions in the United States (50 in Wisconsin).

[10] EPA (2001) refers to manure collectively as manure, litter, and process wastewater.

[11] As one exception, Section 319 of the Clean Water Act provides grants for non-point source pollution protection of watersheds.

[12] The permit requirements of the 2003 EPA rule consider spreading manure on fields as discharge events and extend to all "large" CAFOs, which are those with over 1,000 animal units. Prior to 2008, these requirements could be waived only if the CAFO could prove that it did not have the potential to discharge. The 2003 rule was challenged in court so the EPA revised regulations in 2008 to only require a NPDES permit if the CAFO discharged or proposed to discharge pollutants. Liability still existed for failing to apply for a permit (Moore 2011). A March 15, 2011 ruling further reduced the permit requirements for non-discharging CAFOs, vacating the 2008 EPA rule that required proposed dischargers to apply for a NPDES permit. The 2011 ruling also vacated the earlier liability provisions for failure to apply for a NPDES permit. "However, the court upheld the requirement that CAFOs discharging manure to waters of the United States are required to apply for a NPDES permit, and upheld the ability to regulate CAFO land application of manure." (Moore 2011). Wisconsin Rule NR243 continues to require all Wisconsin CAFOs to obtain a permit, regardless of discharge status. Additionally, AFOs with confined livestock can be considered "small" or "medium" CAFOs if they contain less than 1,000 animal units and have the potential to discharge waste to surface waterbodies. These operations are then required to obtain NPDES permits.

[13] Only Massachusetts, New Hampshire, New Mexico, and Idaho are not authorized to implement the NPDES program.

[14] The summary document is available at https://www.epa.gov/sites/production/files/2018-05/documents/track-sum_endyear_2017.pdf. NPDES CAFO regulations require all discharging CAFOs to obtain permits. However, these regulations are size based. The numbers provided in the summary document are for those AFOs that exceed the 1000 animal unit threshold necessary to be considered a CAFO. See above for further details.

[15] We discuss this data source in greater detail below.

[16] For nutrient readings per 100 square miles (rather than readings for all pollutants), these values are 3.63 for Wisconsin and 0.75 for other states.

[17] We define the corn belt as those states identified by Green et al. (2018): South Dakota, Nebraska, Minnesota, Iowa, Wisconsin, Illinois, Indiana and Ohio.

[18] Cow and swine manure are typically stored in liquified form, so it is more expensive and difficult to transport relative to poultry manure, which is typically stored in dried form.

[19] We also estimate our primary specification (equation (1)) using HUC10 level variation and fixed effects. Point estimates on our main coefficients of interest (marginal effects of CAFOs on nutrient levels) resemble those reported in this article (in sign and magnitude) and are statistically significant at the 10% level. There are 357 HUC10 regions in Wisconsin so we have less water quality variation within HUC10 regions. It is also possible that HUC10 areas are small enough that "treated" areas would spill into neighboring "control" areas because of manure spreading practices.

[20] We use daily water quality readings matched with daily CAFO intensity (from CAFO permit data) as our baseline. However, we also show that our results are robust to aggregating to monthly observations.

[21] We begin our analysis in 1995 due to the paucity of data available between 1990 and 1994. There are only six CAFOs in Wisconsin for these years and the CAFO data do not contain information on several key measures, e.g., location, animal units. Furthermore, water quality sampling was apparently not as widespread prior to 1995 in Wisconsin. For example, there are only around 5,000 total phosphorus readings from Wisconsin in 1990 as compared to the annual sample average of around 10,000 (1995-2017).

[22] The discrepancy between the number of CAFOs in our dataset and the number of CAFOs reported as permitted in EPA's summary document is because of a single case where the WDNR considers more than 20 CAFOs under a single "general" permit while EPA considers these individual CAFOs.

[23] Figure 1 shows that CAFOs and animal units are almost perfectly correlated over time. The pairwise correlation coefficient is 0.830 for the total phosphorus sample and 0.861 for the ammonia sample. We therefore use the number of CAFOs as our primary independent variable for our analysis. Online Appendix Table A3 presents results using animal units in place of CAFOs; results are consistent with those presented for CAFOs.

[24] All of these sources have been aggregated to the publicly available Water Quality Portal; see https://www.water-qualitydata.us/portal/ for details. NWIS contains historical water quality data on surface water and groundwater from over 1.5 million sites throughout the United States. STORET contains similar water quality information dating back to the 1960s. Biodata contains bioassessment data collected by local, regional, and national USGS projects.

[25] The original data are used in Schlenker and Roberts (2009) and the lead author maintains updated records on his personal website (Schlenker and Roberts 2020). For a more detailed description of these data, see http://www.wolf-ramschlenker.com/dailyData/dataDescription.pdf.

[26] Paudel and Crago (2018) estimate the effect of fertilizer usage on water quality. The authors use a measure of fertilizer usage purchased from the Association of American Plant Food Control Officials. Because we only include

fertilizer usage as a control and are not interested in the causal effect of fertilizer usage on surface water quality, we use the data measure that is publicly available.

[27] We examine these concentrations in terms of water quality indices in the following sub-sections.

[28] The average monitoring location for each analysis sample is exposed to roughly 26,000 CAFO animal units. This value suggests that most CAFOs contain more than the 1,000 animal units that are required for permits.

[29] During our sample period, there were three policy changes that affect surface water quality and CAFO management. First, at the state level, NR151 sets agricultural performance standards and ATCP50 guides how farmers meet the performance standards. Second, the EPA CAFO rule implemented in 2003 required more CAFOs to be permitted under the CWA and for CAFOs to submit nutrient management plans; this rule was updated in 2008 (Sneeringer et al. 2011; Chen et al. 2019). Changes to these regulations that cause changes in nutrient concentrations and are experienced by all HUC8s in our sample are absorbed by the year fixed effects.

[30] We do not include in our primary regression specification controls for two measures that could affect the magnitude of our estimates because they could be endogenous. First, it is possible that the legacy nutrients present in surface waterbodies affect nutrient concentrations. Thus, one could model both the stock and the flow of pollutants in hydrological networks. However, inclusion of a lagged dependent variable or a series of lags of CAFO exposure likely introduces bias into our specification (Nickell 1981; Paudel and Crago 2018). Second, the purpose of our primary regression specification is to estimate the effect of CAFOs on surface water quality, independent of other agricultural and livestock operations. As such, we include control factors for agricultural land use and land cover. One could also argue that we should control for the total number of non-CAFO animals in a HUC8 region (animals at AFOs other than CAFOs) because this measure could be correlated with CAFO intensity and affect nutrient levels. However, the number of non-CAFO animals could also be an outcome of the CAFO treatment, in which case we would not want to control for it in our regression. Nonetheless, we estimate equation (1) with these additional controls as robustness checks in the "Sensitivity analysis" sub-section. The inclusion of these controls does not meaningfully change our estimates of treatment effects.

[31] Estimation results for the control factors used in our primary empirical specification are tabulated in Online Appendix Table A2. We include these controls to more precisely estimate the primary regressor coefficients and to mitigate omitted variable bias. Given this purpose, we do not claim that the estimated coefficients on controls represent causal effects on our outcomes. Nevertheless, the control factor coefficients are all reasonable in magnitude.

[32] Equation (1) includes year fixed effects, so one-way clustering at the HUC8 level should be sufficient for common time shocks. However, two-way clustering could be appropriate if there are heterogeneous effects of state level time shocks (Petersen 2009; Cameron et al. 2011). Furthermore, we have a relatively small number of clusters in the year dimension (23) so we use the wild cluster bootstrap (Cameron et al. 2008). We use Roodman's boottest module within Stata (Roodman 2015; Roodman et al. 2019). As recommended by MacKinnon et al. (2019), we cluster on both dimensions and bootstrap along the dimension with the smallest number of clusters (year).

[33] We use four years of pre-treatment indicators because CAFO permits significantly expanded in 1999 (WDNR 2011), which is four years after the start of our panel. Thus, including pre-treatment indicators greater than four years in this specification significantly reduces the statistical power for those years.

[34] Appendix G of EPA (2009) provides complete details. Other references for this approach include Bateman and Jones (2003), Johnston et al. (2005; 2006), Shrestha et al. (2007) and Rosenberger and Phipps (2007).

[35] Online Appendix C performs this same exercise for water quality levels using a trophic state index, which is one measure that Wisconsin uses to identify its impaired waters for the CWA 303(d) list (WDNR 2019).

[36] These surface water quality measures are consistent with Wisconsin's most recent water quality report to Congress. In that report, WDNR reports that 82% of assessed waterbodies are healthy. A waterbody is considered healthy if it meets at least one designated use (recreation, aquatic life, or fish consumption) and is not impaired for any use (WDNR 2019).

[37] We also perform the analogous calculations using the Carson and Mitchell (1993) methodology that EPA used in older reports, e.g. EPA (2002b). We find a 95% confidence interval for per household present discounted values of approximately $310-$763 ($566 central estimate) for the water quality changes predicted by our model.

[38] Keiser and Shapiro (2019) similarly aggregate and weight by the number of underlying pollution readings. Results without using analytic weights are qualitatively similar and are shown in Online Appendix Table A4.

[39] We winsorize readings at the 1% and 99% level and measure pesticide concentrations in mg/L.

[40] Heavy metals, e.g., mercury, cadmium, and light metals, e.g., magnesium, silver, are distinguished by their density. Heavy metals are those with higher density and are more dangerous as water pollutants in low concentrations.

[41] We choose these metals and estimate them separately for several reasons. First, the very different atomic weights of various metals make it difficult to estimate the effect of an aggregated metal measure, even in similar concentration units (see, e.g., the conversion of ammonia to ammonia as nitrogen). Second, we wish to include both heavy and light

metals as placebo measures. Third, we choose metals that have not been linked to CAFO waste. As examples, mercury

and has been found in surface waterbodies near CAFOs (EPA 2001). Finally, we do not estimate a specification for

non-detects of metals because concentrations of metals are larger and the prevalence of non-detects is much lower

than for pesticides.