Regulatory Risk and Firm Decision-making: Evidence from the Waters of the United States and US Farms*

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Abstract

Federal regulatory changes often impose substantial costs on directly affected firms. This paper asks a more nuanced question: Does the regulatory process itself, including the threat of regulatory changes, also impose substantial costs? We leverage a proposed jurisdictional change to the Clean Water Act, which led to regulatory changes in some states and only regulatory risk in others, in tandem with variation in the share of cropland potentially affected by the jurisdictional change in each county. We estimate an exposure difference-in-differences design to measure the effects of regulatory exposure on the reservation price for farming, as measured by rents from the Conservation Reserve Program. Using a willingness-to-pay-style analysis, farms subject to regulatory risk experience costs that are about 60% as large as the costs associated with the regulatory change itself. Moreover, due to a provision in the Clean Water Act which exempts certain types of pollution that accompany "regular" farming, we see that the threat of future regulation acted as an incentive to expand cropland in advance of any changes. This eroded other policy goals, in this case establishing new farming practices at the expense of the preservation of certain types of conservation lands. A simple back of the envelope calculation suggests that after accounting for both regulatory risk and the direct cost of regulation, the Clean Water Rule had a total cost to farms of about $2.9 Billion (2022 USD) annually.

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1 Introduction

In the US Constitutional System, Congress writes the laws while the President promulgates rules to implement them. In doing so, the President often exercises some degree of discretion when Congressional intent is vague. Every US President since Ronald Reagan has required economic impact statements to accompany new rules, which are justified on the basis of increasing societal welfare (Sunstein, 2024). While economists and agency staffs have spent many pages discussing the costs and benefits of proposed regulations, including the best frameworks for conducting cost-benefit analysis, much less attention has been given to the costs of the regulatory process itself (Sen, 2000).[1] These costs could be substantial. Using data from Office of Information and Regulatory Affiars (2024), Figure 1 shows that about half of all proposed rules are never finalized. Moreover, the rule-making process takes time, and even after rules are finalized they can be challenged in court, delaying their implementation and causing firms to wait before making costly and partially irreversible investments.[2] This paper investigates how regulatory risk created by proposed rules can impact firms' decisions, and relates the costs of regulatory risk to the direct costs of regulation.[3]

We use the Obama administration's 2014 attempt to expand the jurisdiction of the Environmental Protection Agency's (EPA) authority to enforce the Clean Water Act (CWA) as a quasi-experimental setting to understand the costs imposed on firms, in this setting US farms, from both regulatory risk and regulation. As it relates to farming, the CWA sets out a permitting system that is required for activities that may impact a covered waterway, such as digging a ditch or raising a new structure. However, for existing farming operations there is a carve out for pollution from "regular" farming activities, including pesticide drainage (Wilcher and Page, 1990). The proposed "Clean Water Rule" (CWR) would have expanded the amount of land regulated under the CWA by changing the definition of "Waters of the United States" (WOTUS), which governs the scope of the EPA's authority to enforce the CWA. Critically, the CWR did not alter the associated environmental regulations, including permits, fees, allowed activities, etc. of the CWA (Mulligan, 2019).[4]

The subsequent legal challenges and administrative actions during the Trump and Biden administrations against the CWR created two sets of states. In the first set of states, which we refer to as "no-stay" states, farms were subject to changes in the scope of the Clean Water Act as the

[1] Although estimates of total costs and benefits of regulation in the US have been difficult, there is a large literature on the specific costs and benefits of examples of different types of regulation. See Bombardini, Trebbi and Zhang (2024) for a more complete discussion.

[2] Regulatory risk is related to, but distinct from, the large literature on the impact of uncertainty on firms (Bloom, Bond and Van Reenen, 2007; Shoag and Veuger, 2016; Bloom et al., 2022, 2018; Fernández-Villaverde et al., 2015; Handley and Limao, 2015; Hubbard, 1994; Hassett and Metcalf, 1999).

[3] A related channel for costs from regulation can be through firms diverting productive resources towards unproductive activities such as lobbying (Krueger, 1974; Bhagwati, 1982; Murphy, Shleifer and Vishny, 1993). Investigating these costs are outside the scope of this work.

[4] The Trump administration would later propose a second, less expansive rule curtailing the land covered by the CWA, compared to both the CWR and the pre-existing WOTUS definition (Rapanos). The Navigable Waterways Protection Rule (NWPR) was proposed and finalized but only briefly implemented as court cases and the incoming Biden administration contested the rule nationwide (Bowers, 2021). These details are discussed in full in Section 2.

CWR was eventually implemented by the EPA and US Army Corps of Engineers (USACE). In the second set of states, "stay states", farms never experience an enforced rule change, but rather experience credible threats of future regulation, which we call regulatory risk (Mulligan, 2019; Bowers, 2023*a*,*b*). We rely on machine learning estimates of the geographic scope of the three relevant rules, Rapanos (pre-Obama), CWR (Obama), and NWPR (Trump) from Greenhill et al. (2024) to identify cropland exposed to WOTUS definition changes across US agricultural counties. Then, we deploy an exposure difference-in-differences design across counties in each set of states separately, which identifies the causal impact of regulation in states that receive regulation changes (no-stay states), and regulatory risk in states that receive only regulatory threats (stay states) on farmer's reservation price for farming and crop acreage choices.[5]

In order to identify the value farmers place on both regulations and regulatory risk, we rely on rents placed on farmland enrolled in the Conservation Reserve Program (CRP). The CRP is a large auction in which farmers offer to set aside farmland for 10-15 years in exchange for a guaranteed rental payment from the United States Department of Agriculture (USDA) (Aspelund and Russo, 2024; Stubbs, 2022). We view changes in these bids as reflections of changes in farmers' reservation price to participate in farming, which may change under both regulation and regulatory risk compared to baseline, as farmers may choose to use the CRP to wait out regulatory risk or continue to derive income from land that regulation has made unprofitable to farm.

Additionally, we use detailed satellite data from the National Agricultural Statistics Service (2024) to identify changes in the amount of cropland, which is a key adjustment farmers may make in response to regulation. Facing regulation, planted cropland may decline as additional acres get enrolled in the CRP or simply go unused, while farmers exposed to regulatory risk may have incentives to establish new farming practices to lighten the burden of CWA regulations.

We find that in states that received changing regulations (no-stay states), CRP rents declined significantly while cropland acres only decreased modestly. In states that received only regulatory risk (stay states) we find declines in CRP rents about 60% as large on a per acre basis as the decreases seen in states that received regulatory changes. Using these estimates, a back of the envelope calculation suggests that the CWR cost about $2.9 Billion (2022 USD) annually to US farms, with about 60% of the total cost coming from acres in counties exposed only to regulatory risk. These costs are well in excess of the $550 Million annual figure used in the official cost-benefit analysis of the CWR (US EPA and USACE, 2015). Additionally, in anticipation of future regulation, counties in states exposed to regulatory risk expanded their cropland acres, likely to take advantage of grandfather clauses for existing farming practices in the CWA if they face regulation in the future (Mulligan, 2019; Wilcher and Page, 1990).

Our work suggests that Federal rule-making can be a significant source of regulatory risk, and that these associated costs can be large even when compared directly to the costs of the regulation itself. Previous research on regulatory risk by Calomiris, Mamaysky and Yang (2020) uses the text of corporate earnings calls to measure the cost of (self reported) regulatory exposure on publicly

[5]For a more complete description of the regulatory changes impacting "no-stay" and "stay" states, see Section 2.

traded firms, showing that exposure to regulation decreases firm performance on a number of metrics. Several papers discuss various ways in which regulations impose costs on firms and impose barriers to entry (Djankov et al., 2002). Ryan (2012) shows that changes in requirements for the cement industry increase the costs associated with entry for firms in a structural model, while Rogers (2023) provides quasi-experimental evidence that decreased regulation for medical devices is associated with increased firm entry and innovation, with little negative safety impacts. More generally, Singla (2023) finds that regulations can explain significant increases in firm market power, and Trebbi and Zhang (2022) uses occupational tasks to measure the labor and capital employed in regulatory compliance, finding that compliance accounts for as much as 3.33% of a firm's wage bill between 2002 and 2014.[6] Our contribution is novel in that we are able to provide quasi-experimental evidence in a unified analysis that can compare the impacts of regulatory risk to the impacts of implementation of the same regulation.

In addition to the regulatory literature, we contribute to the body of research on the costs and benefits of the Clean Water Act. Carson and Mitchell (1993) uses survey evidence and official cost figures to suggest that the national goal of making all water "swimmable" may not pass the cost-benefit test.[7] Keiser and Shapiro (2019*a*) show that grants to increase water treatment plant quality under the CWA increased water quality, but willingness to pay measured by home values does not exceed of costs. Focusing on surface water, Keiser and Shapiro (2019*b*) suggests that the literature typically finds benefit to cost ratios below 1. Finally, Taylor and Druckenmiller (2022) uses flood insurance records to value wetlands, finding that wetland loss is valued at $770 (2021 USD) per acre. These estimates suggest that if the CWR could restore all of the wetland loss since 2001, the benefits would be about $600 Million annually, which is below our estimated cost to the farm sector alone.

This paper proceeds as follows. We provide institutional background on Federal rule-making, the CWR, and the CRP in Section 2. Then we describe how we estimate the costs of both regulatory changes and regulatory risk in Section 3 and present the results in 4. In Section 5, we offer concluding remarks.

2 Background and Institutional Details

2.1 US Rule-Making Process

Lawmaking in the United States is a complicated process that involves all three branches of the federal government: Congress, the President, and the Courts. Congress writes laws, which are signed by the President, but the executive branch must administer the laws, which oftentimes

[6] At the local level, production regulations on housing have been shown to be large and impose costs on homebuyers through limiting supply and increasing prices. Our results suggest that discretion and community engagement in the local permitting process may be one channel in which these costs arise (Bartik, Gupta and Milo, 2024; Glaeser, Gyourko and Saks, 2006; Kahn, Vaughn and Zasloff, 2010; Brooks and Lutz, 2019; Severen and Plantinga, 2018; Brooks and Liscow, 2023).

[7] Sunding and Zilberman (2002) show that permitting for the CWA can impose direct costs that are substantial to agriculture, about $300 Million per year, and are associated with long wait times for permits.

requires rules to fill in the gaps left in the legislation. These rules are the ways in which laws actually impact the real economy (Sunstein, 2024). Since the exact powers that legislation gives the executive branch (Federal Agencies) are vague and bounded by both the text of the law itself and the US Constitution, court cases often arise when a rule that may not be lawful impacts businesses (or other interested parties) (White, 2022). Moreover, as courts take cases challenging rules that may go beyond Congress' will or the Federal Government's authority, they frequently issue orders called stays that temporarily block rules from taking effect nationally or within certain jurisdictions while the legal process proceeds (Mulligan, 2019). However justified, this process can be onerous and leave businesses unsure of their exact regulatory environment, both in the present and future, as administrations write rules that are then challenged in courts.

The rule-making process naturally involves the executive branch interpreting the laws passed by Congress as well as their authority under the Constitution to write rules, and these judgments might change as the Presidency is held by different occupants. Moreover, the rule-making process itself is governed by the Administrative Procedures Act, and many proposed rules do not become finalized rules (Sunstein, 2024; Mulligan, 2019; Bowers, 2023*b*). Figure 1 uses data from the Office of Information and Regulatory Affiars (2024) to show the fraction of all rules (the dashed orange line) and "important" rules (the solid blue line) that ever become final rules by the year the rule was introduced.[8] About half of these proposed rules survive the entire rule-making process and become final rules, and many will go on to be challenged and possibly never take effect even after being finalized.

Many of the rules shown in Figure 1 are justified by new pieces of legislation, or enabling legislation that requires regular rule updates. However, some of these rules can be seen as reinterpretations of enabling legislation that itself has not changed. This provides a way in which the Presidency can impact the quantity and quality of federal rules. A recent study from the Brookings Institution has brought to light that a large fraction of rule-making in the Trump and Biden administrations has been directly in response to rule-making in the previous administration (Wallach, 2020). This regulatory "pendulum" could be an additional source of regulatory uncertainty, and therefore likely imposes costs.

2.2 Water of the United States and the Clean Water Act

This paper will focus on one particular example of the regulatory "pendulum" in which the Obama administration expanded the jurisdiction of the EPA's authority to administer the Clean Water Act. The Clean Water Act gives the EPA authority to regulate certain activities that may pollute the Waters of the United States (WOTUS). However, the federal government generally has authority over interstate commerce, so Waters of the United States must be distinguished from purely intra-state waterways. Even so, these intra-state waterways that don't contribute to interstate commerce may be hydrologically connected, through surface water, ground water, or runoff, to covered inter-

[8] Rules that are estimated to have an impact of over \$100 Million USD are considered "important" rules (GW Regulatory Studies Center, 2025).

state waterways. This creates the need for a rule defining which waterways are included in the jurisdiction of the Clean Water Act (Mulligan, 2019; Bowers, 2021, 2023*b*,*a*).

As it relates to farming, the CWA is primarily focused on limiting soil erosion, dredged material, and other runoff from entering covered waterways through issuing permits, imposing fines, and requiring environmental impact reviews (Doering, 2015). However, there is an exemption for runoff associated with ongoing farming operations from normal cultivation and plowing (Wilcher and Page, 1990). This means that the CWA permits and regulations would primarily impact decisions to expand cropland, make substantial upgrades (e.g. irrigation) to existing fields, or erect structures that would require digging.

In 2014, the Obama administration proposed and in 2015 finalized the Clean Water Rule (CWR), which replaced the (pre-2015) Rapanos definition, which had been used to determine the EPA's jurisdiction. The CWR was seen as more expansive than the previous Rapanos definition, encompassing land not previously regulated by the EPA. Critically for our purposes, the Clean Water Act itself was not amended or modified, but rather the administration determined a new rule was necessary on its own. The new WOTUS definition only changed the jurisdiction in which the EPA can apply the Clean Water Act's regulations, but it did not modify the regulations themselves, such as penalties or covered activities, which can be quite substantial (Sunding and Zilberman, 2002; US Environmental Protection Agency, 2024; Wilcher and Page, 1990).[9] Following the finalized rule, several court cases challenged the rule's legality, and the Sixth Circuit Appeals Court issued a nationwide stay, blocking the Clean Water Rule's application nationally. However, the Supreme Court determined in 2018 that this action was improper, which then revealed a patchwork of state-by-state stays issued by several district courts. These stays blocked the EPA's use of the CWR in states covered by the stay, but in 21 states the rule went into effect in 2018 (Mulligan, 2019). Figure A.2, reproduced from Mulligan (2019), shows the 21 states without a stay in which the CWR would go into effect and the 27 states with a stay in which the Rapanos rule is applied throughout the period covered in this paper (2009 to 2023).[10][11] During this time, the challenges to the CWR proceeded in federal court.

The Trump administration would move to rescind the Clean Water Rule and replace it with the Navigable Waterways Protection Rule (NWPR) in 2020 (Bowers, 2021). The NWPR was a more

[9] President Obama made this type of action a focal point of his administration, stating in an address "[we] are not just going to be waiting for legislation in order to make sure that we're providing Americans the kind of help that they need. I've got a pen, and I've got a phone. And I can use that pen to sign executive orders and take executive actions and administrative actions that move the ball forward" (Kaplan, 2014).

[10] We exclude Alaska and Hawaii from our Anlaysis as Mills (1967) does not include data for these states.

[11] The map in Figure A.2 shows these two groups of states. States that do not receive a stay of the CWR are Oklahoma, California, Washington, Oregon, Minnesota, Illinois, Michigan, Ohio, Tennessee, Virginia, Maryland, Delaware, Pennsylvania, New York, New Jersey, Connecticut, Rhode Island, Vermont, Massachusetts, New Hampshire, and Maine (21 states). These states see their regulatory environment change from the Rapanos Rule, to the CWR, then back to Rapanos over the study period. The states that receive a stay only experience the Rapanos regulation, but have the credible threat of regulation expansion under the CWR and limitation under the NWPR. These stay states are Florida, Idaho, Montana, North Dakota, South Dakota, Nebraska, Nevada, Arizona, Utah, New Mexico, Colorado, Kansas, Texas, Wyoming, Missouri, Iowa, Wisconsin, Indiana, Kentucky, West Virginia, North Carolina, South Carolina, Georgia, Alabama, Mississippi, Arkansas, and Louisiana (27 states).

narrow construction of the definition of the Waters of the United States, moving away from the CWR's broad "significant nexus" standard for included tributary wetlands and waters. However, the NWPR was quickly contested in court. Then, in 2021, the Biden administration removed the NWPR and stopped supporting its defense in federal courts (Bowers, 2021, 2023*a*,*b*). Following a Supreme Court decision centered around WOTUS, *Sackett v. Environmental Protection Agency* in 2023, the Biden administration wrote a revised rule, called the 2023 rule, to comply with the holding in *Sackett*. This rule has also been challenged, but we will focus on the episode surrounding the 2015 CWR revision given our data constraints.

2.3 Conservation Reserve Program

In order to measure the impacts of the changing WOTUS definitions we leverage data on the Conservation Reserve Program (CRP). The CRP is a voluntary land set-aside program in which farmers can offer to not farm parcels of their land in exchange for a guaranteed rental payment from USDA. Land is submitted in a single round sealed bid auction, in which farmers offer amounts of land which get ranked by their environmental benefits. USDA ranks bids by their environmental benefits (which include a measure of costs) and accept bids in order of environmental benefit until they hit their congressionally set acre limit, regardless of the total program cost. We view changes in these bids as a reflection of farmers' changing reservation prices for farming their land.

CRP contracts last between 10 and 15 years, and land can be re-enrolled (Hellerstein, 2017; Stubbs, 2014; Aspelund and Russo, 2024). If individuals wish to terminate CRP contracts early, they are required to pay back all rents as well as interest on rent payments, calculated using the USDA's Commodity Credit Corporation interest rates which change monthly. On January 9th, 2017, as an attempt to help incentivize transfers of farmland to new farmers, the Farm Service Agency and USDA started waiving these early termination penalties if the land under contract was going to be sold or leased to an individual not currently operating as a farmer. Additionally, the CRP has a per-county acreage cap of 25% of all cropland. For a full discussion of the CRP and its evolution, see Hellerstein (2017).

3 Data and Methodology

Our analysis relies on measuring the exposure of cropland to changes in the definition of WOTUS. We build our exposure measure by projecting estimates for three versions of the WOTUS rule produced by Greenhill et al. (2024) on to US cropland raster data from National Agricultural Statistics Service (2024) using K-nearest neighbors (KNN). Intuitively, this uses the nearest WOTUS points from Greenhill et al. (2024) to predict whether or not a given raster cell of cropland would be included or excluded in WOTUS by the Rapanos (pre-2015), CWR (Obama), or NWPR (Trump) definitions. We then classify these cropland cells into three mutually exclusive groups. Always WOTUS cells are likely to be included in all three definitions of WOTUS. For example, farmers on the banks of the Potomac River are covered by every WOTUS rule. The second group included cells that are never defined as covered by WOTUS. Farmers in the high desert of Utah are likely never covered by WOTUS. Finally, our third group lies between the previous two groups. There are some farms that might be included in a more expansive definition of WOTUS (e.g. the CWR), but excluded in a narrower definition (e.g. the NWPR). The group that is sometimes exposed to WOTUS definitions is exposed to regulatory changes in the states that don't receive a judicial stay of the CWR, and exposed to regulatory risk in states that receive a judicial stay of the CWR and face only the credible threat of future regulations. We use the share of cropland (measured between 2009 and 2013) in each county that is sometimes covered by a WOTUS definition as our measure of exposure. Appendix B discusses the creation of our exposure surface in more detail.

In Figure 2, we show a map of county-level exposure to regulation for the lower 48 states. In Sub-figure 2a we can see that the share of cropland sometimes covered by definitions of WOTUS are located around major navigable waterways.[12] In Sub-figures 2b and 2c we show histograms of the support for the share of county cropland included in only one or two definitions of WOTUS ("sometimes WOTUS") for states that do not receive a judicial stay of the CWR (in orange) and states that receive a stay (in blue). Across the counties in both groups of states we see a full support, with the share of county cropland sometimes included in a WOTUS definition ranging from 0% to 100%. Table 1 shows that in states without a stay, 25% of cropland is sometimes exposed to WOTUS rule changes, whereas only 19% of cropland is exposed in states with a stay.

Our main outcomes of interest are annual average rents paid to farmers by the Conservation Reserve Program (CRP), which we argue reflect a farmer's reservation price for farming. We then use this as a measure similar to willingness to pay to assess costs imposed by regulatory changes and regulatory risk. We get publicly available county level statistics from US Department of Agriculture (2024) on the total rents paid and acres enrolled in the CRP from 1987 to 2022, and we recover the county average rent per acre by dividing rents by acres and then deflating using the personal consumption expenditure price index to convert to 2022 USD (U.S. Bureau of Economic Analysis, 2024). Since we only have aggregate enrollments, and we want to measure new bids, we need to add a series of controls that reflect the program constraints of the CRP when running regressions including CRP rents. These controls are discussed in more detail below.

Our second set of outcome variables measure annual farm acre allocation choices and come from the National Agricultural Statistics Service (2024) raster data, which we aggregate to the county level and convert from 30 by 30 meter grid cells to acres. These data are available from 2008 to 2023. We focus on changes in total cropland, which is one measure of farmer's capital investment that should be sensitive to regulations under the Clean Water Act. Bringing new land into use requires dredging and other activities that will change the erosive properties of the land, which is explicitly covered under the Clean Water Act and would require a permit. Secondarily, we can look at what types of land farmers choose to bring in to (or out of) production. We focus on conservation lands and wetlands, here.[13] Conservation lands include types of land cover that have

[12] Figure A.1 shows the original data from Greenhill et al. (2024) summarized at the county level. This measure includes all points, even those not near farmland. The pattern is similar to Sub-figure 2a.

[13] We define conservation lands as switchgrass, fallow cropland, pasture and grasslands, forests (all types), shrub-

environmental benefits, and generally exclude activities such as farming and development. We also present separate estimates for wetlands since they are of specific interest to the Clean Water Act.

Given that the National Agricultural Statistics Service (2024) data are estimated with noise, we trim 123 counties from our sample that are in either the lowest 5% of cropland coverage nationally before 2013 or in the highest 5% of the distribution of coefficients of variation for total cropland before 2013. These estimates are meant to drop urban counties and national parks that erroneously have acres of row crops attributed to them or for some other reason show abnormally volatile estimates in our pre-period. We show comparisons of the full and trimmed sample stats in Table A.1 and a scatter of trimmed and untrimmed counties in Figure A.3.

We need to include CRP program controls to identify changes driven by new bids from farmers. These include 10 through 15 year lags of rents and acres as well as the amount of cropland that could potentially be enrolled given the 25% acreage cap. As contractions of cropland acres can lead to counties being over-enrolled, we additionally include a dummy for over-enrolled counties with a one year lag. These controls ensure that we are isolating changes from current farmer behavior.

As a robustness check, we also include specifications that control for agricultural futures prices as expectations about agricultural prices are important inputs for farmers making forward looking planting and CRP enrollment decisions. We use data on 11 futures series from investing.com to create a county-specific average future series. For this county index, we weight each futures series based on a county's share of acres in each land category.[14] The index is constructed so that 2007 is the base year. In Table 1, we can see that on average counties in both sets of states have similar exposure to expected price changes, with no-stay states having higher expected price increases than stay states.

We estimate two difference-in-differences models in order to understand how exposure to WOTUS rule changes effects farmers' reservation price for farming, as measured by CRP bids, and their crop acreage choices. We run these regressions in states that do not receive a stay of the CWR (21 states) and states that do receive a stay (27 states) separately. We run regressions of the following form using data from 2009 to 2023:

$$Y_{ct} = \alpha + \beta(ExpWOTUS_c \cdot Post_t) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct} \tag{1}$$

where Y_{ct} is the outcome of interest in county c and year t. $ExpWOTUS_c$ is our county level measure of exposure to changes in WOTUS definitions, which takes a value of 1 if all pre-2013 cropland in a county is likely regulated by only one or two versions of the WOTUS definition, and a value of 0 if all of the county cropland is either covered by all three WOTUS definitions or none of the WOTUS definitions. We then interact this exposure measure with the dummy $Post_t$, which

land, and wetlands following the categories predicted in the raster data from National Agricultural Statistics Service (2024).

[14] The futures series and land categories are: corn, cotton, OJ (citrus), rice, soybeans, sugar, wheat, and meat. Whereas meat is the average of feeder cattle, hog, and live cattle futures and is attached to pasture.

takes a value of 1 after and including 2014, which is the year in which the CWR was introduced. In states without a stay, we interpret our coefficient of interest, β, as capturing the direct impact of the changing regulations, since these states will actually be regulated using both the expanded CWR definition and original Rapanos definitions of WOTUS. In contrast, for regressions run in states with a stay, we interpret β as capturing the effects of regulatory risk. In these states, only the Rapanos rule is applied, but the CWR definition and NWPR definition both get introduced and stayed, but never actually applied in these states. In specifications using CRP outcomes, we include program controls described above in $\vec{X}_{ct}$. For robustness, we can also include the futures index. We also include county and year fixed effects, which are κ_c and τ_t, respectively. In order to account for potentially changing policies targeting wetlands, we can also include wetland bin by year fixed effects to limit comparisons to counties that have similar acreage shares in wetlands before 2014. We define bins by decile of wetland acre shares of county cropland acres in pre-period data. ε_{ct} is an error term, and we cluster our standard errors by county and year following Newey and West (1987)[15]. In addition to our simple difference-in-difference model, we can estimate a more flexible event study, which will also serve as a pre-trends test. We run regressions of the following form for states that do not receive a stay and states that receive a stay separately using data from 2009 to 2023:

$$Y_{ct} = \alpha + \sum_{t \neq 2013} \beta_t (ExpWOTUS_c \cdot I\{Year = t\}) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct} \tag{2}$$

where β_t gives a set of estimates relative to the base year of 2013, which is excluded. Similar to Equation 1, we include year and county fixed effects and use year and county clustered standard errors following Newey and West (1987). For robustness, we can also include controls as well as wetland by year fixed effects.

Both sets of models in Equations 1 and 2 rely on assumptions in order to produce causal estimates of the impact of exposure to regulation on reservation prices and cropland choices. First, we need to assume that counties with higher exposure shares would have maintained a parallel trend to low exposure counties absent the introduction of the CWR in 2014. Second, we also need to assume that there is no other policy introduced in 2014 that would overlap with the WOTUS exposure variable. We will address these assumptions in the following sections when we present our results.

4 Results

Before we discuss our main findings, we can first show support for our parallel trends assumption using the pre-trend coefficients in Figure 3. Each panel shows coefficients for β_t from Equation

[15] The estimation error present in our main regressor, the share of sometimes WOTUS cropland in a county as well as in some of our outcome variables, land coverage shares coming from remotely sensed classification models mean that in a world without computational constraints we should bootstrap our standard errors in accordance with Davison and Hinkley (1997). However, the size of the input datasets involved make that infeasible to perform.

2 discussed above. The first column shows estimates for no-stay states that receive changing regulatory environments after the introduction of the CWR, and the second column shows results for states that have a stay of the CWR and therefore get exposed to regulatory risk. The top row shows results for annual average county CRP rents and includes CRP program controls. The bottom row shows results for annual average county cropland acreage. In all four panels we see evidence in support of the parallel trends assumption as only one estimate of β_t is statistically different than zero across the figures.[16]

We report our main estimates for changes in CRP rents in Column 1 of Table 2. After 2014, our results in Panel A suggest that farmers in states that received changing regulations (no-stay states) decreased their CRP bids, which reflects their decreasing reservation price for farming as regulation decreases the value of their land. Our point estimate suggests that in a county with 25% of their cropland exposed to WOTUS changes the average CRP rent dropped \$6.82 per acre. In Panel B, in Column 1 we report estimates for states that receive a stay of the CWR and face increased regulatory risk after 2014. We see that farmers facing regulatory risk also see their reservation price for farming decrease. In a county with 25% of its land exposed to WOTUS reduces the average CRP rent by \$4.22 per acre. These results suggest that farmers' value decreases from regulatory risk are about 60% of the value decreases from actual regulation changes. These results are robust to additional controls and wetland by year fixed effects, which we show in Table A.2

In Sub-figure 3a we report event study estimates of the impact of expanded WOTUS jurisdiction on CRP rents in no-stay states. Here we can see initially modest point estimates while the CWR was nationally stayed, but then the point estimates continue to drop after the CWR expands the definition of WOTUS in the No-stay states in 2018. In Sub-Figure 3b we show the same event study estimates for states that received a stay of the CWR and faced regulatory risk throughout the post-2014 period. Here we can see the decreases in the farming reservation price that eventually level off around 2018.

We can take these estimates for the impact of regulatory exposure on CRP rents to do a back of the envelope calculation of costs of the announcement and implementation of the CWR. These calculations will take the following form:

$$TotCost = N_n \cdot \underbrace{\overline{Cropland}_n \cdot \overline{ExpWOTUS}_n}_{\text{Avg. Exposed Acres to Regulation}} \cdot \beta_n + N_s \cdot \underbrace{\overline{Cropland}_s \cdot \overline{ExpWOTUS}_s}_{\text{Avg. Exposed Acres to Risk}} \cdot \beta_s \tag{3}$$

where $TotCost$ is the total (average) annual cost of the CWR. This includes a component from the no-stay states that experience regulatory changes and a component from the stay states that experience regulatory risk. N_n and N_s are the number of in-sample counties in no-stay and stay states, respectively. We calculate average exposed acres to regulation in no-stay states and to regulatory risk in stay states by multiplying the average acres of cropland in each county before

[16]In Sub-figure 3d, the high estimate in 2010 likely reflects the high commodity prices associated with the Great Recession that would induce farmers to bring additional land into production (Trostle et al., 2011).

2013 to the average share of cropland sometimes included in WOTUS definitions. Finally, we take the estimates of β from Table 2 Panel A Column 1 for no-stay states and Panel B Column 1 for stay states as our estimates for per-acre decreases in farm reservation prices, which here is analogous to willingness to pay. This gives an annual total cost estimate of about \$2.9 Billion (2022 USD), with the average no-stay state county losing about \$1.25 Million (2022 USD) from regulation and the average stay state county losing \$912 Thousand (2022 USD) from regulatory risk.[17] These costs are much larger than the initial cost-benefit analysis, US EPA and USACE (2015), which projected the costs from the CWR to be \$550 Million (2022 USD).

Next we turn to our results for farm acreage, which are reported in Table 2. In Panel A Column 2, we can see that counties in states exposed to regulatory changes saw farmers decrease acreage on average after 2014. In a county which had 25% of its cropland exposed to changes in WOTUS definitions farmers decreased cropland by about 1,540 acres compared to pre-2014 levels. Columns 3 and 4 show that these decreased acres, however, were not associated with detectable increases in conservation lands overall or specifically for wetlands in states that faced regulatory changes.

In contrast, in Panel B we see that farmers in counties in states exposed to regulatory risk significantly increased their cropland. A county with 25% of its cropland exposed to regulatory risk by about 5,687 acres compared to the pre-period, which is about a 2% increase in total cropland. This behavior is likely in anticipation of being included in an expanded definition of WOTUS in the future, such as the CWR definition. Farmers that can establish an existing farming practice on a plot can use their land and even pollute rivers due to pesticide runoff so long as they don't dig a ditch, dredge soil, or do one of the activities that explicitly requires a permit. We show that our total cropland results are robust to additional controls and wetland by year fixed effects in Table A.2. This anticipatory behavior comes at the expense of conservation lands overall, which decrease after 2014 as shown in Panel B Column 3. However, wetlands increase by 6.8% on average compared to the pre-period. These results suggest that regulatory risk induced farmers to expand croplands in ways that may not have been environmentally desireable, but that potentially limited their future exposure to CWA constraints under more expansive definitions of WOTUS.

5 Conclusion

In this article we have exploited a unique set of facts created by the Obama administration's Clean Water Rule, and the subsequent legal and administrative challenges, to show how the Federal rule-making process can impose costs on firms even in the absence of finalized and implemented new regulations. This example also allows us to compare the regulatory risk created by the rule-making process with the actual implementation of the same rules contemporaneously. We find that regulatory risk can have costs about 60% as large as those from the regulation's implementation.

[17] This exercise suggests that if the nation-wide injunction wasn't removed in 2018 the cost of the CWR would have been reduced by \$445 Million (2022 USD) annually. Conversely, if no states received a stay and every county was exposed to regulatory changes costs would have increased about an additional \$1 Billion (2022 USD) annually over the actual estimate reported above.

When combining the costs associated with exposed acres in both the states that receive regulatory change and those that receive regulatory risk, we find the total cost of the Clean Water Rule on farms to be $2.9 Billion (2022 USD) annually, over five times as large as those calculated by the initial EPA cost benefit analysis (US EPA and USACE, 2015). If we impose the estimates for acres in states exposed to regulatory risk on all exposed acres, the hypothetical scenario in which all states are treated with regulatory risk only decreases the costs to $2.5 Billion (2022 USD) annually. We hope that this work encourages future research on the Federal rule-making process and on the costs of regulatory discretion and risk at all levels of government.

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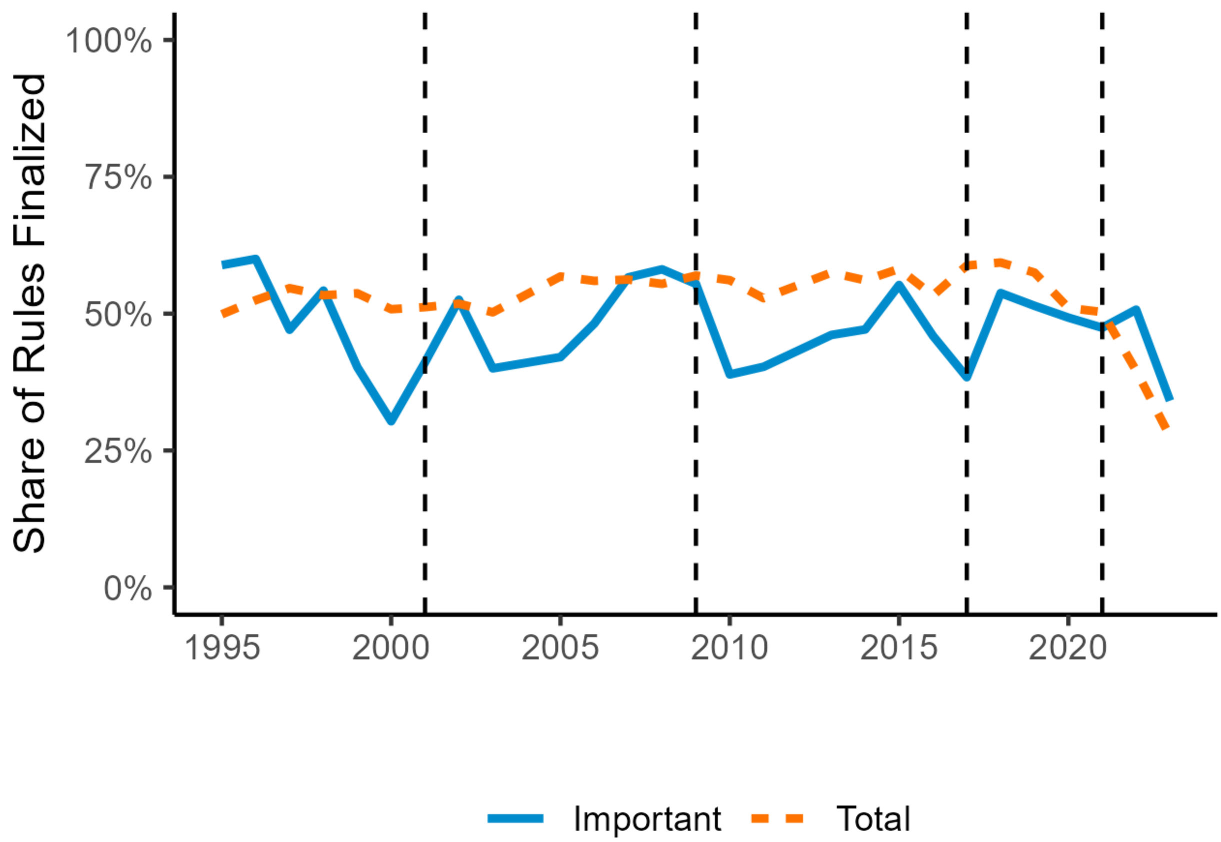
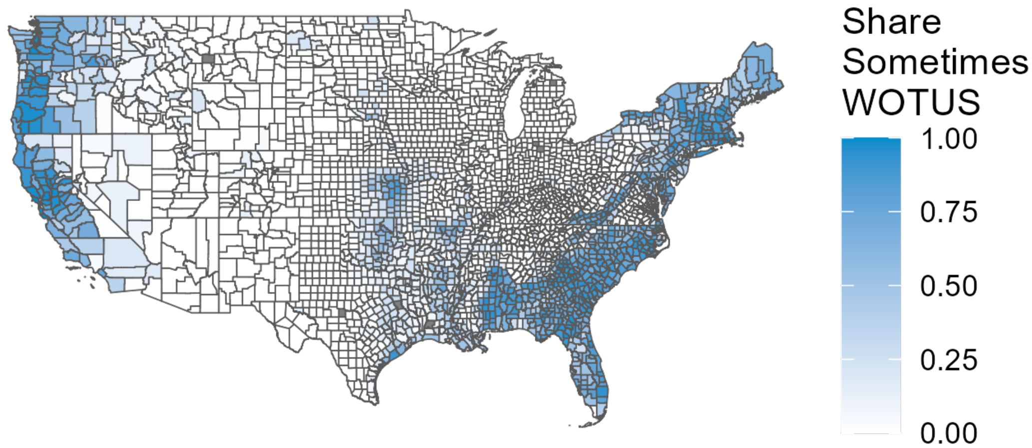
Figure 1: Time Series of the Share of Rules Ever Finalized by Introduction Year



This figure shows time series for the share of rules proposed that are ever finalized by the year in which the rule is introduced. The orange dashed series shows the share of all rules that are ever finalized. The solid blue line shows the share of "economically important" rules that are ever finalized. The Office of Information and Regulatory Affairs (OIRA) determines a rule to be economically important if it has a projected economic impact of over $100 Million USD. New administrations are marked with vertical dashed lines. Data from Office of Information and Regulatory Affairs (2024).

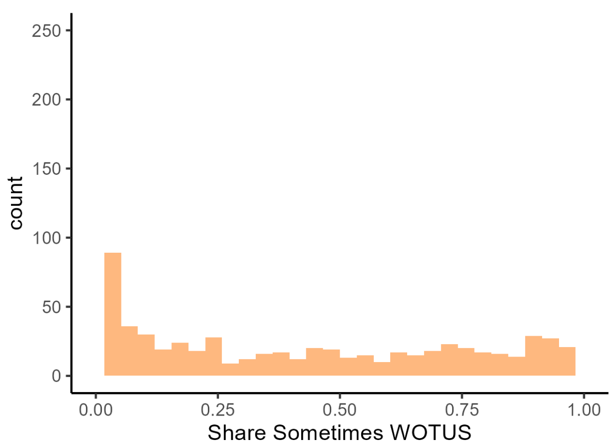
Figure 2: Map and Histograms of Exposure to WOTUS Definition Changes

Regulatory Exposure

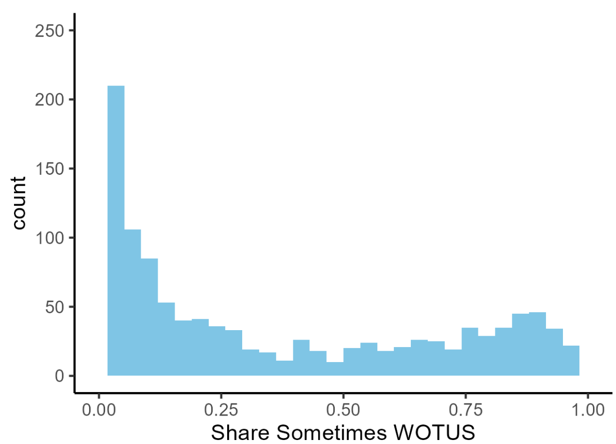


(a) Exposure Map for All States

Histograms of Regulatory Exposure



(b) No-Stay States (Regulation Treatment)

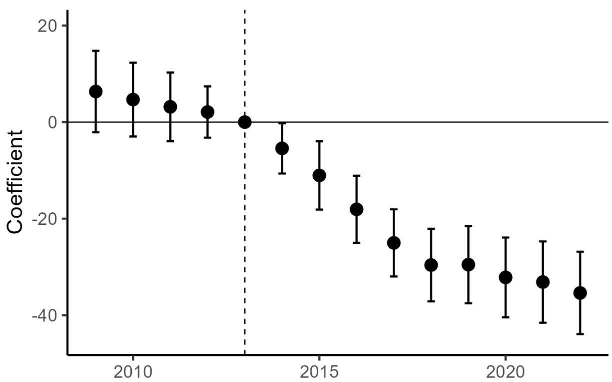


(c) Stay States (Risk Treatment)

Note: The map shows our interpolation of the Greenhill et al. (2024) points on to cropland that are sometimes included in definitions of WOTUS for each county, which is our measure of regulatory exposure. The histogram in Panel B (orange) shows the support for the share of cropland sometimes covered by WOTUS in states with no-stay, which shows county exposure to regulatory changes. The (blue) histogram in Panel C shows the support for the share of cropland sometimes covered by WOTUS in states with a stay, which represents county exposure to regulatory risk.

Figure 3: Effects of Regulatory Exposure on CRP Rental Payments per Acre (2022 USD) and Acres of Cropland in No-Stay and Stay States

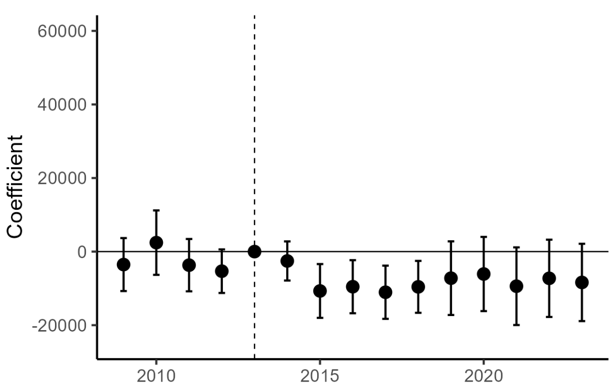
CRP Rent Per Acre (2022 USD)



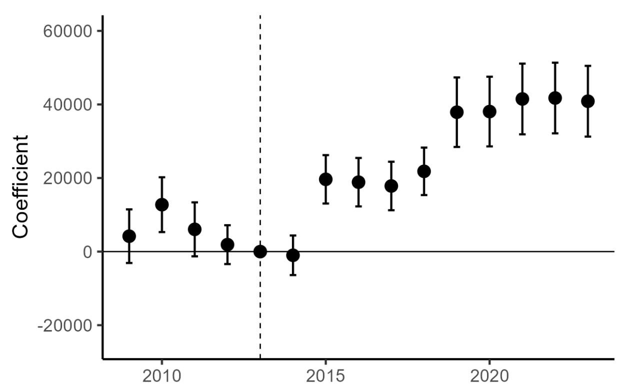
(a) No-Stay States (Regulation Treatment)

(b) Stay States (Risk Treatment)

Acres of Cropland



(c) No-Stay States (Regulation Treatment)



(d) Stay States (Risk Treatment)

Note: These figures show estimates of Equation 2 for counties in no-stay and stay states separately. These estimates take the following form: $Y_{ct} = \alpha + \sum_{t \neq 2013} \beta_t(ExpWOTUS_c \cdot I\{Year = t\}) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct}$, where c indexes counties and t indexes years. All regressions include interactions of year dummies $I\{Year = t\}$ with the regulatory exposure measure $ExpWOTUS_c$, which takes a value of 1 if all cropland in a county is sometimes covered by WOTUS and a value of 0 if all cropland in a county is either never or always covered by WOTUS. Estimates in Panels A and B use CRP rents per acre (2022 USD) as their outcome variable and include CRP program controls. Estimates in Panels C and D use total acres of cropland as their outcome variables. All estimates include year and county fixed effects and Newey and West (1987) standard errors are clustered at the year and county level. Data for this figure come from US Department of Agriculture (2024), National Agricultural Statistics Service (2024), Greenhill et al. (2024), and Mulligan (2019).

Table 1: Summary Statistics by No-Stay and Stay States, 2009 to 2013

	No-Stay (Regulation)	Stay (Risk)
Total Acres	503,976	614,819
	(542,449)	(774,265)
Acres of Cropland	185,889	278,911
	(203,118)	(335,338)
Conservation Land Acres	240,005	271,791
	(411,460)	(641,099)
Wetland Acres	24,032	29,381
	(66,587)	(64,686)
CRP Acres	6,868	12,191
	(20,686)	(25,694)
CRP Rent per Acre (2022 USD)	89.13	65.31
	(62.43)	(46.44)
Share of Cropland Always WOTUS	0.11	0.03
	(0.26)	(0.11)
Share of Cropland Sometimes WOTUS	0.25	0.19
	(0.33)	(0.30)
Agricultural Futures Index	1.18	1.16
	(0.19)	(0.19)
CRP Eligible Acres	39,604	57,496
	(44,225)	(72,902)
Observations	4,645	9,650

Note: This table reports summary statistics for counties in states with no-stay and states with stays of the CWR separately for the years 2009 to 2013. Averages are reported with standard deviations in parentheses. Data for this table come from National Agricultural Statistics Service (2024), Greenhill et al. (2024), Mulligan (2019), US Department of Agriculture (2024), and investing.com.

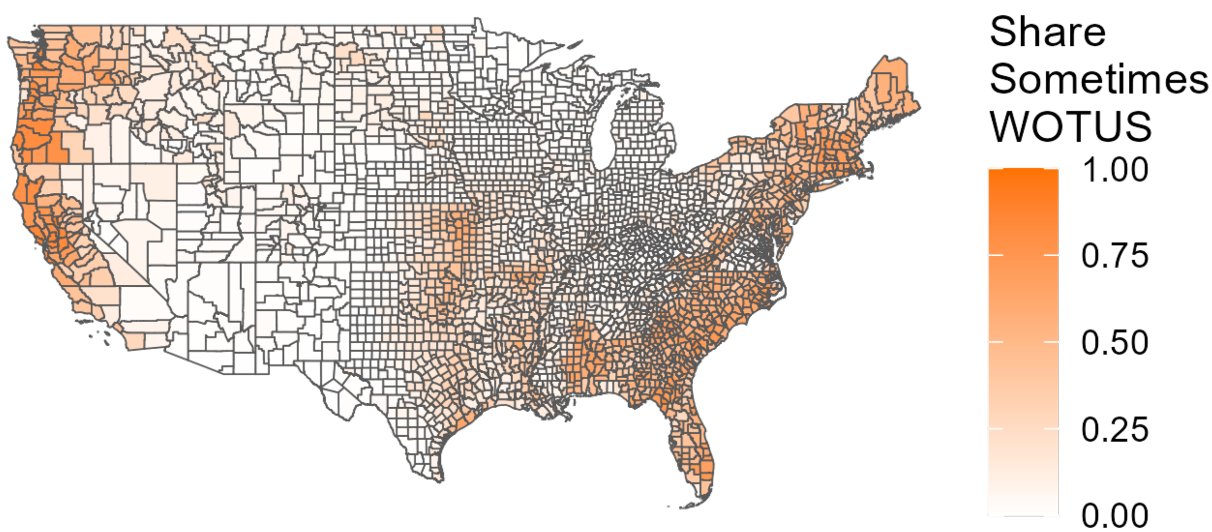
Table 2: Exposure Difference-in-Differences Estimates of the Impact of Exposure to Regulation on Farm Outcomes

	Panel A: No-Stay (Regulation Treatment)			
	CRP Rent	Cropland	Cons. Land	Wetlands
	(1)	(2)	(3)	(4)
$ExpWOTUS_c \cdot Post_t$	-27.29***	-6,161***	3,429	-461
	(1.67)	(1,976)	(2,124)	(748)
CRP Controls	✓			
County FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Adjusted R^2	0.92	0.97	0.99	0.98
Observations	13,006	13,935	13,935	13,935
Dep. Var. Mean	89.13	185,889	240,005	24,032
	Panel B: Stay (Risk Treatment)			
	CRP Rent	Cropland	Cons. Land	Wetlands
	(1)	(2)	(3)	(4)
$ExpWOTUS_c \cdot Post_t$	-16.88***	22,748***	-36,306***	8,037***
	(0.73)	(1,869)	(1,977)	(574)
CRP Controls	✓			
County FEs	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓
Adjusted R^2	0.92	0.97	0.99	0.99
Observations	26,978	28,950	28,950	28,950
Dep. Var. Mean	65.31	278,911	271,791	29,381

Note: This table shows estimates of Equation 1 for counties in no-stay and stay states separately. These estimates take the following form: $Y_{ct} = \alpha + \beta(ExpWOTUS_c \cdot Post_t) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct}$, where c indexes counties and t indexes years. All regressions include interactions of the dummy $Post_t$, which takes a value of 1 in 2014 and after, with the regulatory exposure measure $ExpWOTUS_c$, which takes a value of 1 if all cropland in a county is sometimes covered by WOTUS and a value of 0 if all cropland in a county is either never or always covered by WOTUS. Estimates in Column 1 use CRP rents per acre (2022 USD) as their outcome variable and include CRP program controls. These controls include acre and rent lags from 10 to 15 years as well as the amount of acres eligible to be enrolled under the county-specific cap last year and a dummy for whether or not the county was over-enrolled last year. Estimates in Column 2 use total acres of cropland, Column 3 uses Conservation land acreage, and Column 4 uses wetland acreage as their outcome variables. All estimates include year and county fixed effects and Newey and West (1987) standard errors are clustered at the year and county level. Dependent variable means for 2009 to 2013 from Table 1 are presented below each estimate. Panel A presents estimates for counties in no-stay states and Panel B presents estimates for counties in stay states. CRP estimates in Column 1 do not have data for 2023. Data for this figure come from US Department of Agriculture (2024), National Agricultural Statistics Service (2024), Greenhill et al. (2024), and Mulligan (2019). $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

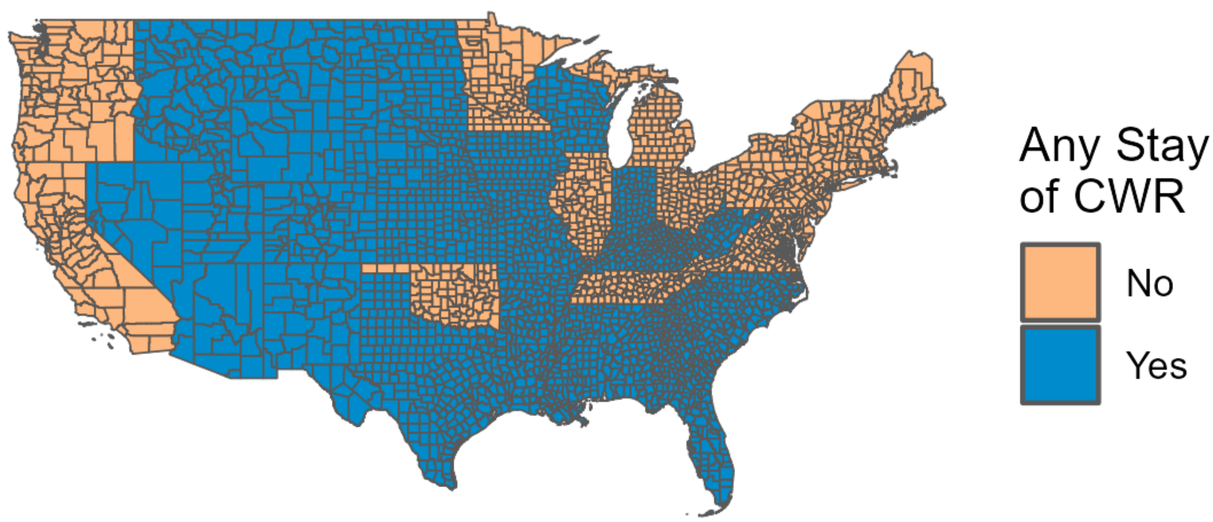
A Additional Exhibits

Figure A.1: Map of Share Sometimes WOTUS using Raw Data from Greenhill et al. (2024), All Points



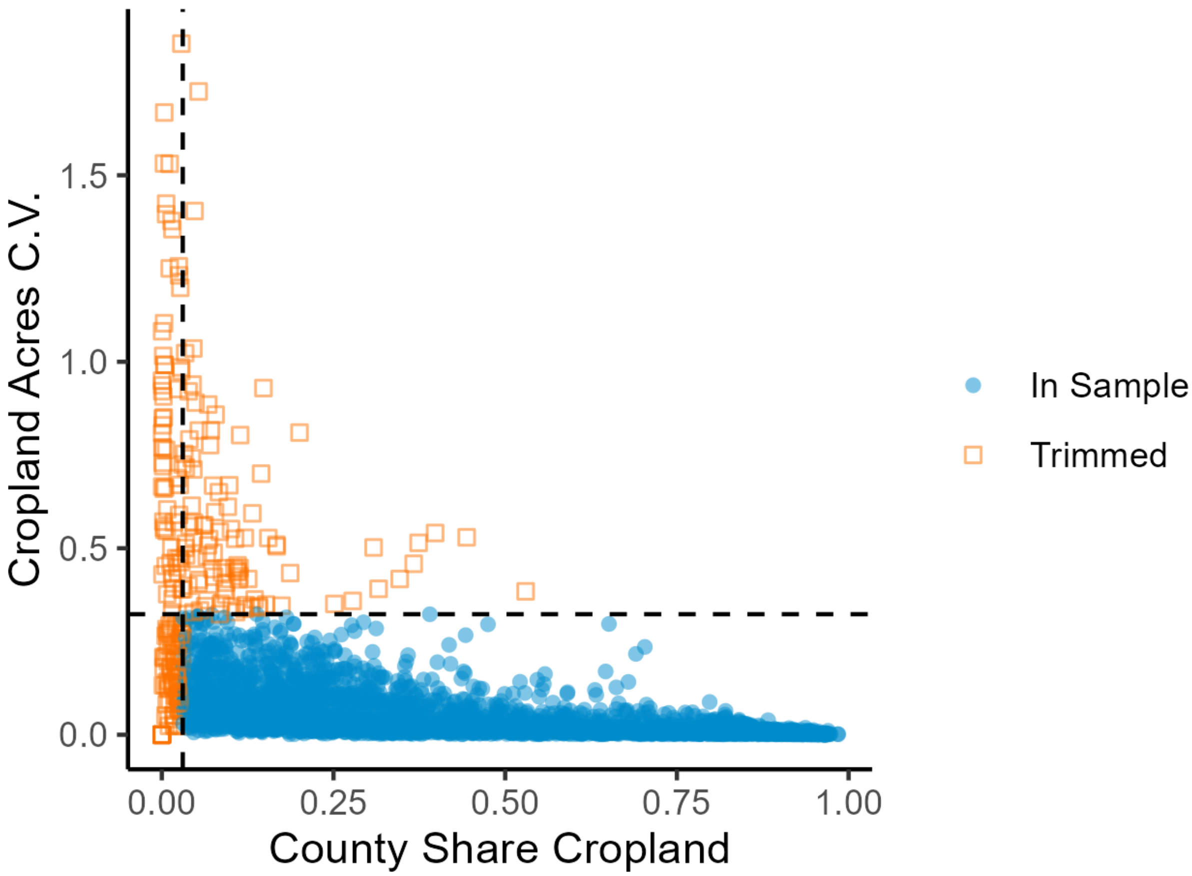
This map shows the share of all points within a county that are sometimes covered by a definition of WOTUS. If a county has a value of 1, then for every sampled point in that county either one or two WOTUS definitions likely included that point. Whereas if the county has a value of 0, then every sampled point in the county either had every WOTUS rule likely including it or no WOTUS rule likely including it. Data are from Greenhill et al. (2024).

Figure A.2: Map of CWR Stays Across States



This map shows states grouped by whether or not they received a stay in federal court of the Clean Water Rule. States in orange did not receive a stay and received regulation changes. States in blue were granted federal stays and did not see their regulatory environment change, however they were subject to regulatory risk. States that do not receive a stay of the CWR are Oklahoma, California, Washington, Oregon, Minnesota, Illinois, Michigan, Ohio, Tennessee, Virginia, Maryland, Delaware, Pennsylvania, New York, New Jersey, Connecticut, Rhode Island, Vermont, Massachusetts, New Hampshire, and Maine (21 states). These states see their regulatory environment change from the Rapanos Rule, to the CWR, then back to Rapanos over the study period. The states that receive a stay only experience the Rapanos regulation, but have the credible threat of regulation expansion under the CWR and limitation under the NWPR. These stay states are Florida, Idaho, Montana, North Dakota, South Dakota, Nebraska, Nevada, Arizona, Utah, New Mexico, Colorado, Kansas, Texas, Wyoming, Missouri, Iowa, Wisconsin, Indiana, Kentucky, West Virginia, North Carolina, South Carolina, Georgia, Alabama, Mississippi, Arkansas, and Louisiana (27 states). Data are from Mulligan (2019).

Figure A.3: Scatter of Counties by Share of Acreage in Crops and Coefficient of Variation in Cropland Acreage from 2009 to 2013



This figure shows trimming of the full county sample to minimize noise in the Cropland Data Layer estimates. We trim the counties with the lowest share of land in crops and the highest coefficients of variation in their cropland acreage estimates. The horizontal axis shows the county share of acreage in crops and the vertical axis shows the county coefficients of variation for total crop acreage. Data fro this figure are from 2009 to 2013. Trimmed observations are shown by orange squares and in sample observations are shown by blue circles. Trimmed observations are in the lowest 5% of cropland share and the highest 5% of cropland acres variation. This results in trimming 123 counties, or 8% of our observations. Data for this figures are fromNational Agricultural Statistics Service (2024).

Table A.1: Summary Statistics by for All Counties and Trimmed Sample, 2009 to 2013

	Full Sample	Trimmed Sample
Total Acres	620,572	578,802
	(841,087)	(709,205)
Acres of Cropland	233,768	248,684
	(296,342)	(302,012)
Conservation land Acres	311,578	261,462
	(726,798)	(576,777)
Wetland Acres	30,957	27,643
	(79,220)	(65,355)
CRP Acres	9,791	10,460
	(23,616)	(24,306)
CRP Rent per Acre (2022 USD)	69.62	73.06
	(54.39)	(53.36)
Share of Cropland Always WOTUS	0.07	0.06
	(0.19)	(0.18)
Share of Cropland Sometimes WOTUS	0.22	0.21
	(0.32)	(0.31)
Agricultural Futures Index	1.16	1.17
	(0.19)	(0.19)
CRP Eligible Acres	48,607	51,676
	(64,251)	(65,515)
Observations	15,540	14,295

Note: This table reports summary statistics for all counties in lower 48 states and counties in our final trimmed analysis sample separately for the years 2009 to 2013. We trim the counties with the lowest share of cropland and the highest coefficients of variation in total acres of cropland before 2014. Details are discussed in the text and shown visually in Figure A.3. Averages are reported with standard deviations in parentheses. Data for this table come from National Agricultural Statistics Service (2024), Greenhill et al. (2024), Mulligan (2019), US Department of Agriculture (2024), and investing.com.

Table A.2: Robustness of Exposure Difference-in-Differences Estimates of the Impact of Exposure to Regulation on CRP Rents

	Panel A: No-Stay (Regulation Treatment)					
	Dep. Var.: CRP Rents per Acre (2022 USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$ExpWOTUS_c \cdot Post_t$	-27.29***	-25.44***	-25.52***	-22.31***	-24.54***	-23.50***
	(1.674)	(1.838)	(1.843)	(1.838)	(1.699)	(1.763)
CRP Controls	✓				✓	✓
Futures Index				✓	✓	✓
Year FEs	✓	✓		✓	✓	
County FEs	✓	✓	✓	✓	✓	✓
Wetland Bin by Year FEs			✓			✓
Adjusted R^2	0.92	0.91	0.92	0.92	0.92	0.92
Observations	13,006	13,006	13,006	13,006	13,006	13,006
Dep. Var. Mean	89.13	89.13	89.13	89.13	89.13	89.13

	Panel B: Yes-Stay (Risk Treatment)					
	Dep. Var.: CRP Rents per Acre (2022 USD)					
	(1)	(2)	(3)	(4)	(5)	(6)
$ExpWOTUS_c \cdot Post_t$	-16.88***	-16.07***	-18.71***	-15.37***	-16.35***	-16.52***
	(0.7313)	(0.7402)	(0.8057)	(0.7153)	(0.7114)	(0.7901)
CRP Controls	✓				✓	✓
Futures Index				✓	✓	✓
Year FEs	✓	✓		✓	✓	
County FEs	✓	✓	✓	✓	✓	✓
Wetland Bin by Year FEs			✓			✓
Adjusted R^2	0.92	0.92	0.92	0.92	0.92	0.92
Observations	26,978	26,978	26,978	26,978	26,978	26,978
Dep. Var. Mean	65.31	65.31	65.31	65.31	65.31	65.31

Note: This table shows estimates of Equation 1 for counties in no-stay (Panel A) and stay states (Panel B) separately for CRP rents per acre (2022 USD). These estimates take the following form: $Y_{ct} = \alpha + \beta(ExpWOTUS_c \cdot Post_t) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct}$, where c indexes counties and t indexes years. All regressions include interactions of the dummy $Post_t$, which takes a value of 1 in 2014 and after, with the regulatory exposure measure $ExpWOTUS_c$, which takes a value of 1 if all cropland in a county is sometimes covered by WOTUS and a value of 0 if all cropland in a county is either never or always covered by WOTUS. Estimates in Column 1 include CRP program controls as well as year and county fixed effects. These controls include acre and rent lags from 10 to 15 years as well as the amount of acres eligible to be enrolled under the county-specific cap last year and a dummy for whether or not the county was over-enrolled last year. In Column 2, we remove these controls. In Column 3, we replace the year fixed effects with a wetland bin by year fixed effect, which limits comparisons to counties in the similar decile bin of county share of land cover in wetlands before 2014. Column 4 returns to using normal county and year fixed effects, but adds a county-level agricultural futures index control. Column 5 adds back in the CRP program controls to Column 4. Finally, Column 6 replaces the year fixed effects in column 5 with wetland by year bin fixed effects. Newey and West (1987) standard errors are clustered at the year and county level. Dependent variable means for 2009 to 2013 from Table 1 are presented below each estimate. CRP estimates in Column 1 do not have data for 2023. Data for this table come from National Agricultural Statistics Service (2024), Greenhill et al. (2024), Mulligan (2019), US Department of Agriculture (2024), and investing.com. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table A.3: Robustness of Exposure Difference-in-Differences Estimates of the Impact of Exposure to Regulation on Acres of Cropland

	Panel A: No-Stay (Regulation Treatment)			
	Dep. Var.: Acres of Cropland			
	(1)	(2)	(3)	(4)
$ExpWOTUS_c \cdot Post_t$	-6,160.5***	-7,469.3***	-5,015.9**	-6,154.8***
	(1,976)	(1,816)	(2,110)	(1,949)
Futures Index			✓	✓
Year FEs	✓		✓	
County FEs	✓	✓	✓	✓
Wetland Bin by Year FEs		✓		✓
Adjusted R^2	0.97	0.97	0.97	0.97
Observations	13,935	13,935	13,935	13,935
Dep. Var. Mean	185,889	185,889	185,889	185,889
	Panel B: Yes-Stay (Risk Treatment)			
	Dep. Var.: Acres of Cropland			
	(1)	(2)	(3)	(4)
$ExpWOTUS_c \cdot Post_t$	22,748.4***	16,990.7***	23,394.7***	19,954.6***
	(1,869)	(1,486)	(1,910)	(1,676)
Futures Index			✓	✓
Year FEs	✓		✓	
County FEs	✓	✓	✓	✓
Wetland Bin by Year FEs		✓		✓
Adjusted R^2	0.97	0.97	0.97	0.97v
Observations	28,950	28,950	28,950	28,950
Dep. Var. Mean	278,911	278,911	278,911	278,911

Note: This table shows estimates of Equation 1 for counties in no-stay (Panel A) and stay states (Panel B) separately for total cropland acres. These estimates take the following form: $Y_{ct} = \alpha + \beta(ExpWOTUS_c \cdot Post_t) + \vec{X}_{ct} \cdot \gamma + \kappa_c + \tau_t + \varepsilon_{ct}$, where c indexes counties and t indexes years. All regressions include interactions of the dummy $Post_t$, which takes a value of 1 in 2014 and after, with the regulatory exposure measure $ExpWOTUS_c$, which takes a value of 1 if all cropland in a county is sometimes covered by WOTUS and a value of 0 if all cropland in a county is either never or always covered by WOTUS. Estimates in Column 1 only include year and county fixed effects. In Column 2, we replace the year fixed effects with a wetland bin by year fixed effect, which limits comparisons to counties in the similar decile bin of county share of land cover in wetlands before 2014. Column 3 returns to using county and year fixed effects, but adds a county-level agricultural futures index control. Column 4 replaces the year fixed effects in Column 3 with wetland by year bin fixed effects. Newey and West (1987) standard errors are clustered at the year and county level. Dependent variable means for 2009 to 2013 from Table 1 are presented below each estimate. Data for this table come from Greenhill et al. (2024), Mulligan (2019), US Department of Agriculture (2024), and investing.com. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B Appendix: Creation of Regulatory Topography

This appendix provides a more detailed description of the procedures we follow to clean, classify, and interpret the data. In this appendix, we present intermediate results to illustrate the consequences of these choices. In short, we use K-Nearest Neighbors (KNN) to project predicted data for roughly 4 Million US Points from Greenhill et al. (2024) on to US cropland from National Agricultural Statistics Service (2024).

B.1 Data Inputs

Our first input is three sets of predictions, one for each WOTUS definition, from Greenhill et al. (2024) for about 4 Million points within the continental US. These points are sampled within large grid cells to ensure complete spatial coverage of the US. These predictions use spatial features, such as soil errosivity measures, distances from waterways, and other inputs to predict whether that point is likely regulated under a particular WOTUS definition. The model uses adjudication data from US Army Corps of Engineers (2024) as its "ground truth" measure of each WOTUS rule's actual scope. These adjudications are voluntary and nonbinding, allowing farmers to ask the US Army Corps of Engineers to assess whether or not the WOTUS definition of their choice applies to their particular plot of land. They can even ask for adjudications under rules that are never actually applied by the EPA, such as the NWPR.

In addition to these points of regulatory predictions, we use cropland raster data from National Agricultural Statistics Service (2024). This 30 by 30 meter grid cell level dataset gives us estimates of the amount of land used for any type of agricultural cultivation, including crops and animal production, excluding lands used for development, conservation lands such as grasslands or forests, wetlands, and other non-agricultural uses.[18] Since we are interested in the impacts of WOTUS definitions on agriculture, we are interested in the extent to which regulatory predictions overlap with pre-treatment cropland. Intuitively, this throws out points applied to urban spaces, national parks, and other land use types that will likely have a limited impact on agricultural production choices.

Finally, we also use data on the navigable waterway network to improve our KNN estimation.

[18] Specifically, we classify the following data layers from National Agricultural Statistics Service (2024) as cropland: Corn, Cotton, Rice, Sorghum, Soybeans, Sunflower ,Peanuts, Tobacco, Sweet Corn, Pop or Orn Corn, Mint, Barley, Durum Wheat, Spring Wheat, Winter Wheat, Other Small Grains, Dbl Crop WinWht/Soybeans, Rye, Oats, Millet, Speltz, Canola, Flaxseed, Safflower, Rape Seed, Mustard, Alfalfa, Other Hay/Non Alfalfa, Camelina, Buckwheat, Sugarbeets, Dry Beans, Potatoes, Other Crops, Sugarcane, Sweet Potatoes, Misc Vegs & Fruits, Watermelons, Onions, Cucumbers, Chick Peas, Lentils, Peas, Tomatoes, Caneberries, Hops, Herbs, Clover/Wildflowers, Sod/Grass Seed, Switchgrass, Fallow/Idle Cropland, Pasture/Grass, Cherries, Peaches, Apples, Grapes, Christmas Trees, Other Tree Crops, Citrus, Pecans, Almonds, Walnuts, Pears, Grassland/Pasture, Pistachios, Triticale, Carrots, Asparagus, Garlic, Cantaloupes, Prunes, Olives, Oranges, Honeydew Melons, Broccoli, Avocados, Peppers, Pomegranates, Nectarines, Greens, Plums, Strawberries, Squash, Apricots, Vetch, Dbl Crop WinWht/Corn, Dbl Crop Oats/Corn, Lettuce, Dbl Crop Triticale/Corn, Pumpkins, Dbl Crop Lettuce/Durum Wht, Dbl Crop Lettuce/Cantaloupe, Dbl Crop Lettuce/Cotton, Dbl Crop Lettuce/Barley, Dbl Crop Durum Wht/Sorghum, Dbl Crop Barley/Sorghum, Dbl Crop WinWht/Sorghum, Dbl Crop Barley/Corn, Dbl Crop WinWht/Cotton, Dbl Crop Soybeans/Cotton, Dbl Crop Soybeans/Oats, Dbl Crop Corn/Soybeans, Blueberries, Cabbage, Cauliflower, Celery, Radishes, Turnips, Eggplants, Gourds, Cranberries, and Dbl Crop Barley/Soybeans.

These data come from US Bureau of Transportation Statistics (2024). Critically, these data give use shape files that describe *navigable* waterways, which are distinct from all water features. This means that rivers such as the Potomac, which connects Washington, DC to the Chesapeake Bay is only included up to just north of Key Bridge, which connects DC and Arlington, Virginia. North of this point the Potomac is not navigable for commercial purposes and therefore excluded.

B.2 Projecting Greenhill et al. (2024) on to Cropland with KNN

Central to the KNN method is selecting the number of neighbors to use to classify a given point, called K. Given the computational intensity of working with millions of points, we do a 5-fold cross-validation using points from the Greenhill et al. (2024) in random sample of 20 counties from the population of 1,000 counties closest to navigable waterways as measured by their centroids.[19] We try values of K between 2 and 50, and we graph the resulting total error rate in Figure B.1. The figure shows that total error is minimized by selecting a K equal to 11. This means that the nearest 11 points are used to project the regulatory topography on to cropland.[20]

With our optimal K in hand, we now turn to the process of projecting Greenhill et al. (2024)'s estimates on to US cropland. Given the magnitude of the computational task, we do each county separately for each of the three WOTUS rules.

For each county shape, we add a buffer of 5 KM around the perimeter of the county and include all points from Greenhill et al. (2024) and all segments of navigable water from US Bureau of Transportation Statistics (2024) in the interpolation. Points from Greenhill et al. (2024) that have a regulatory probability above 0.5 are considered regulated. These inputs are shown in Sub-figure B.2a. This figure shows the likely un-regulated points as red "X's" and the likely regulated points as blue circles as well as a segment of the Mississippi River for an example county in Tennessee.

Then for each county, we scale the latitudes, longitudes, and distance to the nearest navigable waterway (if one is within the buffer) by subtracting the county mean and dividing by the county standard deviation. We then use the 11 closest points from Greenhill et al. (2024), determined using these three measures to determine whether each cell of cropland in that county is likely regulated or not. We can write this calculation as follows:

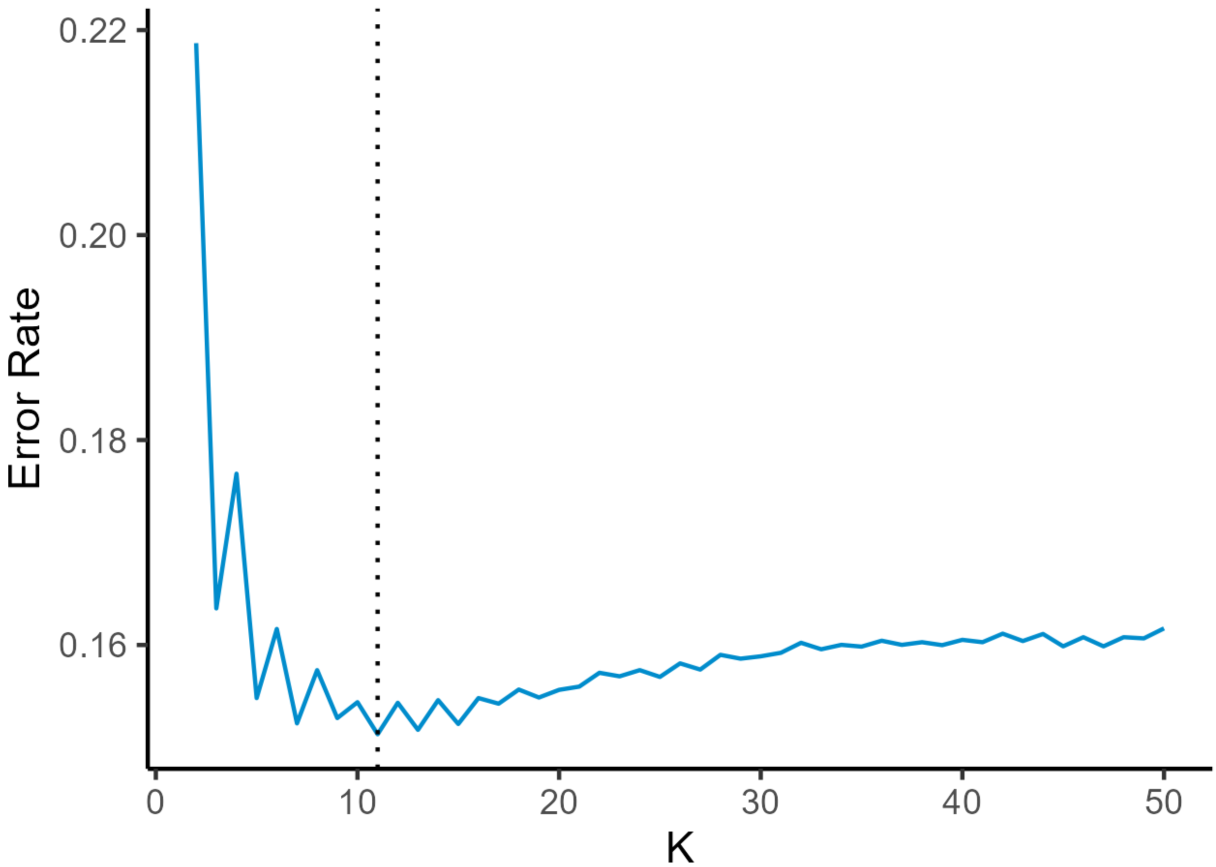
$$P(WOTUS)_i = \frac{1}{11} \sum_{j \in K=11} I\{Regulated\}_j \tag{4}$$

where each cropland cell i's probability of being in WOTUS is determined by the average of the indicators for whether or not the nearest 11 points, $j \in K = 11$, from Greenhill et al. (2024) are predicted to be regulated by WOTUS for a given rule. Cells with more than half of their nearest points predicted to be regulated are then classified as regulated. We repeat this process for every

[19] For an overview of the K-Nearest Neighbors algorithm, see Gareth et al. (2015).

[20] Type 1 and type 2 error are balanced at a much lower value of K, in this case K equal to 4, without loosing too much in terms of total error. Our results are robust to this choice of K as well.

Figure B.1: Optimal Choice of K

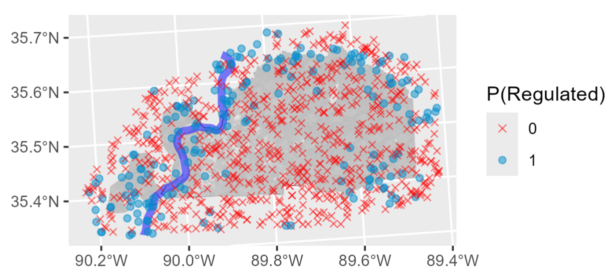


This figure shows the total error rate for the 5-fold cross-validation exercise described in this appendix. This figure uses data from US Bureau of Transportation Statistics (2024) and Greenhill et al. (2024).

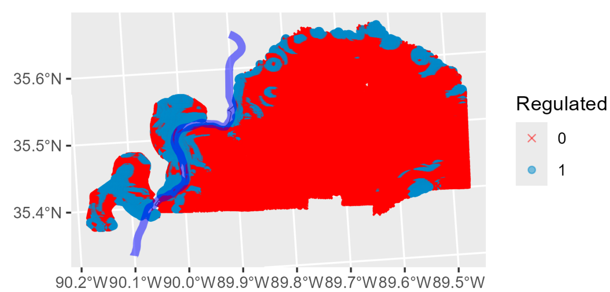
county and all three rules separately.

The resulting projection can be seen in Sub-figure B.2b, where un-regulated land is shown in red and regulated land is shown in blue. Notice that the regulated land hugs the navigable river in the Western part of the county, and then follows a non-navigable branch of the river which defines the norther county border. Our final county level measure is shown in Figure 2a.

Figure B.2: Projecting Greenhill et al. (2024) WOTUS Points on to Cropland Example



(a) Points from Greenhill et al. (2024)



(b) Projected on to Cropland from National Agricultural Statistics Service (2024)

Note: This figure shows the inputs, in Sub-Figure A, and the outputs, in Sub-Figure B, of our projections of regulatory predictions from Greenhill et al. (2024) on to cropland from National Agricultural Statistics Service (2024) using KNN for the Rapanos definition of WOTUS for an example county in Western Tennessee. This figure uses data from Greenhill et al. (2024), National Agricultural Statistics Service (2024), and US Bureau of Transportation Statistics (2024).