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Environmental Impacts and Resilience of Food and Agricultural Production

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Environmental Impacts and Resilience of Food and Agricultural Production

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Abstract

Agricultural production grew dramatically since 1950. While this growth improved food security, it also introduced harmful tradeoffs. A few of those tradeoffs are environmental externalities and market power in food and agricultural markets. The sustainability and resilience of the modern food system require that research and policy carefully weigh the consequences associated with productivity growth. This dissertation evaluates the environmental and supply chain tradeoffs of modern agricultural production.

Chapter 1 quantifies costs of nitrate contaminated drinking water, which largely results from agricultural production. Nitrate contamination of drinking water is a widespread environmental concern and threatens human health. The magnitude of the environmental health consequences depend on an individual's ability to avoid exposure. This paper uses an event-study framework to uncover the heterogeneity in avoidance behavior following Safe Drinking Water Act nitrate violations. Using weekly store-level scanner data, I estimate that consumers spend approximately $4.7 million annually on bottled water and soda to avoid nitrate contaminated drinking water. However, consumers in resource-constrained areas exhibit substantially less protective behavior. This leads to 143 additional infant deaths per year relative to areas with less-costly access to safe drinking water. These results underscore substantial costs from nitrate pollution and that these costs are disproportionately distributed to those with less ability to protect themselves.

Chapter 2 calculates the groundwater impacts of drought and extreme heat in California agriculture. Adaptation to climate and weather shocks can be costly for producers, but it also may impose negative externalities on vulnerable populations. We study this in the context of groundwater in California and evaluate the effects of annual fluctuations in weather and surface water supplies on agricultural well construction and access to drinking water. Using the population of geocoded wells, we show that farmers respond to extreme heat and surface water scarcity through new well construction. This mitigating behavior by agricultural users imposes costs: Extreme heat and surface water scarcity also lower local groundwater levels and cause domestic well failures. While groundwater extraction helps producers reduce the damage from environmental shocks, it also harms access to drinking water supplies in marginalized communities.

Chapter 3 evaluates the efficiency and resilience tradeoffs of different supply chain policies.

Recent extreme events and the disruptions they caused have made food supply chain resilience a key topic for researchers and policymakers. This paper provides input into these discussions by evaluating the efficiency and resilience properties of the leading policy proposals. We develop a conceptual model of a prototype agricultural supply chain, parameterize the model based on the empirical literature, and conduct simulations to assess the impacts on resilience and economic welfare of four key policy proposals: (i) intensified antitrust enforcement to improve market competition, (ii) subsidization of entry of additional processing capacity, (iii) prevention of price spikes through anti-price-gouging laws, and (iv) diversification of production and processing across multiple regions. Results show that some of the policies have the potential to improve supply-chain resilience, but their impacts depend on the existing market structure, and resilience gains often come at the cost of reduced efficiency.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction to the Essays

Agricultural output grew threefold since the 1960s. This growth reduced global food insecurity by outpacing the increases in food demand (Alston and Pardey 2014). This trend, in part, stemmed from input intensification, technological change, and the specialization of food supply chains. While many substantially benefited from this change, it also introduced harmful tradeoffs. In more recent years, these tradeoffs have manifested as market failures in the form of environmental externalities and market power in food and agricultural markets. In response, agricultural and environmental research and policy priorities have focused more acutely on the sustainability and resilience of modern agricultural production and food supply chains.

Market failures have emerged from, or were exacerbated by, many of the same factors that led to agriculture productivity growth. While many examples exist, three of the most urgent are the focus of this dissertation: i) Global fertilizer consumption increased by over 300% since 1960 (U.S. Department of Agriculture, Economic Research Service 2022), and consequently, a consensus has emerged that agricultural nutrients are a primary contributor to water quality degradation. ii) Over the same period, irrigated acreage doubled in response to new irrigation technologies and increased water demand due to climate change (Taylor 2023). The over-extraction of groundwater resources for agriculture has led to aquifer stress in the US and around the world. Furthermore, climate change threatens water availability in many parts of the world, including water for agricultural irrigation. iii) Lastly, four-firm concentration ratios (CR4) across food manufacturing increased by at least 30% since 1960 (Rogers 2001; Sexton and Xia 2018). Market power within food processing and distribution presents numerous concerns for consumers and farmers, including its impact on the resilience of supply chains when extreme shocks occur. The sustainability and resilience of food systems depend critically on carefully balancing the costs along with the benefits of these three characteristics of modern agricultural production.

The urgency of these three topics is exemplified in the fact that recent *The State of Food and Agriculture* reports from the United Nation's Food and Agriculture Organization urge solutions in these areas: (i) Climate change, agriculture, and food security (United Nations Food and Agriculture Organization 2016), (ii) Overcoming water challenges in agriculture (United Nations Food and Agriculture Organization 2020), and (ii) Making agrifood systems more resilient to shocks and stresses (United Nations Food and Agriculture Organization 2021). Despite this urgency, there remains considerable opportunity for economic research to fill knowledge gaps and inform policy to achieve productive, sustainable, and resilient food systems (Fan et al. 2021).

Chapter 2 calculates the social costs of nitrate pollution in US drinking water sources. Nitrates in water bodies are primarily a non-point source pollutant resulting from input-intensive agricultural production – both from synthetic nitrogen fertilizer and animal waste (Griffin and Bromley 1982; Paudel and Crago 2021; Raff and Meyer 2022). I quantify the extent to which individuals respond to nitrate contamination in their drinking water sources and the related health impacts. In the United States, the Safe Drinking Water Act (SDWA) regulates water systems to ensure that individuals are notified when their water quality reaches unsafe levels. Through this notification, consumers are prompted to avert their behavior to alternative drinking water sources, like bottled water. Consumers who are unable to access safe alternatives are prone to be exposed to contamination and experience harmful health impacts. Infants in particular are vulnerable to nitrate contamination since heightened nitrate levels in drinking water are a known cause of "Blue-Baby Syndrome" that may lead to infant death. I use the timing of SDWA violations to estimate the consumer impacts through bottled water purchases and the net health impacts on birth outcomes and infant mortality. I also uncover how the health impact differs based on characteristics correlated with levels of protective behavior.

Chapter 3 measures the extent to which California farmers use groundwater as a mitigation strategy to climate-change-induced shocks and calculates the subsequent costs imposed on other users of groundwater resources. This project examines how groundwater levels are affected by annual fluctuations in heat and surface water scarcity. We decompose this effect on groundwater levels into the extensive margin, measured by the construction of new agricultural wells, and the intensive margin, extracting more water from existing wells. Groundwater has been traditionally unregulated, and therefore, historically extracted more than the socially optimal level. Residential users of groundwater bear the burden of these damages through the channel of groundwater scarcity. We empirically measure these effects by evaluating the changes in the depth of the water table in response to heat and surface water curtailments. Then, we evaluate the reduced-form relationship of heat and surface water scarcity on domestic well failures, which restricts households' ability to access groundwater. Finally, we offer insight into the behavioral mechanisms of this response by quantifying the number of new agricultural wells drilled as a response to heat and surface water scarcity.

We find that extreme heat and reductions in agricultural surface water supply significantly lower the depth to the groundwater table. A one acre-foot (AF) reduction in the agricultural surface water allocation to every California cropland acre lowers local groundwater levels by an additional 4 feet. An additional harmful degree day reduces groundwater levels by 0.5 inches. Declining water tables suggest that the costs of climate change may be larger in the long run if farmers cannot buffer with groundwater resources.

Reductions in groundwater levels result in domestic well failures, imposing external costs to households that rely on groundwater for drinking and other residential uses. A one AF per acre reduction increases the likelihood that domestic wells fail in that region by 5%, and an additional harmful degree day increases the probability of failure by 0.2%. These well failures are unequally distributed among rural, minority, and low-income households in California's Central Valley. This underscores one significant externality of the over-extraction of groundwater and the inequality with which those costs are borne.

Farmers respond to heat and surface water scarcity both through the construction of groundwater wells and by pumping additional water from existing wells. We estimate that for each acre foot (AF) of reduced surface water allocations for agriculture, 460 new agricultural wells are drilled in the contemporaneous year. Using an approximated cost of $75,000 to construct an agricultural well, this translates to a back-of-the-envelope 35 million dollars invested annually in extensive-margin adaptation behavior by California farmers. Additionally, we calculate that for every lost AF per acre of surface water, farmers pump an additional 0.44 AF per acre from groundwater. Farmers also respond to extreme heat. For every additional harmful degree day, farmers construct 13 new agricultural wells and extract 42,000 more AF of groundwater on aggregate. These numbers provide a lower-bound estimate on the avoided climate damages to California agriculture.

Chapter 4 constructs a framework to analyze the efficiency and resilience implications of four key policies on agriculture and food supply chains. We utilize the calibrated model and simulation framework to study four policy proposals that have emerged in the resilience debate. First, we investigate the role of concentration and market power in the processing/retailing sector on resilience of supply chains in response to extreme shocks. On January 3, 2022, the Biden Administration announced plans for stricter enforcement of antitrust laws in the meatpacking industries. In addition, legislation known as the Meat and Poultry Special Investigator Act of 2022 has been introduced in the US Congress to give the US Department of Agriculture (USDA) authority to investigate competition issues in the meat and poultry industries. USDA has announced plans to partner with the US Department of Justice to enforce antitrust laws vigorously and to step up its own enforcement of competition under the Packers and Stockyards Act. Market power exercised by intermediaries is shown to raise prices to consumers and depress prices received by farmers, but its impacts on supply chain resilience are not well understood.

Overall, we find that, while some of these policies can reduce relative volatility of welfare outcomes for farmers and consumers, their impacts on resilience and efficiency depend critically on the structure and competitive conditions in the market. Policies aimed at increasing resilience must carefully assess the probabilistic nature of extreme events and the related efficiency trade-offs. This paper facilitates these discussions by providing a quantitative framework that enables the resilience-efficiency trade-offs of the major policy proposals to be assessed under extreme shocks.

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Chapter 2

Nitrate Pollution in Drinking Water

Nitrate pollution is one of the United States' most costly and widespread environmental problems (Environmental Protection Agency 2022). Nitrogen contamination in water systems harms aquatic life, limits human recreational activity, and threatens human health. Nitrates, when ingested at excessive levels, affect infant health, causing "blue-baby syndrome" (or methemoglobinemia) that may be deadly (Walton 1951). Other evidence also suggests that nitrates annually lead to about 1,700 occurrences of pre-term births and 6,500 nitrate-attributable cancer cases (Temkin et al. 2019). Rural areas are especially vulnerable to nitrate pollution since agricultural production is nitrogen-intensive, and nitrogen fertilizers leach into water systems over time (Paudel and Crago 2021; Metaxoglou and Smith 2022).

The magnitude of the public health damages from pollution largely depends on individuals' ability to avoid the environmental hazard. Many environmental regulations, like the Safe Drinking Water Act (SDWA), use information disclosures and public notices to alert consumers of drinking water quality violations in an effort to mitigate the public health risks. However, consumers respond to water quality information heterogeneously (Zivin, Neidell, and Schlenker 2011; Allaire et al. 2019; Marcus 2021). Resource constraints, like income, market access, and other infrastructure gaps, may limit individuals' ability to reduce exposure to drinking water pollution. These factors may be particularly acute in rural areas, where residents disproportionately experience SDWA nitrate violations (Allaire, Wu, and Lall 2018).

This paper quantifies the willingness to pay to avoid nitrate contamination in drinking water and how avoidance behavior and the subsequent health impact differs across demographics. I study this in the context of SDWA nitrate violations in the United States using an event-study framework. SDWA violations simultaneously indicate an increase in nitrate contamination to a dangerous level and serve as information shocks about water quality, where the latter may induce a consumer response.[1] I uncover how this response differs for residents in areas that are income-constrained and those living in food deserts.[2] I use the timing of SDWA violations to estimate the net health impacts on birth outcomes and infant mortality, and how the health impact differs based on characteristics correlated with levels of protective behavior.

Building on Harrington and Portney (1987), I propose a theoretical framework to illustrate that the net effect of worsening water quality on health is ambiguous. Worsening drinking water quality, which triggers SDWA violations, heightens the health risk of those residents. However, public notifications that accompany violations likely cause consumers to engage in more protective action, like relying on bottled water and other beverages, which may improve health outcomes ceteris peribus. I extend Harrington and Portney (1987) to allow individuals to face differential implicit prices for protective behavior, where differences arise from geographic or socioeconomic resource constraints. The analytical results from this model predict that individuals facing higher implicit prices will engage in less averting behavior, and as a result, there are higher realized human health costs.

To empirically test for avoidance behavior, I estimate the effect of different water quality violations and subsequent public notifications on beverage purchases, as measured by bottled water and soda sales at local retail outlets, using an event-study framework. The staggered timing of violations in public water systems (PWS) across the United States represent shocks to both water quality and consumers' information, which allows the estimation of the response after a violation occurs relative to the weeks preceding a violation. Two-way fixed effects control for fixed differences across stores and seasonality in bottled water sales. To account for potential bias in heterogeneous treatment across time, I use an unbiased estimator proposed by Gardner (2021).[3] I also allow for

[1] Residents typically have imperfect information about local water quality (Keiser and Shapiro 2018) and would have limited ability to anticipate a SDWA violation. The exception may be for SDWA violations that coincide with natural disaster events, like hurricanes and bacterial coliform (Beatty, Shimshack, and Volpe 2019). Chemical nitrate contamination, however, builds gradually as a legacy contaminant and is unlikely to be correlated with extreme events.

[2] Importantly, the behavioral response is only a portion of the total economic costs of nitrate violations because it fails to account for the health consequences imposed on those who remained exposed (Harrington and Portney 1987).

[3] Goodman-Bacon (2021) and others document the potentially severe treatment effect bias when using two-way fixed effects when treatment is heterogeneous over time. I expand on these issues in the empirical section.

heterogeneity in the estimates of avoidance behavior by census tract measures of income, percent of population in food deserts, SNAP participation, and vehicle access. This analysis highlights factors that may leave vulnerable populations exposed even after SDWA public notifications. In the second stage of the analysis, I estimate the effect of nitrate violations and subsequent public notifications on health. I uncover the average net effect on health, as well as, heterogeneous impacts based on factors that may limit avoidance behavior.

I use data from the Safe Drinking Water Information System (SDWIS) through the Environmental Protection Agency (EPA) on PWS characteristics, violation, and enforcement data from 2010 to 2020. These data report the date of violation and public notification and the subsequent return to compliance for SDWA contaminant rules. I pair these violation and notification records with weekly store-level retail scanner data from 2010 to 2019. The weekly panel of beverage sales allows me to measure the response each week following a violation event and the average treatment effect of an active violation. This empirical design also investigates anticipatory action or uncovers other pre-trends. I interact census tract demographics and measures of grocery-store accessibility to test for heterogeneity in response. Lastly, I use within county variation of proprietary, monthly infant health statistics to estimate the effects of nitrate exposure in drinking water with varying levels of protective behavior on health outcomes.

A first central result is that nitrate violations lead to of significant avoidance behavior through bottled water and soda purchases. Public notifications due to nitrates induce an approximately 17% increase in bottled water sales and 11% in soda sales relative to the weeks preceding a violation. This translates to $4.7 million annually in averting expenditures in the United States, which is relatively inexpensive compared to other environmental damages of agricultural fertilizer pollution (Dodds et al. 2009; Taylor and Heal 2022). Second, food accessibility and income constraints significantly limit avoidance behavior through purchasing bottled beverages by 31 and 26 percentage points, respectively, which illustrates the implicit higher barrier these residents face to avoid contaminated water.

Finally, I find that the public notifications from SDWA nitrate violations improve the rate of infant mortality by 7.7% in areas that have proximate access to alternative beverage sources. This is consistent with the model in which informational provisions induce protective behavior among affected households. However, areas with food-access constraints experience a net 6.3% increase in infant mortality relative to pre-violation weeks. This implies that roughly 143 infant deaths each year, or health costs of \$1.5 billion, in the United States are attributable to nitrate violations in vulnerable populations.

This paper contributes to the social costs of nitrate pollution from agricultural production by uncovering the substantial health costs associated with nitrogen exposure in drinking water. The costs of nitrate pollution in surface water, resulting in algal bloom and "dead-zone" (or hypoxic zones) in the Gulf of Mexico, are estimated to be large, ranging between \$2.2 to \$7.3 billion annually (Dodds et al. 2009; Taylor and Heal 2022). Less is known about the extent of economic damages of nitrate pollution in drinking water sourced from groundwater.[4] Zivin, Neidell, and Schlenker (2011) estimate that consumers spend \$1.7 million annually to avoid nitrate contaminated drinking water, but do not incorporate the health costs. Identifying the health costs in this context is empirically challenging due to endogenous sorting, and much of the current knowledge about the impact of nitrates on health relies on case-studies or cross-sectional exposure analyses (Walton 1951; Ward et al. 2018; Temkin et al. 2019). I give evidence that the human health costs of nitrate pollution far exceed the avoidance behavior costs and that the health costs are disproportionately realized despite existing regulation.

Second, I add to the body of work that calculates the health costs of water pollution and the effectiveness of current regulation. The economic impacts of water pollution remain understudied, especially relative to air pollution (Keiser and Shapiro 2018). Bennear and Olmstead (2008) and Bennear, Jessoe, and Olmstead (2009) study the effectiveness of SDWA regulations on monitoring and water quality. A more recent body of work has uncovered novel significant health impacts of drinking water pollution for a variety of contaminants (Currie et al. 2013; Marcus 2020, 2021; Hill and Ma 2022; Christensen, Keiser, and Lade 2023). I contribute to these studies by estimating both the behavioral and health impacts of nitrate pollution and highlight an area where the SDWA falls short in mitigating public health externality.

Lastly, the recent environmental justice literature has revealed that low socioeconomic groups are unequally exposed to pollution (Banzhaf, Ma, and Timmins 2019), especially in the context of air pollution in urban areas (Currie 2011). These sub-populations also may exhibit a dampened

[4] Nitrate contamination issues in drinking water are sourced almost exclusively from groundwater. Pennino, Compton, and Leibowitz (2017) state that about 95% of the SDWA violations occur in groundwater sources.

behavioral response, exacerbating the inequality of environmental health damages. My results suggest that geographic constraints – specifically food deserts – also limit individuals' ability to protect themselves from the negative health consequences of nitrate pollution. This paper documents that water pollution raises significant environmental justice concerns in the rural United States.

2.1 Background

2.1.1 Safe Drinking Water Act

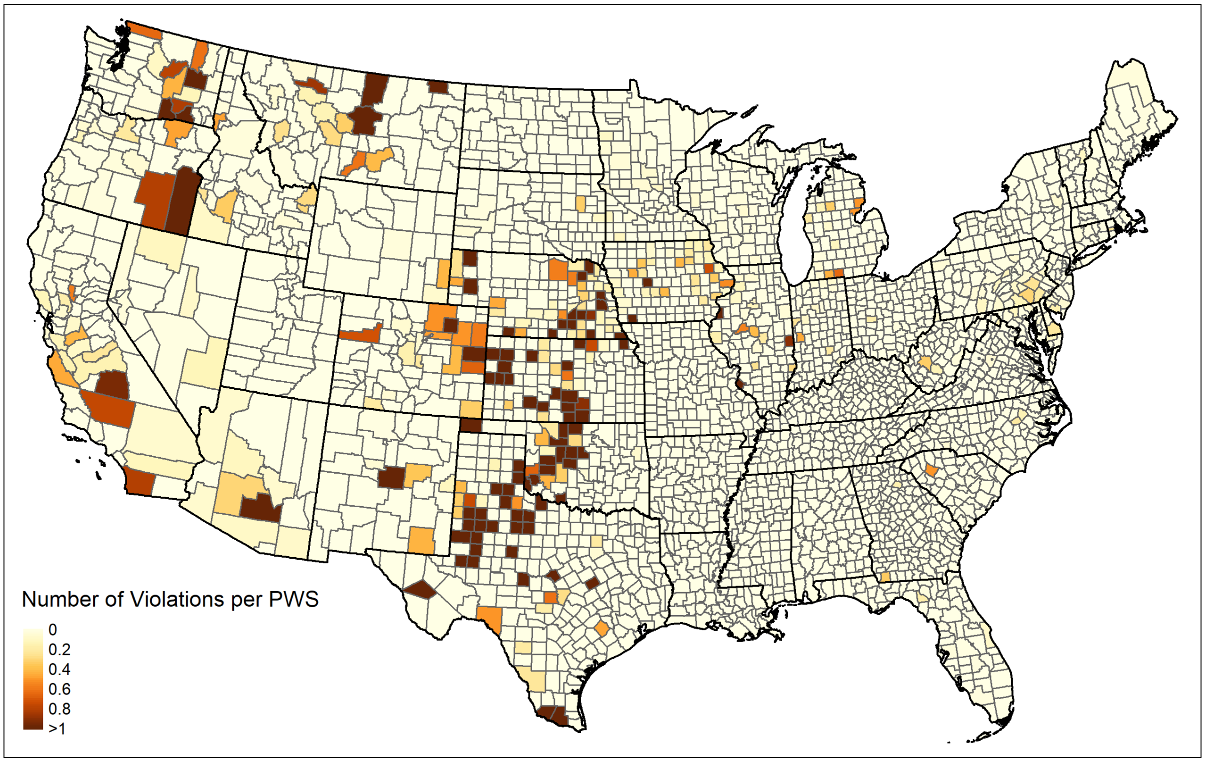
The SDWA, initially passed in 1974, regulates drinking water systems that serve at least 25 individuals and aims to protect individuals from drinking water pollution or waterborne illness. It requires regular monitoring and reporting of drinking water quality by systems and establishes maximum contaminant levels (MCL) for over 90 contaminants. Some contaminants are short-lived and quickly treatable in-home, while others are legacy pollutants and are costly to rectify by households or public water systems. MCLs are determined by the threshold at which contaminants pose a potential health threat to certain populations.

Once a violation occurs, the SDWA relies on public notifications to alleviate the public health risk. The public notification requirements establish 3 tiers. Tier 1 violations pose an immediate threat to human health and notification must occur within 24 hrs of detecting contaminants above the MCL. Nitrates and some violations of the Total Coliform Rule are the two contaminants classified as Tier 1 violations. These notices are required to be hand delivered, published in local news outlets, and posted in public areas based on these tiers. Tier 2 violations include arsenic, lead, copper, among others. Tier 3 violations are often due to reporting or monitoring failures. Notification must occur within 30 days and 365 days, respectively, for tier 2 and 3 violations.

SDWA violations and subsequent notifications have been widely used in economic studies as treatment in quasi-experimental settings (Bennear and Olmstead 2008; Zivin, Neidell, and Schlenker 2011; Allaire et al. 2019). Most recently, Marcus (2020) utilizes the variation in public notification tiers to identify health and averting behavior for Total Coliform Rule (TCR) violations in North Carolina. Similarly, this paper uses SDWA public notification to study the mechanisms through which notification-based environmental regulation yields limited response in some populations and the related health costs.

Figure 2.1 plots the spatial variation in nitrate violations by county in the United States from 2010 to 2019. Larger numbers of violations happen in the Great Plains and the West.[5] This pattern also loosely follows the spatial variation of farm nitrogen application in the United States, discussed in the next section.

Figure 2.1: Number of SDWA Nitrate Violations per PWS in the County, 2010-2019



Note: Author's creation from EPA's SDWIS database. Figure displays the count of nitrate SDWA health-based violations from 2010 to 2019.

2.1.2 Nitrate Pollution

While nitrogen pollution is the result of a number of anthropogenic activities, agriculture is the primary source. In the United States, agricultural fertilization accounted for approximately 93% of commercial nitrogen use in 2010.[6] Figure 2.2 plots 2010 agricultural nitrogen use by county.

[5] This relationship also coincides with a greater dependency on groundwater as approximately 95% of all nitrate violations are sourced from groundwater Pennino, Compton, and Leibowitz (2017). A heavy concentration of violations through Texas, Oklahoma and Kansas closely follow the boundaries of the Ogallala Aquifer. The same is true in California's central valley.

[6] Authors calculations from Brakebill and Gronberg (2017)

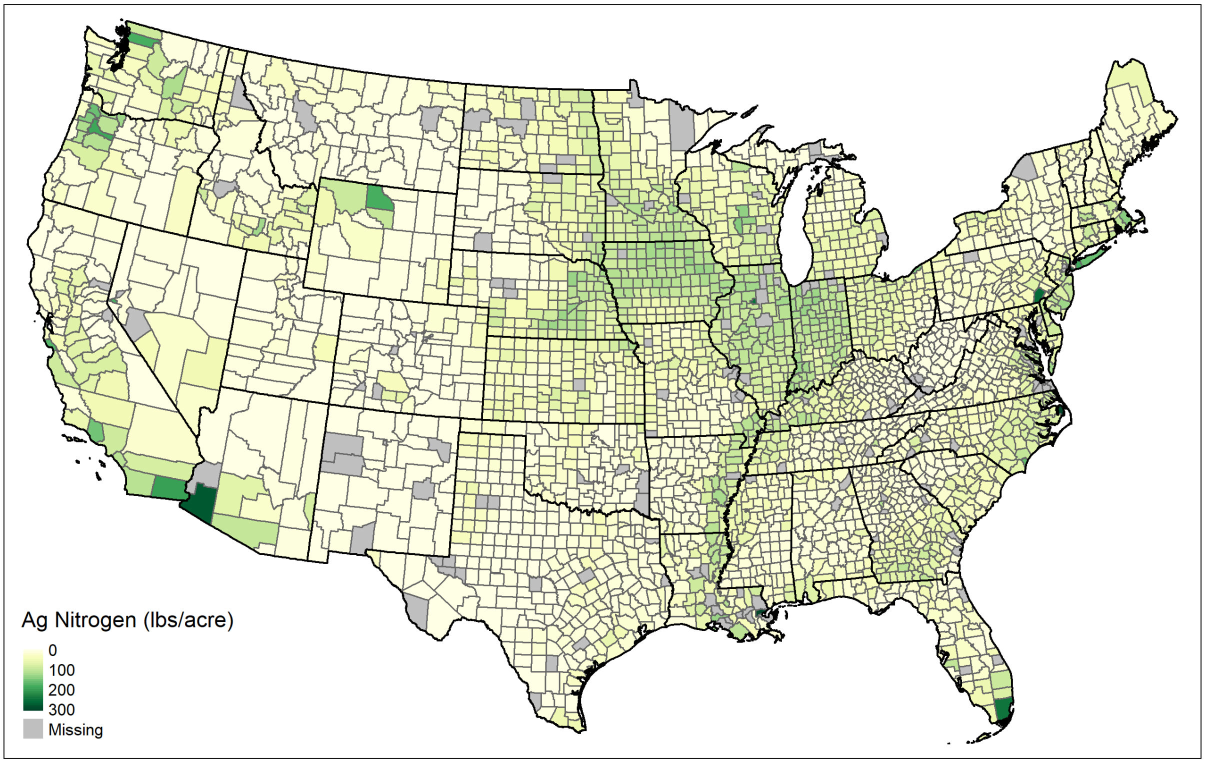


Figure 2.2: Agricultural Nitrogen use by County, 2012

Note: Author's creation from USGS data Brakebill and Gronberg (2017). Figure displays estimated county-level agricultural nitrogen use in 2010.

Unsurprisingly, the most heavily concentrated areas span across the Corn Belt and in California's Central Valley.

Nitrates in groundwater are an irreversible pollutant and often require households or water suppliers to identify new sources once detected. Approximately 90% of rural residents in the United States rely on groundwater for domestic use (Power and Schepers 1989). PWS that source from groundwater account for 95% the historical SDWA violations (Pennino, Compton, and Leibowitz 2017).[7] Nitrates are leached through the soil into groundwater basins over time, so the full externality is not realized until many years, even decades, after the polluting activity (Harter et al. 2012). Unlike bacterial contaminants, boiling the water does not eliminate the concentration and the long-term solutions are costly to the public water system. Once a groundwater source is contaminated with nitrates, contamination levels persist – they are unlikely to decline. Thus, public

[7] This does not include households that rely on private wells for domestic use. Private groundwater wells are perhaps even greater risk of environmental harm since these wells are outside the jurisdiction of the SDWA and do not require regular monitoring.

water systems must identify new sources of water, which are also susceptible to contamination, or build an expensive water treatment plant.[8]

Assessing the total environmental costs of nitrogen pollution remains a challenge for economic researchers (Keiser, Kling, and Phaneuf 2020). Nitrogen contamination in surface waste and associated environmental harm manifests primarily through algal blooms (Hendricks et al. 2014). Algal blooms create dead zones (or hypoxic zones) in bodies of surface water, which are detrimental to aquatic life and costly to human recreation (Egan et al. 2009). Tracking non-point source nitrogen pollution in surface water remains an active field of research (Paudel and Crago 2021; Taylor and Heal 2022).

2.1.3 Human Health Impacts

While (Temkin et al. 2019) argue that nitrate ingestion is also carcinogenic, and that current EPA thresholds should be much lower, identifying the health risks to adults is empirically challenging due to the unobserved exposure risks over the entire lifetime of an adult. For these reasons, infant health outcomes are typically assessed in the environmental health economics literature (Almond and Currie 2011). Infants have a relatively short window for which exposure, either *in utero* or postnatal, leads to adverse health outcomes.

Furthermore, exposure to nitrates poses the highest health risk for infants and pregnant mothers. High levels of nitrate exposure is correlated with an increased risk of methemoglobinemia (or blue-baby syndrome), which limits adequate oxygenation of the blood. The 10 mg/L MCL threshold set by the EPA is based on a 1951 survey, which identified that 2.3 percent of Methemoglobinemia cases were associated with nitrate concentrations above 10 mg/L (Walton 1951). The World Health Organization shares this same guideline internationally. Once a water system reports nitrate level in excess of this threshold, pregnant mothers are advised to identify a safe source and that the tap water should not be used in infant formula.

[8] Anecdotal evidence suggests industrial water treatment costs upwards of $3 million, and requires additional year-to-year operational costs.

2.1.4 Constraints to Averting Response

A number of economic factors may limit an individual's ability to respond to information about environmental quality. These factors lead to smaller observed marginal willingness to pay (MWTP) for environmental improvement. However, estimates of MWTP in the presence of significant constraints underestimate the true MWTP. The lack of reliable news outlets in an area, for example, leads to a dampened local response to public notifications of pollution (Marcus 2021). However, the same individuals may chose a meaningfully different response in the presence of broadly communicated information about pollution to a population. Policy aimed at limiting pollution exposure must also carefully consider constraints that may vary across populations.

This study highlights the interaction between food deserts and SDWA nitrate violation, two realities that are acute in the rural United States (Bitler and Haider 2010). Generally, food and beverage items have higher retail prices in food deserts due to higher operating costs. Residents living in food deserts also face higher travel costs to reach distant supermarkets. Food deserts and their impacts on inequality and nutrition have long been debated (Allcott et al. 2019).

For this paper, I use USDA's definition of a food desert (or low access) as a census tract with at least 500 people, or 33 percent of the population, living more than 1 mile in urban or more than 10 miles in rural areas from the nearest supermarket, supercenter, or large grocery store. Figure 2.3 plots rural food deserts in the United States. Rural food deserts are highly prevalent in the Western United States. Tables 2.5 and 2.6 in the appendix, respectively, show that consumers in food deserts and rural areas face higher prices for both bottled water and soda.

2.2 Conceptual Model

I develop a stylized conceptual framework similar to Harrington and Portney (1987), which I extend to illustrate how resource constraints may limit averting behavior. Consumers derive utility from health, H, and a composite good, X. H is a dose-response function of health, dependent on pollution, T, and protective behavior, B. B is consumption of a safe alternative beverage. The dose-response function for health is a decreasing function of pollution, $H_T < 0$. Alternative beverages provide a means to lessen exposure to the potential pollutant.

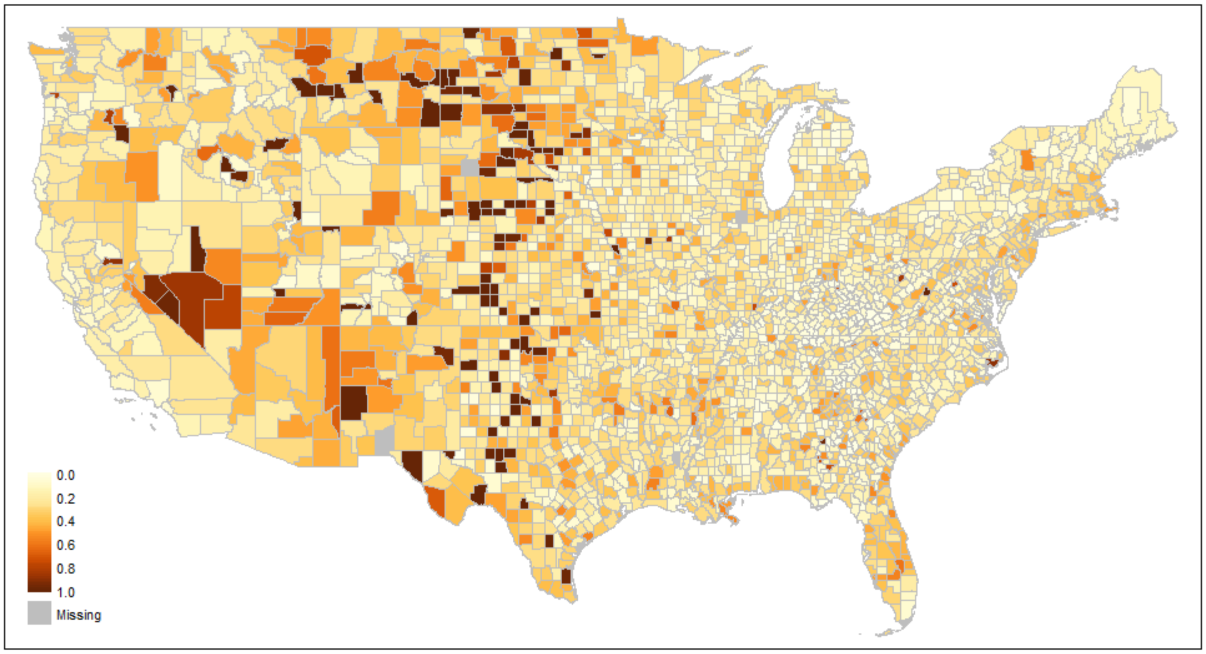


Figure 2.3: Share of County Population in Food Desert, 2015

Note: Author's creation from USDA Food Research Atlas data. Figure displays the share of the county's population that is over 10 miles away from a grocery store in rural areas or 1 mile away in urban areas.

$$U = U(H, X)$$
$$H = H(T, B(T))) \tag{2.1}$$

Totally differentiating H with respect to T yields equation 2.2, where the first term, H_T, indicates the direct health effect of exposure to the pollutant. The second term indicates the behavioral response through which consumers may choose to protect themselves to some extent through pollution avoidance behavior, indicated by B. Together, $\frac{dH}{dT}$ yields the net effect of an exogenous change in pollution on health. In observational studies, the net effect, rather than the direct effect, of pollution on health is observed in practice. Failing to account for this reality will undoubtedly lead to inaccurate conclusions about the pollutant's effect on health.

$$\frac{dH}{dT} = H_T + H_B B_T \tag{2.2}$$

Consumers maximize utility subject to a budget constraint, Y. I follow Abrahams, Hubbell, and Jordan (2000) and assume that the price of tap water is equal to zero, and denote the price of purchasing beverages at retail by p_B^i, which is the unique price faced by each individual. Each consumer also experiences a unique implicit price, $p_I^i \geq 0$, in order to obtain the safe alternative. For the context of this paper, implicit prices arise due to limited accessibility. The price of the composite good is normalized to 1 and utility is monotonically increasing in the composite good. Therefore, the budget constraint holds with equality, and $X = Y - (p_I^i + p_B^i)B$. The consumer solves the utility maximization problem with respect to one non-negative variable, B. The Lagrange multiplier for the non-negativity constraint is represented by μ.

$$\max_{B \geq 0 \ [\mu]} \ U(H(T,B), Y - (p_I^i + p_B^i)B) \tag{2.3}$$

The first-order conditions and the solutions to the maximization problem are presented in the appendix. The solutions to this maximization problem yield a demand function for the protective behavior that is dependent on the level of pollution, T, and the total price of averting response, $p_I^i + p_B^i$. An exogenous change in T will yield a non-negative change in demand for safe beverages, represented by the partial $B_T(Y, p_I^i + p_B^i)$.

In empirical settings, this reduced-form change in demand for an exogenous environmental quality change captures the *average* averting response in the sample. The average behavioral response, however, fails to express the distribution of avoidance behavior. Implicit costs are one explanation why the behavioral response differs by sub-populations. That is, $B_T(Y, p_B^i) \geq B_T(Y, p_I^i + p_B^i)$ for $p_I \geq 0$. High implicit costs, p_I^i, may contribute to why the valuation for environmental goods has been found to be lower in developing country settings.

Bottled water and other beverages for residents in food deserts in rural areas may be relatively more expensive due to either higher transportation costs or higher baseline retail prices. Grocery access in food deserts increases the cost for consumers to substitute bottled water for tap water. Holding all other factors constant, I hypothesize that averting behavior is dampened in food deserts due to the interaction of costly grocery access in rural areas. I measure this effect by interacting food access statistics with the public notification information shock.

Consumers in food deserts also may be less likely to consume bottled water due to a higher retail price in the local retail stores. As the price of bottled water increases in equation (2.10), the necessary marginal utility of the composite good for a corner solution becomes smaller. Hence, even in the event of a positive shock to T, the shadow value remains small enough for consumers to stay at the corner solution.

Importantly, a distribution of B_T can also be informative of the direct health impacts of the pollutant. Consider, again, equation 2.2. For smaller values of B_T, the gap between the net health effect and the direct health effect, $\frac{dH}{dT} - H_T$, lessens. This theoretical model underscores the distributional relationship to empirically estimate both the behavioral and health response to nitrate pollution, which may differ by an individual's context.

2.3 Data

SDWA violations and subsequent notifications provide a quasi-experimental context to study averting behavior. This research design assumes that consumers cannot predict an impending SDWA violation and that notification serves as an exogenous shock to perceived water quality. I provide evidence that consumers only respond in the weeks after a violation occurs, not prior, which is a necessary exogeneity condition for this design. To measure averting response heterogeneity, I assemble a store-by-week panel from 2010-2019. I exploit weekly within-store variation in SDWA nitrate violation events to identify average treatment effects and observe cross-sectional heterogeneity across resource constraints.

2.3.1 Water Quality Violations

Enforcement and Compliance History Online (ECHO) through the EPA contains a record of SDWA violations and enforcement actions for PWS across the United States. To ensure a precisely identified exogenous shock to perceived water quality, I use tier 1 public notifications from SDWA nitrate violations and notifications as the main sample for my estimation strategy.[9] Throughout the remainder of the paper, I use the terms violations and notifications interchangeably since the events occur on the same day for tier 1 violations.

I define that treatment occurs in the weeks between the date of public notification to the return to compliance date. Figure 2.7 in the appendix illustrates the timing of these occurrences throughout the year, showing that some violation types are more seasonal than others.

2.3.2 Beverage Sales

Beverage sales data come from Information Resources Inc (IRI), which provides the most geographically comprehensive scanner data available. These retail scanner data cover over 48,000 stores nationally and measure weekly sales by product code (UPC). The widespread coverage of these data is particularly helpful in measuring the impacts in rural areas, where data availability is typically sparse. I disaggregate beverage sales into two categories: bottled water and soda. Each measure is the sum of weekly store revenue from all types of bottled water or soda. Soda sales are the cumulative of carbonated beverage, sugar- and calorie-reduced beverage (i.e., diet sodas), and seltzer sales. Bottled water captures non-carbonated, natural or regular water in both small bottles and multi-gallon, refillable jugs. These data are reported for a variety of store types as exhibited in Figure 2.6.

2.3.3 Infant Health Outcomes

Nitrate contamination in drinking water poses the most serious health threat to infants and pregnant mothers. I use proprietary infant health statistics from the CDC's National Center for Health Statistics. I aggregate birth statistics in the United States from 2010-2019 to about 190,000 county-month observations across the United States. Specifically, I use the rate of low-birthweight and infant mortality to study how SDWA public notification, and how heterogeneous levels of averting response affect infant health outcomes. Though nitrate ingestion is a known cause of infant deaths related to "blue-baby syndrome", the CDC does not uniquely categorize these deaths in the data.

[9] While the public notification date is included in the data, leakages of information or slow dissemination of water quality information may happen between the violation date and the public notification. This possibility threatens the experiment design and may lead to an anticipation effect.

Instead, the primary health outcomes measures total infant mortality in a county measures death stemming from all causes.

A limitation of this study is the inability to precisely identify the residence of infants and mothers. Several recent studies use birth-certificate records, latitude and longitude of residence, and mother fixed effects to control for unobservable characteristics (Currie et al. 2013; Marcus 2021; Hill and Ma 2022). However, at a national level, county-month observations provide the most geographic and temporal granularity available and provide sufficient power to identify environmental health effects and are used in a number of settings (Taylor 2022; Hansen-Lewis and Marcus 2022).

2.3.4 Grocery Access & Demographics

The Food Access Research Atlas from the USDA provides cross-sectional census-tract level food access statistics determined by the distance to the nearest grocery store or source of healthy food. The Food Access Research Atlas also contains characteristics that may limit food access, like income and vehicle ownership. This dataset is primarily derived from the 2010 Census, the 2014-2018 American Community Survey, and the 2019 STARS (Store Tracking and Redemption System). These data provide the primary community characteristics through which I evaluate heterogeneity in averting behavior.

Given that these data are cross-sectional, they will be unable to capture any variation in demographics over the course of the sample. For example, water pollution may cause local residents to move to reduce exposure to the pollutant – a more long-run and extreme form averting behavior. However, given that this type of out-migration could take years to be fully realized, this possibility is unlikely to bias the short-run averting response through beverage sales.

2.4 Empirical Model

2.4.1 Averting Behavior and Heterogeneity

The staggered nature of SDWA violations in communities across the United States allows for the implementation of a dynamic difference-in-difference (DD) empirical specification. A number of studies have similarly used the exogenous and staggered timing of SDWA violations as a quasi-experimental research design. However, a large and growing literature documents the potential bias in difference-in-difference estimated using two-way fixed effects (TWFE) with variation in treatment timing (Goodman-Bacon 2021). Generally, TWFE controls time-invariant differences and macroeconomic shocks. However, the bias arises because TWFE also residualizes the treatment variable, and already treated units are used as implicit counterfactuals. The magnitude of the TWFE bias is dependent on the degree of heterogeneity across time and has potentially severe consequences for the interpretation of TWFE coefficients.

While this potential bias is now well understood, subsequent work has proposed alternative estimators to TWFE to uncover unbiased estimates in staggered DD settings (Callaway and Sant'Anna 2019; Gardner 2021). For this setting, Gardner (2021) provides an ideal alternative, estimating DD in two-stages. Using only pre-treated units, the time and individual fixed effects are estimated in the first stage. The remaining variation in the outcome variable, after controlling for fixed effects, is used to identify the unbiased treatment effect in the second stage. I demonstrate this small bias by comparing the TWFE estimates, which are similar to Allaire et al. (2019), with the estimator from Gardner (2021).

To estimate the response to tier 1 SDWA public notifications, I estimate equation (2.4), where B_{ist} are beverage sales in cents at store i and in state s in week-year t. Treatment, Vio_{ist} is equal to 1 during active violation weeks, and 0 otherwise. I multiply treatment by w_i, which is the percentage of the store's census-tract affected by the violation. Together, $Vio_{ist} \times w_i$ capture the community treatment intensity. The vector $\boldsymbol{X_{ist}}$ captures time-varying controls (e.g., weather). The base specification uses week-by-year fixed effects denoted by λ_t, which absorbs national seasonality in beverage sales and macroeconomic shocks. I also include store-by-event fixed effects, α_i, which capture time-invariant factors, like store location and size of the consumer population.[10] Additionally, state-by-year fixed effects, ϕ_s, capture state-year specific regulatory differences.[11] Standard errors are multi-clustered at the store and violation level (Cameron, Gelbach, and Miller 2011). This accounts for potential serial correlation within individual stores over time and between stores affected by the same violation. Following Gardner (2021), I estimate equation 2.4.

[10]Population size and demographics of the local population could obviously change over the course of the panel. This change is a potential omitted variable if it correlated with treatment timing (i.e. out-migration due to poor water quality). This implies that my point estimates underestimate the full averting behavior taken by consumers, but estimating the out-migration effect is beyond the scope of this paper.

[11]State agencies carry out the enforcement and monitoring of SDWA requirements among PWS.

$$\text{(2.4)} \quad \begin{gathered} \textit{With not yet treated sample: } \log(B_{ist}) = \boldsymbol{\phi' X}_{ist} + \lambda_t + \alpha_i + \phi_s + \varepsilon_{ist} \\ \textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\phi' X}_{ist} + \mu_{ist} \end{gathered}$$

I additionally estimate the dynamic version (or event-study) of equation 2.5 to offer insight into the evolution of the treatment effect in the weeks following a violation and detect persisting effects beyond a return to compliance. This specification also offers evidence to support the identifying assumption that, conditional on fixed effects and covariates, beverage purchases would have not significantly differed in the absence of violation. For the event-study, I use an eight week window before and after the violation.[12] I ensure a balanced panel during the event-study window. Following Schmidheiny and Siegloch (2023), I bin all other observations outside the event-study window into the window endpoints. I use the third week prior to violation as the baseline week, which allows this specification to detect any anticipatory effect in the two prior weeks.

The event-study results are estimated with equation 2.5, where $Week_{iw}$ indicates if store i's observation is w weeks away from the violation. I also interact this event-week dummy with Vio_{iswt} because PWS return to compliance at different points post-violation. Therefore, a PWS that returns to compliance seven weeks post-violation may yield a more lasting response than a PWS with only a week-long violation. This specification tests for the differing effects between post-violation and compliant versus post-violation with an active violation.

$$\text{(2.5)} \quad \begin{gathered} \textit{With not yet treated sample: } \log(B_{iswt}) = \boldsymbol{\phi' X}_{iswt} + \lambda_t + \alpha_i + \phi_s + \varepsilon_{iswt} \\ \textit{With full sample: } \hat{\varepsilon_{iwt}} = \sum_{w=-8}^{w=8} \beta_{1w} Week_{iw} + \sum_{w=-8}^{w=8} \beta_{2w} Week_{iw} * Vio_{iswt} + \boldsymbol{\phi' X}_{iswt} + \mu_{iswt} \end{gathered}$$

An identifying assumption of this event-study framework is that beverage sales would not have changed in absence of treatment. In equation (2.5), this assumption is supported if β_{1w} for all $w \in [-8, -1]$ are not statistically distinguishable from zero.

To test for heterogeneity by community demographics, I will estimate equation (2.6), which

[12] Eight weeks is chosen as the window since all nitrate violations in the sample are resolved in 7 weeks or prior of initial violation.

interacts the violation and public notification dummy variable with cross-sectional characteristics. The vector $\boldsymbol{Z_i}$ contains time-invariant demographic variables for socio-economic indicators or resource access measures. Elements of $\boldsymbol{\gamma}$ will report the difference relative to β across values of $\boldsymbol{Z_i}$. Importantly, the heterogeneity analysis should not be interpreted as causal estimates since Z_i is non-randomly distributed. However, γ can still uncover true heterogeneous treatment effects and this analysis can be suggestive of the causal mechanisms.

$$\begin{aligned} &\textit{With not yet treated sample: } \log(B_{ist}) = \boldsymbol{\phi' X}_{ist} + \lambda_t + \alpha_i + \varepsilon_{ist} \\ &\textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Vio_{ist} * w_i + \boldsymbol{\gamma Z_i} * Vio_{ist} * w_i + \boldsymbol{\phi' X}_{ist} + \mu_{ist} \end{aligned} \tag{2.6}$$

2.4.2 Infant Health Impacts

The SDWA public notification primarily serves to protect consumers from contaminated drinking water and the negative health impacts. Averting behavior through beverage sales protects consumers from that threat. However, where aversion does not take place, residents may remain exposed to the potential health consequences. This project will study the health implication of averting behavior, or lack thereof, using infant health statistics and drinking water violation and quality records.

To estimate the impacts of nitrate violations on infant health, I use the same exogenous treatment timing of SDWA violations and public notifications used above to estimate the behavioral response. However, this specification deviates in two primary ways. First, at the national level, proprietary infant health outcomes are only available at the county-month level.[13] Second, SDWA informational provisions identify infants under 6 months and pregnant mothers as the subset of population most susceptible to nitrate exposure. Therefore, the harmful health impacts of nitrate exposure may manifest themselves anytime nine months after the violation. I estimate the average local infant health impacts for the nine months after violation. I uncover the reduced form health impacts by estimating equation 2.7.

[13] Some states provide researchers access to birth-certificate level data. However, county-month is the most granular available for a national assessment.

$$
\begin{aligned}
&\textit{With not yet treated sample: } \log(Y_{it}) = \boldsymbol{\phi' X}_{ist} + \lambda_t + \alpha_i + \varepsilon_{ist} \\
&\textit{With full sample: } \hat{\varepsilon_{ist}} = \beta Notif_{ist} + \boldsymbol{\gamma Z_i} * Notif_{ist} + \boldsymbol{\phi' X}_{ist} + \mu_{ist}
\end{aligned}
\tag{2.7}
$$

Here, Y_{it} are infant health outcomes in county i in month t. $Notif_{ist}$ is a dummy equal to 1 if a public water system in county i in state s experienced a SDWA nitrate violation and subsequently distributed public notifications to their residents in the prior nine months. Similar to the behavioral response, I also test for heterogeneous treatment effects across possible geographic and socioeconomic constraints.

2.5 Results

2.5.1 Bottled Water

For the baseline estimates of averting behavior, I disaggregate beverage sales into bottled water sales – the traditional measure of averting behavior in averting behavior studies – and soda. For nitrate violations, bottled water is the recommended alternative source included in public notifications. Boiling water, for example, does not eliminate nitrates and potentially makes nitrates more concentrated. One alternative in-home treatment method that removes nitrates from water is a costly water-treatment system. Purchasing one of these systems reflects a long-run response since it would protect against all future potential water quality risks. Therefore, bottled water sales capture the short-run, lower-bound of averting response by consumers.

Figure 2.4 displays the dynamic response of bottled water sales for the weeks around nitrate violations. The parallel trends assumption is supported since no pre-treatment week (or binned pre-treatment) is significantly different than the baseline week (i.e. three weeks prior to violation). Positive averting response occurs for active violation the 2nd through the 7th weeks after the initial violation. This delayed response is suggestive of slow dissemination of information throughout a community. There does not appear to be a persistent effect after water systems return to compliance.

Table 2.1 displays the results of the average treatment effect across all active violation weeks. Columns (1) and (2) report the biased estimates from TWFE. These point estimates are similar to

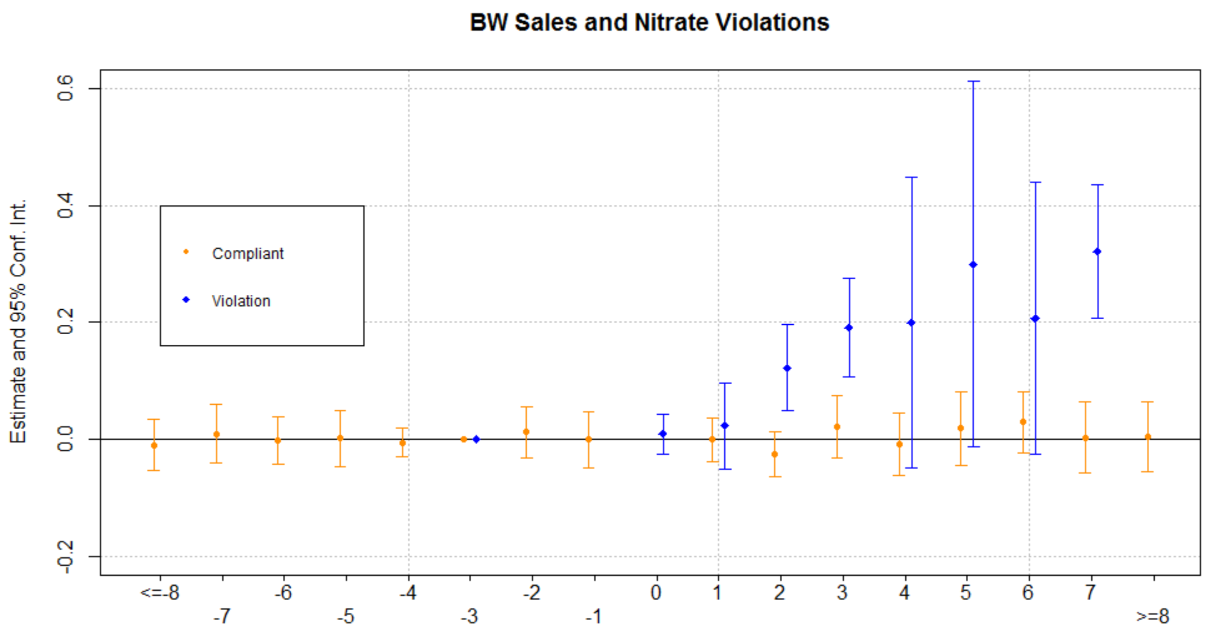


Figure 2.4: Event-Study Results: Bottled Water Sales Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event-study coefficients of logged bottled water sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in bottled water sales relative to 3 weeks prior to the violation. Violation indicates that the observation remained in an active violation, and compliant indicates the local PWS returned to compliance. The regression includes, event by store, week-by-year, state-by-year fixed effects, and weather controls. Standard errors are multi-clustered at the store and violation level.

those of Allaire et al. (2019), suggesting that my sample doesn't differ in a statistically meaningful way. Columns (3) and (4) report the two stage DD results from Gardner (2021) and an intention-to-treat effect of 17.3%. In this context, the TWFE does bias the point estimate to zero, but the bias is economically small.

2.5.2 Soda

Instead of substituting bottled water, some consumers may substitute contaminated tap water with other beverage options, like soda. Soda sales are an alternative form of averting behavior and should not be ignored in calculating the full response from exogenous changes in nitrate contamination in drinking water. Analysis of soda additionally gives insight into the indirect effects of drinking

Table 2.1: Bottled Water Sales during SDWA Nitrate Violation

	log(Bottled Water Sales)				
	(1)	(2)	(3)	(4)	(5)
Panel A. TWFE					
Nitrate Vio x w_i	0.170	0.164	0.229*	0.128*	0.124*
	(0.103)	(0.104)	(0.112)	(0.055)	(0.053)
Num.Obs.	721 897	721 897	721 897	721 897	721 897
Panel B. DiD2s					
Nitrate Vio x w_i	0.273*	0.303*	0.315*	0.173***	0.185***
	(0.122)	(0.124)	(0.125)	(0.032)	(0.033)
Num.Obs.	721 897	718 634	614 478	614 478	614 478
Std.Errors	Store & Vio	Store & Vio	Store & Vio	Store & Vio	Store & Vio
Event by Store	X	X	X	X	X
Week	X	X	X	X	X
Year	X	X	X	X	X
Week-Year		X	X	X	X
State-Year			X	X	X
Weather Controls				Linear	Quadratic

Note: Dependent variable is logged bottled water sales in cents. Each regression includes store by event, week by year, and state by year fixed effects and are weighted by the percent of population affected by the violation. Standard errors are multi-clustered at the store and violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

water pollution, as consumers may substitute to beverage options that have their own set of health externalities.

Figure 2.5 presents the event-study results, where the outcome is sales of soda. Again, the parallel trends assumption prior to a violation holds. Similar to bottled water, soda sales generally increase as a result of active nitrate violations. These coefficients are dampened relative to bottled water, but consumers do respond through alternative beverage forms other than just bottled water – indicating that local drinking water contamination induces a secondary effect on those affected, which have negative ramifications for health.

Table 2.2 presents the average treatment effect over all active violation weeks. As with the bottled water sales, there is bias in the TWFE estimates, but the corresponding point estimates are not significantly different than each other. Therefore, the TWFE bias is small in this setting.

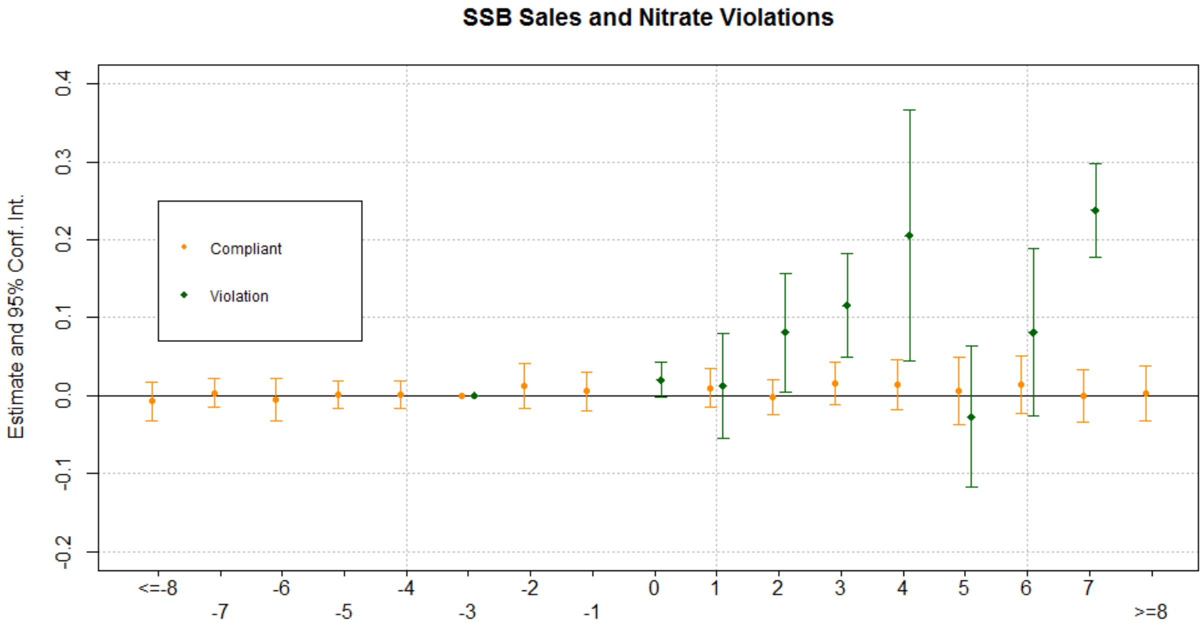


Figure 2.5: Event-Study Results: Soda Sales Pre- and Post- SDWA Violation

Note: Presents the two-stage difference in difference event-study coefficients of logged soda sales for the weeks before and after a SDWA violation. The vertical axis measures the % difference in soda sales relative to 3 weeks prior to the violation. Violation indicates that the observation remained in an active violation, and compliant indicates the local PWS returned to compliance. The regression includes, event by store, week-by-year, state-by-year fixed effects, and weather controls. Standard errors are multi-clustered at the store and violation level.

2.5.3 Treatment Effect Heterogeneity

A key contribution of this paper studies the mechanisms through which demographics and resource constraints limit observed averting behavior. To estimate these effects, I estimate equation 2.6. For ease of interpretation, I convert all continuous demographic variables into discrete indicators, where $Z_i = 1$ if census-tract $i's$ proportion of the population for measure Z is above the sample median.

Table 2.3 presents results from selected measures of heterogeneity. Most notably, column 3 shows significant 31.4% lower averting behavior in low access, food deserts relative to non-food deserts. Additionally, the average treatment effect in non-food deserts is almost twice that reported in table 2.1. This suggests that the implicitly higher price limits these residents' ability to access alternative drinking water in the weeks after a SDWA violation.

Table 2.2: Averting Behavior Through Soda

	log(Soda Sales)				
	(1)	(2)	(3)	(4)	(5)
Panel A. TWFE					
Nitrate Vio x w_i	0.174**	0.149**	0.142*	0.094*	0.093*
	(0.053)	(0.050)	(0.055)	(0.037)	(0.037)
Num.Obs.	621 618	621 618	621 618	621 618	621 618
Panel B. DiD2s					
Nitrate Vio x w_i	0.217***	0.220***	0.179***	0.113**	0.127***
	(0.054)	(0.057)	(0.040)	(0.039)	(0.033)
Num.Obs.	621 618	618 423	516 315	516 315	516 315
Std.Errors	Store & Vio	Store & Vio	Store & Vio	Store & Vio	Store & Vio
Event by Store	X	X	X	X	X
Week	X	X	X	X	X
Year	X	X	X	X	X
Week-Year		X	X	X	X
State-Year			X	X	X
Weather Controls				Linear	Quadratic

Note: Dependent variable is logged soda sales in cents. Nitrate Vio equals 1 when the local PWS has an active violation. w_i is the percent of the census tract affected by the violation. Each regression includes store by event, week by year, and state by year fixed effects and is weighted by w_i. Standard Errors are multi-clustered at the store and violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Additionally, other resource constraints are associated with lower averting response, including income and a more expensive retail price for bottled water. These results indicate that populations remain disproportionately exposed to the health impacts of nitrate contaminated drinking water. Regulation that assumes individuals have the same portfolio of averting responses available may exacerbate environmental inequality since low-resource communities are unable to protect themselves in the same manner as areas with higher-resource availability.

Second, table 2.8 displays the results for soda sales. Similarly, food desert census-tracts display negative, but not significant, averting response relative to non-food deserts. While none of the heterogeneity coefficients are statistically significant, they are the same direction and similar relative magnitude to those of bottled water. These patterns are consistent across both bottled water and soda purchases – suggesting that the resource constraints limit the purchasing ability for all products, rather than capturing a systematic correlation between consumer preferences between

Table 2.3: Heterogeneity in Averting Behavior: Bottled Water Sales

	log(Bottled Water sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Nitrate Vio×w_i	0.173***	0.463***	0.249***	0.407***	0.180***	0.161***
	(0.032)	(0.128)	(0.042)	(0.078)	(0.027)	(0.026)
x Food Desert		−0.314*				
		(0.122)				
x Low Income			−0.264**			
			(0.089)			
x > Price				−0.344**		
				(0.113)		
x > SNAP					−0.075	
					(0.149)	
x > Low Vehicle Access						0.059
						(0.099)
Num.Obs.	614 478	614 478	614 478	614 478	614 478	614 478
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X	X	X	X
FE: Store by Event	X	X	X	X	X	X
FE: Week by Year	X	X	X	X	X	X

Note: Dependent variable is logged bottled water sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

soda and bottled water.[14]

Infant Health

The public health externality of drinking water pollution depends on the residents' ability to respond to the hazard. As I show in the previous section, the responses vary widely across locations. For sub-populations that exhibit a relatively lower response to nitrate violation notifications, their health outcomes are expected to be worse than populations that do engage in protective behavior as predicted by the stylized theoretical model.

I test this hypothesis by estimating equation 2.7. The first outcome of interest is infant mortality transformed by the inverse hyperbolic sin. Hence, the main coefficients approximately report the proportional change in infant mortality in the nine months after a SDWA nitrate violation

[14] One long-standing claim is that consumers use SNAP funds to purchase more soda compared to the non-SNAP population. This claim is not supported in these findings, at least in the context of averting response, comparing estimates from comparing column 5 in tables 2.3 and 2.8.

(i.e. $\beta \times 100 = \%$ change) (Bellemare and Wichman 2019). Importantly, I also differentiate the health impacts by low-access and low-income groups, since tables 2.3 and 2.8 report consistently lower averting behavior after a SDWA nitrate violation. Table 2.4 displays the reduced-form net impact on infant mortality for the nine-months after a SDWA violation. Panel A tests for heterogeneity in these estimates based on low access to grocery stores, and panel B does the same for low income counties.

The results in column 1 indicate that, on average across all locations, potential exposure to dangerous levels of nitrates in drinking water does not significantly change infant health outcomes. However, columns 2 through 5 show that infant mortality significantly increases in populations with lower access to grocery stores and lower incomes. The preferred specification in column 5 implies that infant morality increases by 6.3% in low-access counties and 4.4% in low-income counties where pregnant mothers or infants were potentially exposed to heightened levels of nitrates.[15]

Conversely, infant mortality rates actually improve in counties with greater access to grocery stores by 7.7% and in higher-income counties by 5.3%. In these populations, these results are suggestive that the SDWA public notifications sufficiently inform the at-risk crowd of the potential health impacts, and residents take the advised action to prevent nitrate exposure. These results are both consistent with the theoretical model that individuals engage in averting action and consistent with the empirical behavioral results.

Second, table 2.10 in the appendix reports the results of the impact of nitrate exposure on the occurrence of low birthweight. Similar to infant morality, the rate of low birthweight is transformed by the inverse hyperbolic sin. The results for the rate of very low birthweight are reported in table 2.11 in the appendix, and are very similar to low birthweight. On average, counties exposed to heightened levels of nitrates in their drinking water actually see an improvement in the rate of low birthweight in the nine-months following a violation. Low-access and low-income areas experience only a negligible, and insignificant difference, contrary to the infant mortality results.

[15] The total effects for these populations are the sum of rows 1-2 and 3-4, since "x Low-Access" captures the relative effect.

Table 2.4: Nitrate exposure's impact on infant mortality

	asin(IMR)				
	(1)	(2)	(3)	(4)	(5)
Panel A. Low Access					
Notified	−0.015	−0.059***	−0.070***	−0.073***	−0.077***
	(0.011)	(0.015)	(0.015)	(0.014)	(0.013)
x Low Access		0.115***	0.119***	0.129***	0.140***
		(0.024)	(0.024)	(0.023)	(0.022)
Panel B. Low Income					
Notified		−0.038**	−0.048***	−0.046***	−0.053***
		(0.013)	(0.013)	(0.013)	(0.012)
x Low Income		0.082***	0.086***	0.085***	0.097***
		(0.024)	(0.024)	(0.024)	(0.024)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependent variable is the inverse hyperbolic sin of infant mortality per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2.5.4 Welfare and Policy Implications

The behavioral costs associated with avoiding contaminated tap water due to nitrate violations can be estimated by equation 2.8. Since all SDWA nitrate violations are not included in my primary estimating sample, I use data from Pennino et al. (2020) on the total number of individuals impacted each year and the average length of violation. This assumes that the behavioral response in my sample is representative of all nitrate violations in the United States and the IRI retail data is representative of all retails.[16] The United States' generates approximately \$19.4 billion in annual bottled water sales and \$29.4 billion in soda sales (International Bottled Water Association 2019;

[16]There is no way to prove that these assumptions are accurate, but Zivin, Neidell, and Schlenker (2011) make the same assumptions about a smaller subset of retail stores in only Nevada and California.

Beverage Industry 2020). Distributing each of these figures uniformly across the population of the United States and the weeks of the year, BW_{pw} and $soda_{pw}$ capture the average expenditure per person per week on bottled water and soda respectively.

$$\text{Behavioral Costs} = \sum_{p}\sum_{w}(\hat{\beta}^{BW} \times BW_{pw} + \hat{\beta}^{soda} \times soda_{pw}) \tag{2.8}$$

This exercise indicates that consumers spend approximately $2.5 million on bottled water purchases and $2.2 million annually on soda annually in the United States as a result of nitrate violations.[17] This figure more than twice exceeds that of Zivin, Neidell, and Schlenker (2011) due to the downward TWFE bias and not accounting for substitution to other beverages. Yet, considering Dodds et al. (2009) estimates nitrogen pollution accounts for $2.2 billion in damages annually in surface water, the expenses paid by the affected residents is relatively small.

However, this number understates the full behavioral costs of nitrate violations due to a number of other, long-term protective actions, like water filtration systems. Bottled beverages capture only a portion of the short-term response, but they provide a relatively inexpensive alternative for protection against the potentially harmful health effect. Furthermore, the PWS themselves and the local taxpayers they serve must undergo expenses to return to SDWA compliance. Jensen et al. (2012) report that these expenses could range from anywhere between $200,000 to $40 million per system, depending on the size of the system and technology.

Furthermore, the economic damages to human health to those who remain exposed are likely higher than the behavioral impact. Over the 10-year panel of this study, about 4.5 million children were born in areas classified at low-access and in the nine months window following a drinking water nitrate violation. Given the estimate in table 2.4 that infant mortality was 6.3% higher in such counties and an average infant mortality rate of approximately 4.9 deaths per 1,000 births in these counties, this equates to roughly 143 additional infant deaths per year associated with nitrate violations in low access areas. Using EPA's value of statistical life measure of $11.17 million (in

[17] A large literature studies the effects of soda consumption and the impacts of obesity (Bleich and Vercammen 2018). An indirect effect of drinking water contamination may lead to worsened health, like increased obesity rates, if consumers opt to substitute water consumption with sodas. These indirect health impacts are not accounted for in this analysis.

2022 dollars), the back-of-the-envelope health costs of nitrate violations per year in food deserts exceeds \$1.5 billion.[18]

It should be noted, again, that the heterogeneous treatment estimates should not be interpreted as causal estimates, but demonstrate that nitrate contamination poses severe health risk to those who do not exhibit avoidance behavior, whether food deserts are the causal mechanism or other confounding factors. The environmental health costs in exposed populations far exceeds the behavioral costs, accentuating the disparity in environmental health outcomes in resource-constrained populations.

2.6 Discussion

Nitrate-contaminated drinking water poses serious health threats to infants, and possibly others. The impacts of this pollution depend on individuals' abilities to adapt to the potential health threat. However, communities affected by nitrate-contaminated drinking water also often exist in resource-constrained areas. These resource constraints may prevent individuals from protecting against the environmental hazard and exposed to the negative health consequences. In this paper, I show that consumers respond, on average, by purchasing 17.3% more bottled water and 11.3% more soda as a response to nitrate violations. These are relatively cheap forms of protection, which translates to roughly \$4.7 million in annual averting expenditures. This amount is likely far less the counterfactual health damages if all individuals remained exposed to heightened levels of nitrates. However, individuals in food deserts and low-income populations exhibit a significantly dampened response.

In reduced-form evidence, I also show that the same constraints which limit averting response are associated with detrimental infant health impacts. In the nine-months following a nitrate SDWA violation, low-access counties experience a 6.3% increase in the infant mortality rate and 4.3% increase in low-income counties. Whereas, counties with fewer constraints actually see an improvement in infant health outcomes. These findings are consistent with the theoretical framework that avoidance behavior protects against the harmful health impacts of nitrate pollution in drinking water. Regulations that induce avoidance behavior through informational provisions do appear to

[18] See link for details on EPA's mortality risk valuation.

protect some from these effects. However, populations where the response is limited experience net negative impacts on infant health.

The results of this paper quantify the externality of nitrate pollution in drinking water both through the channels of behavioral response and net health impacts. While there are no federal policies considering the regulation of nitrogen use in agriculture in the United States, I provide further evidence that the costs of nitrate pollution are large and far-reaching. I also show that the SDWA sufficiently protects some residents from the health costs associated with drinking water pollution, but others remain exposed and experience these health impacts, potentially worsening environmental health inequality.

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2.7 Appendix

2.7.1 Theoretical Solutions

This utility maximization problem yields the following set of first-order conditions:

$$
\begin{aligned}
&U_H H_B(T) - U_X(p_I^i + p_B) + \mu = 0 \\
&B \geq 0
\end{aligned}
\tag{2.9}
$$

Case 1: $(B = 0)$

Under this scenario, consumers utilize only tap water for their residential and drinking needs. For a corner solution to exist for other beverage consumption the inequality in equation (2.10) must hold, where the right-hand side represents the shadow value of avoiding health damages from tap water consumption. The corner solution emerges when the marginal rate of substitution between the composite good and health is greater than the shadow price of perceived health damages. Equation (2.10) implies that either (i) the perceived damages from drinking tap water are sufficiently small and (ii) that the price of alternative beverages is sufficiently high relative to the marginal utility of the composite good, X, so that the consumer chooses to not purchase other beverages.

$$
\frac{U_X}{U_H} > \frac{-H_T}{p_I^i + p_B}
\tag{2.10}
$$

Case 2: $(B > 0)$

In case 2, the consumer purchases a positive amount of the alternative source. Demand for B will satisfy equation (2.11) and will be a function of the exogenous water quality (T), income (Y), the retail price (p_B), and the unique implicit price faced by each consumer, (p_I^i). This equation represents the tradeoff between investing in additional units of a clean source of drinking water and the composite good.

$$
\frac{U_X}{U_H} = \frac{-H_T}{p_I^i + p_B}
\tag{2.11}
$$

2.7.2 Additional Tables and Figures

Table 2.5: Price of Bottled Water by Store and Location Characteristics

	log(Bottled Water Price)			
	1	2	3	4
(Intercept)	0.525***	0.092***	0.677***	0.648***
	(0.002)	(0.001)	(0.002)	(0.001)
Food Deserts	0.092***			
	(0.002)			
Convenience		1.081***		
		(0.001)		
Dollar		0.180***		
		(0.001)		
Drug		0.262***		
		(0.001)		
Mass Merchandiser		0.254***		
		(0.002)		
Urban			−0.081***	
			(0.002)	
Low Income				−0.111***
				(0.001)
Num.Obs.	747 449	747 449	747 449	747 449

Note: Dependent variable is the logged price of bottled water in cents. Coefficients on store types are relative to the price at grocery stores.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.6: Price of Soda by Store and Location Characteristics

	log(Soda Price)			
	1	2	3	4
(Intercept)	1.248***	1.016***	1.345***	1.337***
	(0.001)	(0.001)	(0.001)	(0.000)
Food Deserts	0.054***			
	(0.001)			
Convenience		0.542***		
		(0.001)		
Dollar		0.042***		
		(0.001)		
Drug		0.237***		
		(0.001)		
Mass Merchandiser		0.088***		
		(0.001)		
Urban			−0.056***	
			(0.001)	
Low Income				−0.105***
				(0.001)
Num.Obs.	644 361	644 361	644 361	644 361

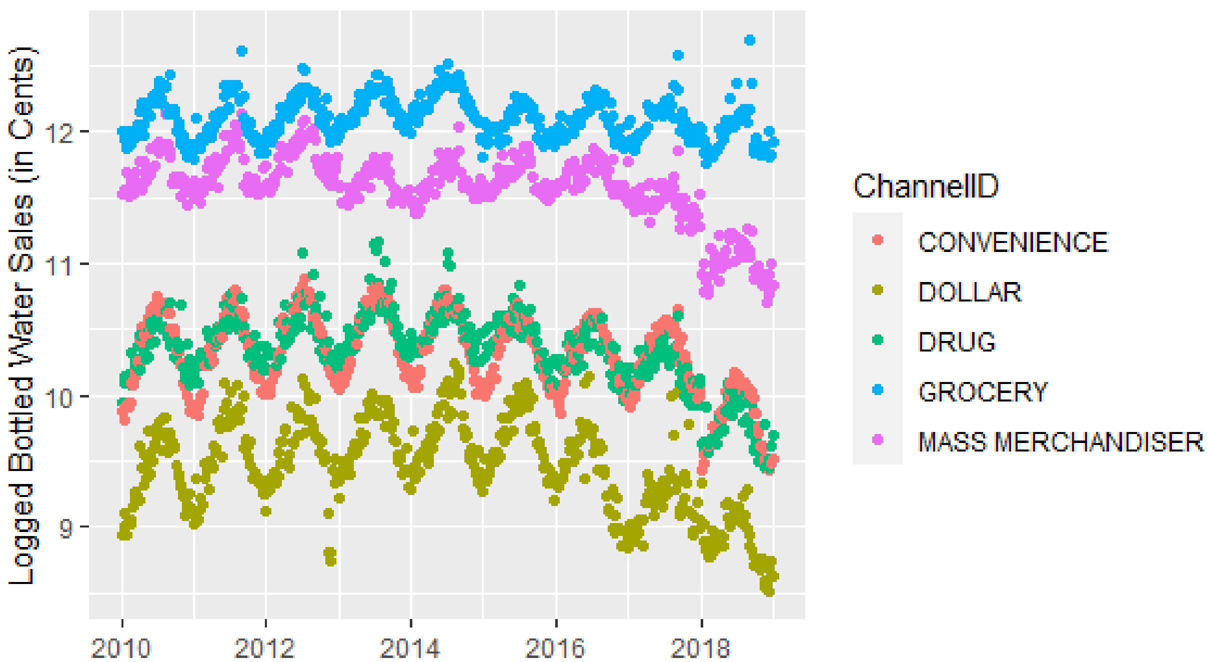
Note: Dependent variable is the logged price of soda in cents. Coefficients on store types are relative to the price at grocery stores.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.7: Heterogeneity in Averting Behavior: Bottled Water Sales

	log(Bottled Water)		
	1	2	3
Nitrate Vio	0.173***	0.266**	0.131***
	(0.032)	(0.087)	(0.035)
x> Non-White		−0.264**	
		(0.085)	
x Rural			0.164*
			(0.068)
Num.Obs.	614 478	614 478	614 478
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X
FE: Store by Event	X	X	X
FE: Week by Year	X	X	X

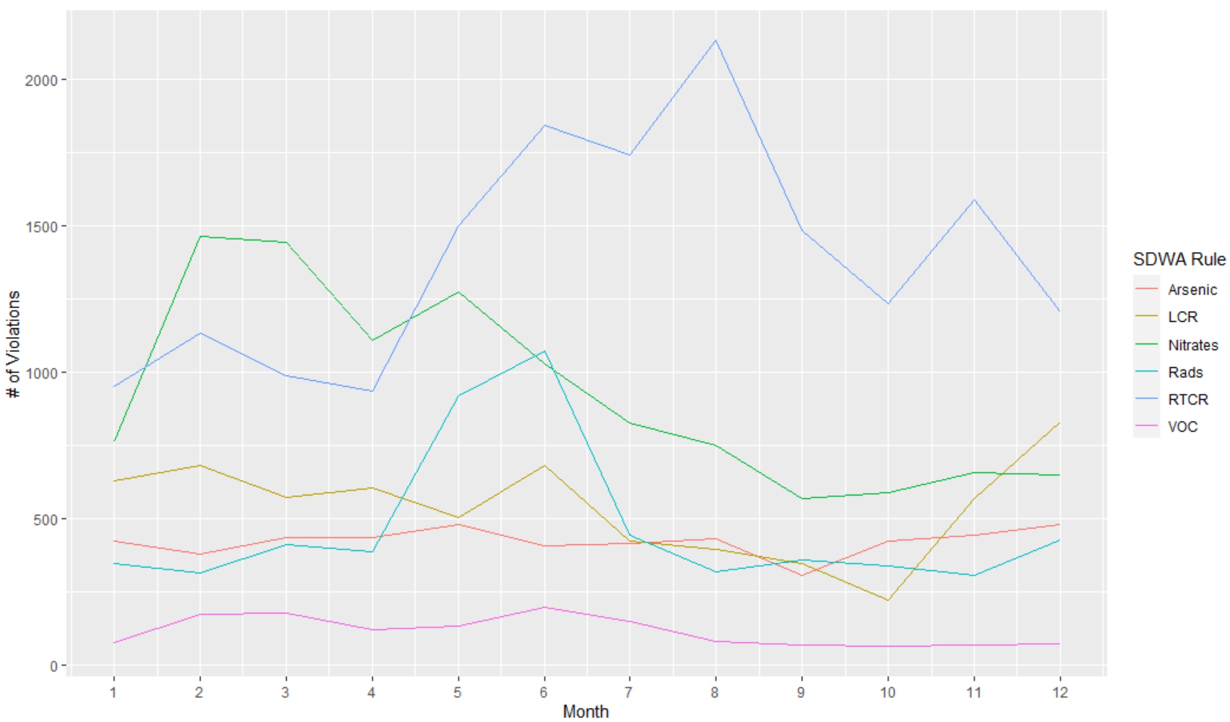
Note: Dependent variable is logged bottled water sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2.6: Raw Bottled Water Sales by Store Type



Note: Figure displays the logged sum of bottled water sales in cents in each week between 2010 and 2019 by store type. Author's creation from IRI Retail Scanner Data

Figure 2.7: Sum of SDWA Violations by Month and Type, 2010-2019



NOTE: LCR = Lead/Copper Rule, Rads= Radionucleotides, RTCR= Revised Total Coliform Rule, VOC= Volatile Organic Compounds.

Figure 2.8: Public Notification Example and Requirements

The Required Elements of a Public Notice

IMPORTANT INFORMATION ABOUT YOUR DRINKING WATER

Tests Showed Presence of Coliform Bacteria

1. Description of the violation

2. When the violation occurred

The Jonesville Water System routinely monitors for coliform bacteria. During the month of July, 7 percent of our samples tested positive. The standard is that no more than 5 percent of samples may test positive.

6. Actions consumers should take

What should I do?

- **You do not need to boil your water or take other corrective actions.** However, if you have specific health concerns, consult your doctor.
- You do not need to use an alternate (e.g., bottled) water supply.
- People with severely compromised immune systems, infants, pregnant women, and some elderly may be at increased risk. These people should seek advice about drinking water from their health care providers. General guidelines on ways to lessen the risk of infection by microbes are available from EPA's Safe Drinking Water Hotline at 1-800-426-4791.

5. Should alternate water supplies be used

4. The population at risk

What does this mean?

3. Potential adverse health effects

This is not an emergency. If it had been, you would have been notified immediately. Coliform bacteria are generally not harmful themselves. *Coliforms are bacteria which are naturally present in the environment and are used as an indicator that other, potentially-harmful, bacteria may be present. Coliforms were found in more samples than allowed and this was a warning of potential problems.*

Usually, coliforms are a sign that there could be a problem with the system's treatment or distribution system (pipes). Whenever we detect coliform bacteria in any sample, we do follow-up testing to see if other bacteria of greater concern, such as fecal coliform or *E. coli*, are present. We did not find any of these bacteria in our subsequent testing.

7. What is being done to correct the violation or situation

What was done?

We took additional samples for coliform bacteria which all came back negative. As an added precaution, we chlorinated and flushed the pipes in the distribution system to make sure bacteria were eliminated. This situation is now resolved.

8. When the system expects to return to compliance

For more information, or to learn more about protecting your drinking water please contact John Jones at (502) 555-1212.

9. Phone number for more information

10. Required distribution language

Please share this information with all the other people who drink this water, especially those who may not have received this notice directly (for example, people in apartments, nursing homes, schools, and businesses). You can do this by posting this notice in a public place or distributing copies by hand or mail.

This is being sent by the Jonesville Water System.

State Water System ID#1234567. Date Distributed: 8/8/09

Figure 2.9: Identifying Variation After Conditioning on Fixed Effects

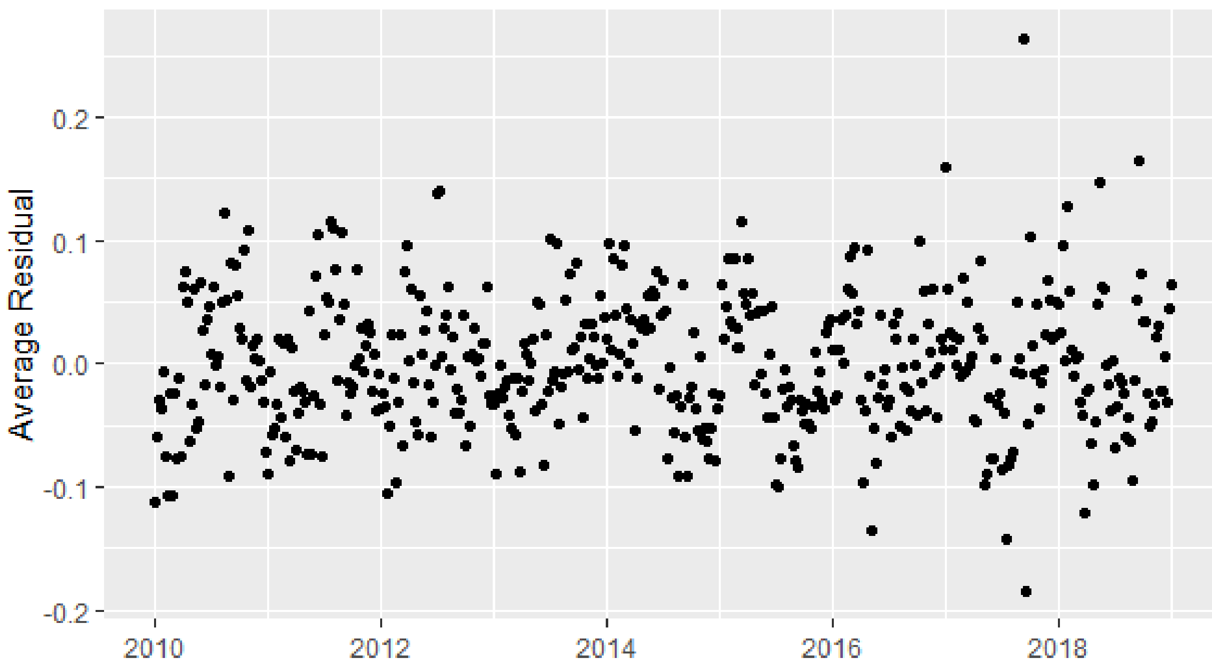


Table 2.8: Heterogeneity in Averting Behavior: Soda Sales

	log(Soda sales)					
	(1)	(2)	(3)	(4)	(5)	(6)
Nitrate Vio*w_i	0.113**	0.275**	0.123**	0.303***	0.117**	0.101*
	(0.039)	(0.105)	(0.039)	(0.080)	(0.042)	(0.045)
x Low Access		−0.175				
		(0.124)				
x Low Income			−0.033			
			(0.048)			
x > Price				−0.267		
				(0.153)		
x > SNAP					−0.038	
					(0.085)	
x > Low Vehicle Access						0.063
						(0.065)
Num.Obs.	516 315	516 315	516 315	516 315	516 315	516 315
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X	X	X	X
FE: Store by Event	X	X	X	X	X	X
FE: Week by Year	X	X	X	X	X	X

Note: Dependent variable is logged soda sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and is weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.9: Heterogeneity in Averting Behavior: Soda Sales

	1	2	3
Nitrate Vio	0.113**	0.093**	0.084*
	(0.039)	(0.033)	(0.039)
x> Non-White		−0.084*	
		(0.042)	
x Rural			0.116*
			(0.051)
Num.Obs.	516 315	621 618	516 315
Std.Errors	Store & Vio.	Store & Vio.	Store & Vio.
FE: State by Year	X	X	X
FE: Store by Event	X	X	X
FE: Week by Year	X	X	X

Note: Dependant variable is logged soda sales in cents. Each column includes violation by store by event, week by year, and state by year fixed effects and are weighted by w_i. ">" indicates above the median demographic. Standard errors are multi-clustered at the store and violation level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.10: Nitrate exposure's impact on low birthweight occurrences.

	asin(Low Birthweight)				
	(1)	(2)	(3)	(4)	(5)
Panel A. Low Access					
Notified	−0.028***	−0.026***	−0.029***	−0.030***	−0.027***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
x Low Access		0.003	0.003	0.001	−0.002
		(0.007)	(0.007)	(0.008)	(0.007)
Panel B. Low Income					
Notified	−0.028***	−0.022***	−0.025***	−0.025***	−0.024***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
x Low Income		−0.006	−0.006	−0.009	−0.009
		(0.008)	(0.008)	(0.008)	(0.007)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependent variable is the inverse hyperbolic sin of low birthweight rate per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.11: Nitrate exposure's impact on the rate of very low birthweight occuraces.

	asin(Very Low Birthweight)				
Panel A. Low Access					
Notified	−0.032***	−0.034***	−0.035***	−0.035***	−0.032***
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
x Low Access		0.005	0.006	0.001	−0.001
		(0.015)	(0.015)	(0.015)	(0.014)
Panel B. Low Income					
Notified	−0.032***	−0.037***	−0.037***	−0.039***	−0.038***
	(0.007)	(0.009)	(0.009)	(0.010)	(0.009)
x Low Income		0.013	0.013	0.012	0.013
		(0.016)	(0.016)	(0.016)	(0.016)
Num.Obs.	192 397	192 570	192 570	192 397	192 397
Vio by County	X	X	X	X	X
Month	X	X	X	X	X
Year	X	X	X	X	X
Month-Year	X		X	X	X
County-Month	X			X	X
Temp. Contrls	X				X

Note: Dependent variable is the inverse hyperbolic sin of very low birthweight rate per 1,000 births. Each regression is weighted by the total birth, and includes multiple specifications of fixed effects. Standard errors are clustered at the violation level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 3

Groundwater and Climate Adaptation

The costs of climate change are expected to be broad in reach and disproportionately borne by the poor (Hsiang, Oliva, and Walker 2019). The latter occurs in part because the magnitude of damages depends on the ability to adapt, and poorer households are less likely to have the means to respond (Dell, Jones, and Olken 2012, 2014; Burke and Emerick 2016; Jessoe, Manning, and Taylor 2018; Rode et al. 2021). Averting actions taken by some to mitigate climate damages may also impose externalities that are disproportionately realized. However, little is known about the extent to which avoidance behaviors taken to reduce climate damages impose costs on others.

I study this in the context of groundwater in California by evaluating the extent to which mitigating behaviors taken in response to heat and surface water scarcity lead to groundwater depletion and drinking water well failures. Historically, the agricultural costs of heat and drought in California have been moderate, partly because precipitation is an inaccurate measure of total water availability for irrigated agriculture (Schlenker, Hanemann, and Fisher 2005, 2007; Edwards and Smith 2018). In California, farmers instead rely on surface water supplies conveyed via canals and water projects and groundwater pumped from wells. This latter resource has operated as a critical mitigation strategy to dampen the agricultural costs of surface water reductions and heat, and may explain why some forecast that the costs of climate change in California will be minimal (Mendelsohn, Nordhaus, and Shaw 1994; Lund et al. 2018).[1] However, this groundwater extraction

[1] Climate change is expected to increase the frequency and severity of extreme heat and drought, make precipitation more variable, and reduce soil moisture (Swain et al. 2018). Collectively, these factors will increase agricultural demand for water and introduce large uncertainty into surface water availability for agricultural irrigation. To buffer against surface water curtailments and increased demand, agricultural users have often drawn from groundwater reserves.

also imposes costs on current users and future users. A declining water table may impose a pumping externality which makes groundwater irrigation costlier for neighboring farms and a stock externality which makes it unavailable to farmers in the future (Provencher and Burt 1993; Roseta-Palma 2002; Brozović, Sunding, and Zilberman 2010; Pfeiffer and Lin 2012; Edwards 2016; Merrill and Guilfoos 2017).

Less well understood is the acute and contemporaneous costs that groundwater pumping may exact on drinking water supplies in surrounding communities. Many households rely on private domestic wells for drinking water purposes. These users are concentrated in California's San Joaquin Valley, and are disproportionately low income and people of color.[2] Access to drinking water supplies among disadvantaged communities is a growing concern, with recent forecasts projecting that 10,500 domestic wells in the San Joaquin Valley are expected to run dry by 2040 (Pauloo et al. 2020).

This paper examines the extent to which new groundwater well construction by farmers, in response to annual fluctuations in heat and surface water scarcity, impacts depth to the water table and access to domestic wells. Myconceptual framework posits that surface water curtailments and heat will induce agricultural users to respond on the intensive and extensive margins, extracting more water from existing wells and building new and deeper groundwater wells. These responses will impact access to drinking water supplies through the channel of groundwater scarcity. I empirically test these hypotheses by first capturing the gross effect on agricultural groundwater demand by evaluating how the depth to the water table changes in response to heat and surface water curtailments. Then, I evaluate the reduced-form relationship of heat and surface water scarcity on domestic well failures, assuming this operates through the channel of groundwater table depletion. Finally, I estimate the effects of extreme heat and surface water curtailments on the response of agricultural producers through the drilling of new groundwater wells.

To empirically measure these impacts, I constructed a panel spanning 30 years on drinking and groundwater access for all agricultural water districts in California. I combined the universe of groundwater wells constructed, data on domestic well failures, groundwater depth data from groundwater monitoring stations, gridded weather data, and annual data on district-level surface water supplies. Information on groundwater well construction and well failures includes the location

[2]California's San Joaquin Valley, a region that is over 50% Latina/o and contains some of the highest rates of poverty and food insecurity in the state.

and date of construction, well depth, and well type for over a million wells. Schlenker and Roberts (2009) provide measures of temperature and precipitation derived from PRISM monthly data and daily weather station observations, and data from Hagerty (2021) measures the universe of surface water allocations in California by area and year from 1993 to 2020. These detailed data allow me to deploy an instrumental variables panel data approach that exploits annual fluctuations in temperature and surface water shocks, and controls for a number of factors, such as fixed differences, and annual shocks, such as recessions, that likely impact water access and agricultural producer's decision making in these local areas.

A first set of results indicates that extreme heat and reductions in agricultural surface water supplies lower the depth to the groundwater table. A one acre-foot (AF) reduction in the agricultural surface water allocation to every California cropland acre lowers local groundwater levels by an additional 4 feet. An additional harmful degree day reduces groundwater levels by 0.5 inches. Declining water tables suggest that the costs of climate change may be larger in the long-run if farmers cannot buffer with groundwater resources (Hornbeck and Keskin 2014; Auffhammer 2018).

A second central result indicates that farmers are responding to heat and surface water scarcity through the construction of groundwater wells. I estimate that for each acre foot (AF) of reduced surface water allocations for agriculture, the annual rate of agricultural well construction increases by 46%. Using an approximated cost of $75,000 to construct an agricultural well (Central Valley Flood Protection Board 2020), this translates to a back-of-the-envelope $37 million dollars invested annually in extensive-margin adaptation behavior by California farmers. This number also provides a lower-bound estimate on the avoided climate damages to California agriculture.

Myfinding that extreme heat will increase groundwater demand brings a new data point to the understanding of how climate change will influence water resources. While climate projections indicate increased year-to-year variation in rainfall, projections on the amount of precipitation are less clear (Jessoe, Mérel, and Ortiz-Bobea 2018). Myresults highlight that even if water supplies remain unchanged, warmer temperatures will increase demand for groundwater, with an additional harmful degree day increasing well construction by 1.2%. They also offer empirical evidence of historical agricultural adaptation to heat, with groundwater extraction serving as a critical buffer to mitigate the costs of extreme heat in California (Burke and Emerick 2016; Hornbeck and Keskin

2014; Barreca et al. 2016; Auffhammer and Schlenker 2014).

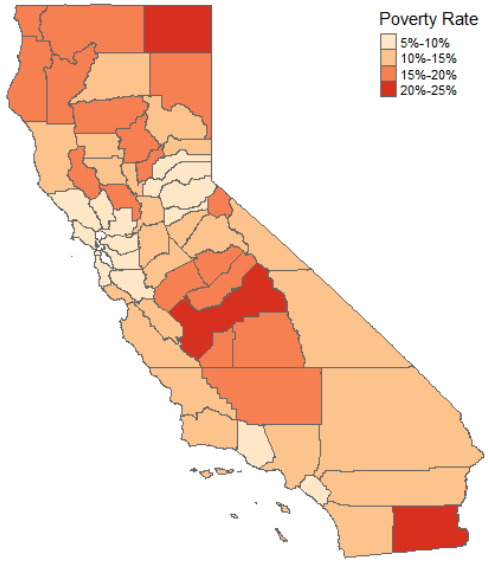
Extreme heat and surface water scarcity also lead to domestic well failures, with a 1 AF decrease in surface water supplies and an extra HDD increasing failures by 5 and 0.2 percentage points, respectively. These results are consistent with a theoretical framework and computational hydrology model in which increased groundwater consumption among agricultural users comes at the cost of drinking water supplies through the channel of a declining water table (Pauloo et al. 2020). More broadly, this work adds a new dimension to the understanding about inequities in exposure to environmental costs (Banzhaf, Ma, and Timmins 2019). A recent literature documents the unequal rate at which disadvantaged communities are exposed to pollution and the relative health costs, as well as the distributional implications of environmental regulations intended to reduce exposure (Currie 2011; Hernandez-Cortes and Meng 2020; Bento, Freedman, and Lang 2015). This work implies that inequities arise from the absence of regulation, specifically that mitigating behaviors by those with access to capital will impose costs on disadvantaged groups. When implementing proactive policy aimed at easing the burden of climate change, policymakers must ensure they are not unintentionally burdening the most vulnerable individuals.

This finding is also informative for the design of drinking water regulations in the United States. Drinking water quality issues impose severe costs in less advantaged communities, and are a growing concern in rural communities in the Southwest (Allaire, Wu, and Lall 2018; Marcus 2021; Christensen, Keiser, and Lade 2023). Drinking water is also becoming increasingly expensive, making affordability a growing concern (Cardoso and Wichman 2022). I find that access to drinking water supplies as measured by domestic well failures and depth to the water table will be exacerbated under climate change, and disproportionately affect disadvantaged communities.

3.1 Agriculture and Rural Communities in California

California agriculture plays a significant role in the global food value chain. The agricultural industry in California employs over 400,000 people and generates over $50 billion in agricultural sales, the most of any state in the United States. California also contributes the entire U.S. supply of some fruits and nuts, like almonds, pistachios, and plums (California Department of Food and Agriculture 2020).

Figure 3.1: Poverty Rate of California Counties



Note: The figure graphs the percent of the population in poverty by California county. Data come from USDA Economic Research Service.

California's Central Valley and other productive agricultural land in the Western U.S. receives insufficient rainfall for agricultural production. Irrigation infrastructure and technology has played a significant role in the development of the agricultural economy in these states (Hornbeck and Keskin 2014; Edwards and Smith 2018). In contrast, agriculture east of the 98th meridian primarily relies on periodic rainfall for crop production. Agricultural irrigation in California consumes over 80% the state's water and occurs via surface water and groundwater, with the latter accounting for roughly 40% of water supplies (Hrozencik and Aillery 2022).

Agricultural production in California is heavily concentrated in the San Joaquin Valley (SJV) in central California. The counties that comprise the SJV are largely rural and experience some of the highest poverty rates in the country as shown in figure 3.1. (A secondary center of agriculture is the Imperial Valley, which appears on the map as the high-poverty county in the southeastern corner of the state.) Many households in rural areas utilize private domestic wells and depend on groundwater wells for residential use and drinking water supply. The geographic intersection of agricultural groundwater use and groundwater-dependent households makes these areas particularly vulnerable to climate change damages.

3.1.1 Surface Water Irrigation

Summertime surface water availability in California is largely determined by the previous winter's snowfall. As the Sierra Nevada snowpack melts, it is captured in reservoirs and later delivered to farmers and irrigation districts through a network of canals. Swings between dry and wet winters in California translate to significant variation in surface water supplies from year-to-year.

Surface water is allocated through a complex first-in-time, first-in-right scheme that has persisted since the early 1900s. A water user or entity will either hold a right to divert water directly from a nearby river or possess a long-term contract to water deliveries through canals operated by the State Water Project or the federal Central Valley Project. Most water rights and contracts are held by irrigation districts – local government agencies – which then supply water to farms within their jurisdiction. Water is typically rationed by quantity rather than price, and by custom or law supplied equally to producers on a per-acre basis.

Rights and contracts do not guarantee water supplies in any given year. Water rights are satisfied in order of seniority, though enforcement is largely informal. In practice most agricultural water rights are senior to the federal and state water projects, which bear the brunt of water shortages in dry years. Contracts with the federal and state water projects constitute a maximum annual volume and a contract category. Each year, the U.S. Bureau of Reclamation and the California Department of Water Resources (DWR) announce a set of allocation percentages, which determine how much of their maximum volume contractors in each category will receive. In recent years, it is common for allocation percentages to be set as low as 0% during droughts. Thus, the impacts of drought manifest through changes in surface water.

Year-to-year fluctuations in surface water allocations are determined by the government agencies through bureaucratic processes that depend on reservoir levels, environmental conditions, and weather forecasts. Allocations are announced prior to the growing season, before producers make input decisions. Actual surface water deliveries can differ from allocations in a few ways. Irrigation districts can purchase additional water mid-season on the spot market, pump water from groundwater banks, or reserve water for up to a year in response to environmental conditions. Hence, actual surface water deliveries are potentially endogenous to drought.

3.1.2 Groundwater Irrigation

Groundwater has traditionally acted as a buffer to fluctuations in surface water supply. Groundwater accounts for 80% of water supplies during times of drought. Changes in surface water deliveries are thus correlated with groundwater pumping which affects the water table. Historically, this sector has been largely unregulated. Owners of land have the right to drill wells and pump groundwater with few restrictions. The open-access nature of groundwater has led to declining groundwater levels, higher costs to pump, and other negative consequences. As a result, a historic groundwater regulation was passed in 2014 – the Sustainable Groundwater Management Act (SGMA) – with the aim to sustainably use and manage groundwater in California by 2042.[3]

The cost of groundwater well construction varies widely based on the completed drilled depth and intended use. Residential domestic wells are typically between 100 and 300 ft deep and cost approximately $10,000. Agricultural wells are drilled between 300 and 500 ft deep on average and cost between $50,000 and $100,000. They are drilled with a wider diameter than residential wells to allow for higher flow rates. New wells are required to be reported to the DWR and are typically constructed in under a week (Central Valley Flood Protection Board 2020).

3.1.3 Drinking Water in Rural Communities

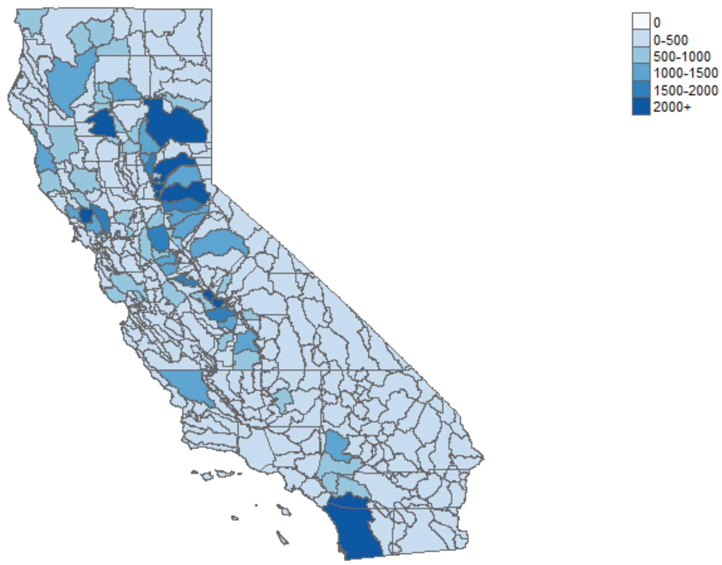
Most individuals in California receive residential and drinking water from community water systems regulated by the Safe Drinking Water Act (SDWA)[4]. However, many individuals outside of community water system boundaries, like households in rural areas, rely on private groundwater wells for their domestic water supply. Figure 3.2 shows the number of domestic groundwater wells constructed from 1993 to 2020 across the state. Deteriorating drinking water quality is pervasive for many of these users, especially since these water sources are outside the jurisdiction of the SDWA. Declining groundwater tables also threaten safe and affordable access to residential water for this subset of the population.

Counties in California's San Joaquin Valley experience some of the highest poverty rates in the country and are a large percent Latino/a (Huang and London 2012). Many of these individuals

[3]Most SGMA sustainability plans were developed and will be enforced by local groundwater sustainability agencies (GSA) starting in 2022, after the sample of study. There remains no direct restrictions on the drilling of groundwater wells in these plans.

[4]Community water systems are public water systems with over 15 connections and serve greater than 25 people.

Figure 3.2: Total Domestic Wells Constructed from 1993-2020



Note: The figure shows a count of the number of domestic groundwater wells constructed from 1993 to 2020 by Detailed Analysis Unit by County, the smallest water management planning unit defined by the California DWR. Data are from DWR.

are also employed by the local agriculture industry (Martin and Taylor 1998). Table 3.1 reports the proportion of reported well failures as a fraction of the total number of domestic wells by local demographics, agricultural intensity, and well characteristics. Wells in census tracts with above median poverty rates and above median percent non-white populations report well failures at a higher rate than populations below the median. Additionally, areas where land is cultivated at a higher percent for agricultural use also experience well failures at a higher rate.

3.2 Conceptual Model

I develop a conceptual model of changes in the depth to the groundwater table as a function of properties of the aquifer and groundwater demand from agricultural pumpers. I decompose the gross effect by changes in new wells constructed (extensive margin) and changes in the intensity of pumping at each well (intensive margin) in the style of Hendricks and Peterson (2012). I model agricultural groundwater use as a function of surface water availability, s, and a measure of extreme

Table 3.1: Probability of Well Failure by Local Demographics and Well Characteristics

	(1)	(2)	(3)	(4)
	Below Median	Above Median	Difference	p-value
Poverty Rate	0.0089	0.0346	0.0258	0.0000
% Cropland	0.0091	0.0426	0.0335	0.0000
% Non-White	0.0085	0.0348	0.0263	0.0000
Population	0.0166	0.0305	0.0139	0.0000
Well Depth	0.0249	0.0264	0.0015	0.1793

Note: Columns 1 and 2 display the probability of domestic well failure for all domestic wells in California by socioeconomic, agricultural, and well characteristics. Demographic data come from the USDA Food Research Atlas and are assigned at the census tract levels. Poverty rate is the percent of households living below the Federal income thresholds by family size. Column 3 calculates the difference between the above median probability and below, and Column 4 reports the p-value for a two-sample t-test of the well failure probabilities.

heat, h. In the context of California, approximately 60% of agricultural irrigation is supplied from surface water. Additionally, warmer growing seasons will likely impact irrigation for crop acres (Rosa et al. 2020). Let $w(s,h)$ then be the number of wells used for agricultural irrigation. Similarly, let $q(s,h)$ determine the average amount of groundwater pumped per well. Together, the total volume of groundwater extracted is equal to $w(s,h) \times q(s,h)$. I multiply this by a constant hydrologic aquifer storage coefficient, κ, to translate the volume of water extracted to a unit decline in the water table per acre in that aquifer.[5] Then, adding the extracted groundwater for irrigation to the baseline groundwater level, DTW_0, I recover the new depth to the water table based on the behavior response by farmers.

Depth to the water table, DTW, is therefore given by:

$$DTW(s,h) = DTW_0 + \kappa \times w(s,h) \times q(s,h) \tag{3.1}$$

Differentiating with respect to either surface water or heat yields:

$$DTW'(s,h) = \kappa\big[w'(s,h) \times q(s,h) + q'(s,h) \times w(s,h)\big] \tag{3.2}$$

[5] κ is defined as the inverse of hydrologic storativity of an aquifer. Storativity measures the hydrologic yield of an aquifer, which is the proportion of space that water can occupy within an aquifer. For example, a storativity value of 0.12, which is typical in California's Central Valley (Department of Water Resources 2020), means that 12% of an aquifer's space can hold water. The other 88% is composed of porous rock and sediment.

where $w'(s,h)$ reflects changes in the number of groundwater irrigation wells used due to surface water or heat shocks – the extensive-margin response. Likewise, $q'(s,h)$ reflects the intensive-margin change in storage, or the change in the average volume of groundwater pumped per well net recharge due to changes in surface water or heat. [6]

In the empirical analysis, I am able to estimate both the gross change in groundwater levels by climate-induced changes in groundwater demand and the extensive-margin effect of farmers adapting to surface water scarcity and heat through new well construction. With a value of the aquifer's storativity used to estimate κ, I can then back out the intensive-margin effect.

Groundwater extraction to buffer against the costs of heat and surface water scarcity may impose external damages on others by increasing the scarcity of groundwater supplies through a lowering of the water table. I assume that these damages are proportional changes to the groundwater level.

That is, the external damages, D, are increasing linearly in the decline of the depth to the groundwater. Equation 3.3 outlines this relationship, where c is the marginal external damage associated with a foot reduction in the water table.

$$D(s,h) = c \times DTW'(s,h) \tag{3.3}$$

In the empirical setting, I shed light on the magnitude of these externalities by showing the extent to which changes in surface water scarcity and heat lead to a lowering of the groundwater table, and ultimately household well failures.

3.3 Data

Panel data on surface water deliveries and allocations, groundwater levels, and well construction and failures form the primary dataset for this analysis. I supplement these data with additional information on local weather. Table 3.2 provides summary statistics.

[6] I do not attempt to model recharge in this decomposition. The intensive-margin response by the farmers to heat and surface water scarcity is actually greater than captured in $q'(s,h)$. I discuss this point further in the empirical conclusions.

Unit of Observation

Due to the nature of the data, it is necessary to define a geographic unit of aggregation for several variables. When necessary, I aggregate to the Detailed Analysis Unit by County (DAU by Co or DAUCO) boundaries. DAUs divide California's hydrologic regions and planning areas into smaller geographic areas for agricultural land use and water balance analysis by California Department of Water Resources. Historically, DAUs followed the United States Geological Service's watershed boundaries (HUC-8). As additional water infrastructure was added to California, DAU boundaries were updated to account for water district boundaries so that water accounting could be completed more accurately. At present, DAUs are a combination of watershed and water district boundaries, which often overlap counties. In these cases, I further disaggregate the unit into DAU by County – the smallest geographic unit of aggregation used by DWR. I use these boundaries to define the count of new agricultural wells annually and the agricultural surface water delivered. Because DAUCOs are definitions of convenience without any special economic significance, I weight the regressions by crop area so that the estimates are representative for the average acre of cropland in California.

Table 3.2: Summary Statistics

	Unit	Count	Mean	SD	Min	Max
Outcomes:						
New Ag Wells	DAUCO	10,416	11.1	19.4	0	316
Depth to Groundwater (ft)	Monitoring Well	575,410	62.9	80.4	0	2714.1
ΔDTW	Monitoring Well	575,399	0.3	6.1	-58.7	56.3
Probability of Domestic Well Failures	Domestic Well	473,940	0.03	0.16	0	1
Independent Variables:						
Ag SW Allocation (AF/crop acre)	DAUCO	9,660	2.3	2.01	0	10
Ag SW Deliveries (AF/crop acre)	DAUCO	10,416	2.2	1.9	0	10
Harmful Degree Days	DAUCO	9,996	97.2	86.8	0	622.3
Growing Degree Days	DAUCO	9,996	3,535.3	659.9	632.5	5,813.04
Annual Precipitation (mm)	DAUCO	9,996	350.3	233.4	11.4	4,668.9
Crop Acres	DAUCO	10,416	169,741.5	131,332.9	.2	502,692.3

Note: The table reports the number of observations, units of and measurement, mean, standard deviations (SD), minimum and maximum for each outcome and explanatory variable. Mean and SD statistics are weighted by crop acres. Water is measured in acre feet (AF).

Depth to the Water Table

I use groundwater monitoring wells from groundwater basins across the state to measure depth to the groundwater table (DTW). I compile these measures from two sources: 1) The State Water Resources Control Board (SWRCB) Groundwater Information System and 2) DWR's Periodic

Groundwater Level data. I append these two datasets and select a single annual measurement for each monitoring well prior to the start of the following year's growing season. For example, I assign the final groundwater depth of 2015 as the observed groundwater depth nearest to March 15, 2016. This ensures that the cumulative effects of groundwater pumping and recharge are realized throughout the current year and prior to the water intensive months of next year. I take the first difference of DTW as the final outcome variable to estimate the year-to-year changes in the groundwater table as a result of surface water scarcity.

To remove outlier observations of DTW, I exclude observations that are more than 1.5 times the inner decile range of all other changes in groundwater levels reported from monitoring wells in the DAUCO over the sample. This rule removes observations that observe drastically different changes in groundwater levels than other local groundwater measures.[7] I study the outcome of changes in DTW at the monitoring well level, where all monitoring wells in a DAUCO are assigned the same volume of surface water allocation and delivery in a given year. Therefore, I cluster the standard errors at the DAUCO level.

Well Construction

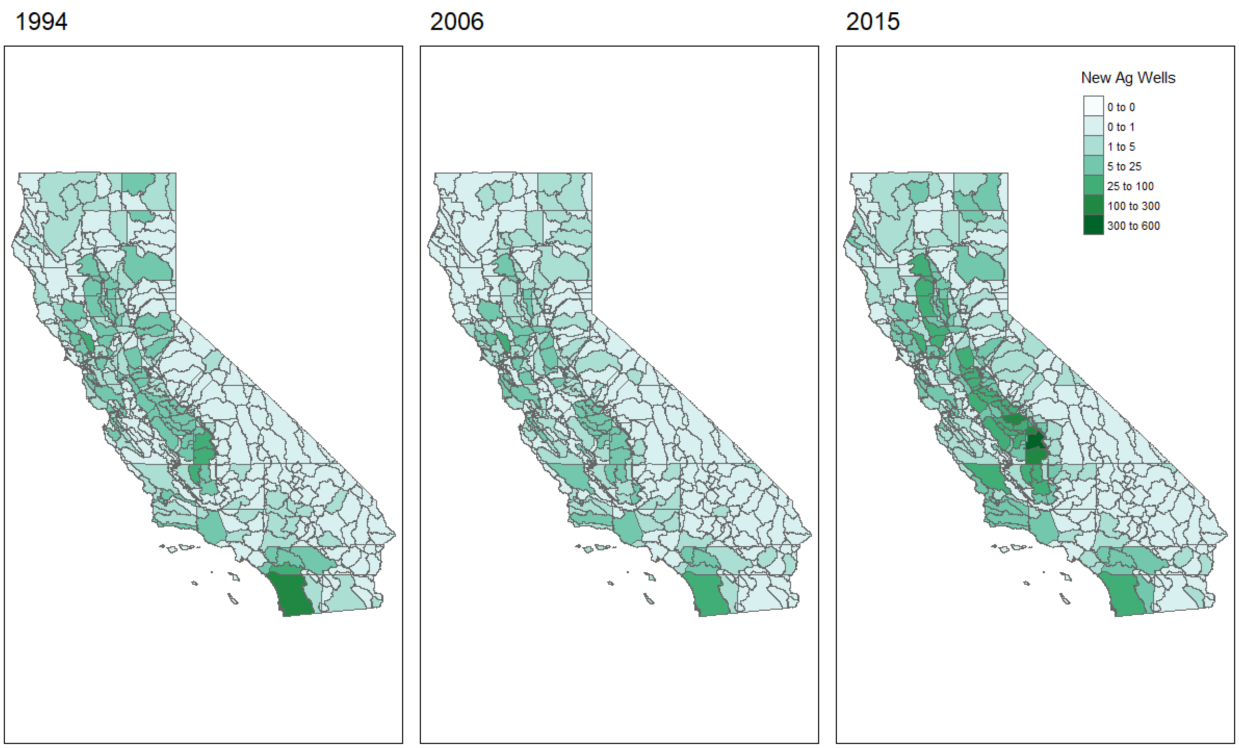
One outcome variable of interest measures the extensive-margin adaptation to surface water scarcity and extreme heat through the metric of new agricultural well construction. I use the universe of Well Completion Reports from DWR, which reports each well's location, the drilled depth of the well, intended use, and other characteristics. To measure adaptive response, I count the total number of new agricultural irrigation wells per DAUCO per year. Figure 3.3 maps new agricultural well construction for the years 1994, 2006, and 2015. The Central Valley of California experiences the most severe shocks to agricultural surface water curtailment, and these areas appear to respond the most in scarce water years by constructing new agricultural wells.

Well Failures

Beginning in 2014, DWR created a system for households to report domestic well failures. These data are now publicly available and regularly updated. These data contain the coordinates for the

[7]Some of these outlier observations are the result of a misplaced decimal, while other errors could occur from monitor errors. I cannot easily identify the source of measurement error in these data in order to assign accurate values, and therefore, remove these observations to reduce measurement error in the coefficient estimates.

Figure 3.3: New Agricultural Well Construction



Note: The figure plots the count of new agricultural wells constructed at the DAUCO level for three snapshots in time: 1994, 2006, and 2015. New agricultural well drilling is predominant in the San Joaquin Valley.

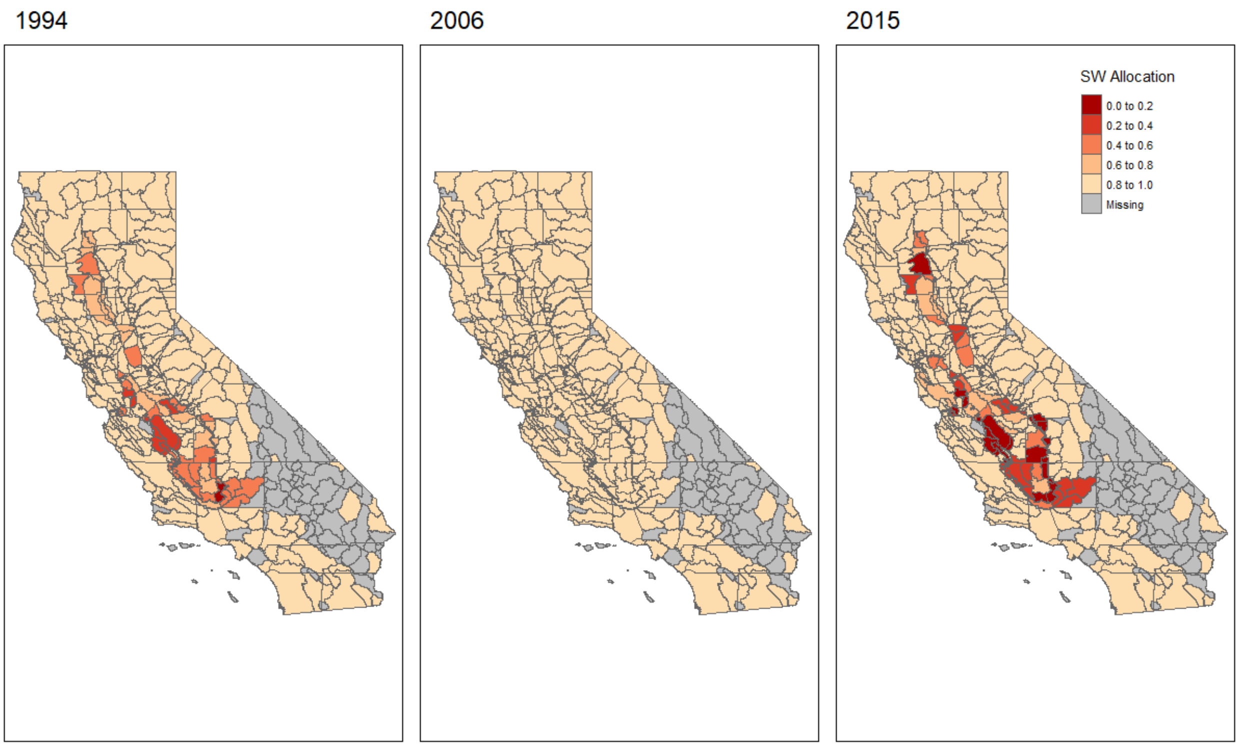
reported dry well, the date the issue started, and if the issue was resolved. I create a panel of all domestic wells in California from the Well Completion Reports. I geographically match the reported failures to the domestic wells from the Well Completion Reports. The final dataset for the analysis on well failures spans from 2014-2021, where *failure=1* for a domestic well in a given year if it is reported in the well failure database. For all other years, I assume *failure=0*. Hence, the primary analysis of the externality created from agricultural adaptation is the linear probability of domestic well failure as a function of surface water and extreme heat. While this may be an undercount of the true number of domestic well failures, since household reporting is voluntary, it is an improvement on past approaches that have had to estimate if a well has gone dry based on assumptions about the relationship between well depth and groundwater table height.

Surface Water Allocations and Deliveries

As measures of water scarcity, I use spatial and temporal variation in agricultural surface water allocations and deliveries throughout California from Hagerty (2021). These annual data provide volumes of water allocations and water deliveries from the Central Valley Project (CVP), State Water Project (SWP), the Lower Colorado Project, and surface water rights from 1993-2020.[8] I spatially aggregate these volumes to the DAUCO level. Because the place of use may differ from the point of delivery, this variable is subject to a greater degree of measurement error as the geographic unit of analysis becomes smaller. I transform total water allocations and deliveries by dividing by cropland acres in each DAUCO. The final measure of surface water supplies captures the volume of surface water delivered in acre feet (AF) per cropland acre in the DAUCO. Because there are a number of extreme values, likely due to measurement error, I Winsorize this variable at 10 AF per acre. Figure 3.4 displays the variation across DAUCO areas within a given year and the locations most impacted by curtailments in drought years, 1994 and 2015. In the wet year of 2006, all areas received high allocation percentages.

[8] All months of 2021 were not yet reported at the time analysis was performed. The partial-year data for 2021 is included in the dataset, but I exclude 2021 in the estimation. Including partial 2021 data does not change point estimates, but standard errors do increase because of this discrepancy.

Figure 3.4: Agricultural Surface Water Allocation Percentages



Note: The figure graphs the fraction of agricultural water entitlements to be received by irrigation districts at the DAUCO level for three years: 1994, 2006, and 2015. Allocation percentages, which are announced by the state prior to the growing season based on environmental conditions, vary over space and time.

Weather

I measure extreme heat and precipitation using weather observations from Schlenker and Roberts (2009) and PRISM climate data. Schlenker and Roberts (2009) provides the data in a 2.5 km by 2.5 km grid and PRISM is available at 4 km by 4 km resolution across the U.S. Schlenker and Roberts (2009) data, which are derived from PRISM weather station observations, ends in 2019. Therefore, I supplement weather observations from the raw PRISM data for 2020 and 2021. I also control for local annual precipitation reported in millimeters. I aggregate these data by taking the average temperature and precipitation of each of these grid centroids within a DAUCO. I measure extreme heat through "harmful degree days" (degree days over 32 degrees Celsius) and "growing degree days" (degree days over 8 and below 32 degrees Celsius). I compute growing degree days and harmful degree day measures from daily average, T, the following definitions:

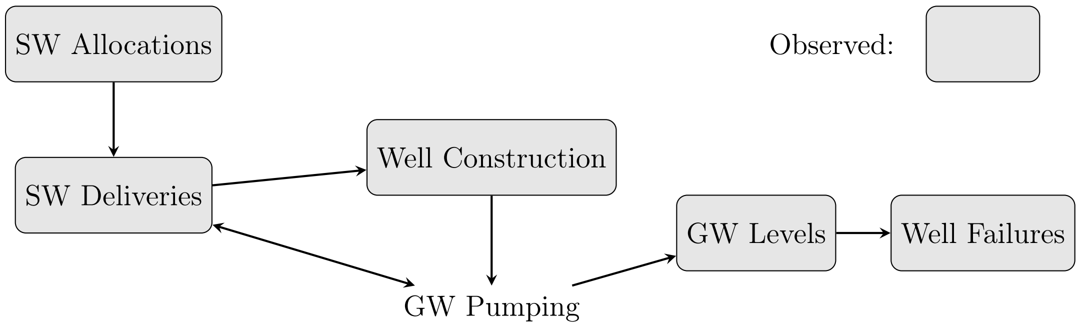
$$GDD(T) = \begin{cases} 0 & \text{if } T \leq 8C \\ T - 8 & \text{if } 8C < T \leq 32C \\ 24 & \text{if } T \geq 32C \end{cases} \tag{3.4}$$

$$HDD(T) = \begin{cases} 0 & \text{if } T \leq 32C \\ T - 32 & \text{if } T > 32C \end{cases} \tag{3.5}$$

3.4 Empirical Model

California presents a rich context to study climate change adaptation strategies and their subsequent external costs. The empirical framework uses annual fluctuations in weather, surface water supplies, agricultural well construction, depth to the groundwater, and domestic well failures from 1993-2020 to measure three reduced-form effects. First, I attempt to causally identify the effects of extreme heat and surface water scarcity on year-to-year changes in the depth to the groundwater table. The lowering of groundwater levels leads to well failures of shallow household drinking water wells, the main external cost of concern. Next, I estimate the reduced-form effect of surface water scarcity

Figure 3.5: Causal Empirical Chain



Note: The figure charts a conceptual framework for the empirical relationships from water scarcity to domestic well failures. Groundwater pumping is unobserved.

and heat on domestic well-failure.

Changes in water table depth in response to heat and surface water scarcity are likely driven by additional groundwater pumping, via both new well construction (extensive margin) and through increased intensity at existing wells (intensive margin). Since groundwater pumping is unobserved, I estimate the effect of drought on new agricultural well construction, an observable measure of adaptation behavior by California farmers. A decomposition of the gross effect on the water table allows me to determine how much of gross adaptation effect on the groundwater levels is due to extensive and intensive margin effects.

3.4.1 Causal Empirical Chain

Figure 3.5 illustrates the empirical link between observable and unobservable variables in this context. A chain for extreme heat and its impacts on groundwater outcomes is analgous by replacing surface water allocations and deliveries by observed harmful degree days.[9] Because groundwater pumping is likely correlated with new well construction, surface water deliveries, and groundwater levels, yet is unobserved, I am limited to the identification of the three reduced-form effects just mentioned. I cannot credibly estimate the effect of agricultural well construction on well failures because the potential instrument for well construction – allocations – would violate the exclusion restriction through its correlation with unobservable pumping.

[9] Extreme heat is unlikely to be endogenous to groundwater pumping in the same way as surface water deliveries since deliveries can be adjusted conditional on the amount of groundwater pumped. Therefore, I expect extreme heat to impact groundwater pumping, while the reverse is not true, which would be depicted by an arrow moving in a single direction from extreme heat to groundwater pumping in the analogous figure.

3.4.2 Estimation and Identification

Outcome 1: Changes in Depth to the Water Table

To estimate the effect of drought on year-to-year changes in groundwater levels, I use annual panel data and begin by estimating a two-way fixed effects model using OLS:

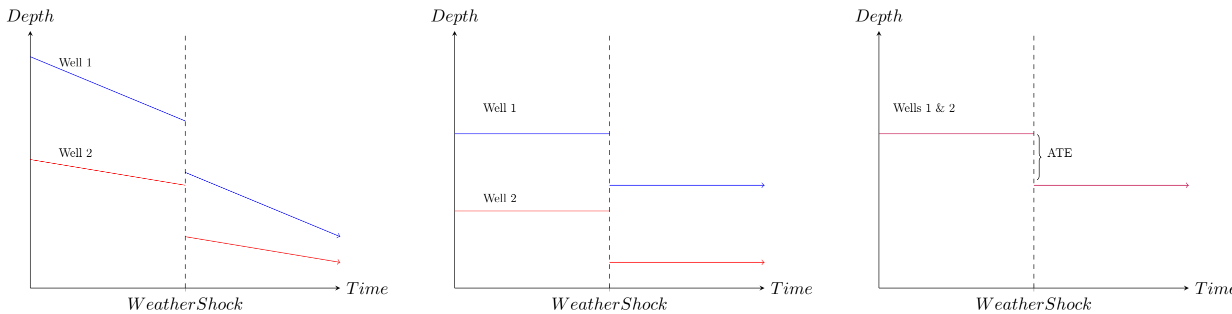
$$\Delta DTW_{it} = \beta_1 SWD_{it} + \beta_2 HDD_{it} + \boldsymbol{B'X}_{it} + \lambda_t + \alpha_i + \varepsilon_{it}. \tag{3.6}$$

The dependent variable, ΔDTW_{it} is the year-to-year change in the depth to the water table for well i in year t. Annual observations of the depth to the water table (DTW) measure the stock of groundwater availability, which represent the cumulative outcome of annual groundwater pumping and recharge. I instead take the first difference of depth to the groundwater, ΔDTW_{it}, so that the outcome measures the annual flow to the underlying stock. The coefficients of interest, β_1 and β_2, measure the annual marginal change in ΔDTW for a unit change in surface water and harmful degrees days, respectively. Fixed effects α_i absorb well-level differential trends over time, allowing for each well to have different linear temporal trends all else equal, as illustrated in Figure 3.6. Year fixed effects are captured by λ_t and control for aggregate annual shocks like changes in statewide policies. The vector $\boldsymbol{X}_{it}$ captures other localized weather shocks, including precipitation and growing degree days. The motivation for conditioning on other weather shocks is that precipitation may be correlated with surface water deliveries or heat and groundwater extraction and thus changes in the depth to the water table.

Of concern is the potential endogeneity between drought and surface water deliveries. In low surface water years, irrigation districts can influence their total delivery amount by purchasing water on the spot market or drawing from water banks. I exploit California's water allocation system, where allocations are set ahead of the season based on plausibly exogenous environmental conditions, as an instrument for surface water deliveries in a two-stage instrumental variables approach, following Hagerty (2021):

$$\begin{aligned} \Delta DTW_{it} &= \beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + \boldsymbol{B'X}_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \\ SWD_{it} &= \gamma_1 SDA_{it} + \gamma_2 HDD_{it} + \boldsymbol{\Gamma'X}_{it} + \lambda_t + \alpha_i + \mu_{it}. \end{aligned} \tag{3.7}$$

Figure 3.6: Difference-in-Differential Trends Framework



Groundwater (DTW) (a) | ΔDTW (b) | ΔDTW + FE (c)

Note: The figure shows a stylized illustration of two wells in two time periods. Panel (a) shows the depth to groundwater trajectory for two wells in the face of a weather shock. By taking the change in the depth to the water table in panel (b), I can measure the annual flow to the underlying stock. Panel (c) illustrates the average treatment effect (ATE) being measured with the inclusion of well fixed effects.

All variables are defined as before but now I instrument for surface water deliveries with surface water allocations, SDA_{it}.

Identification of the effect of surface water scarcity hinges on two assumptions related to the instrument. The first is that allocations affect changes in the groundwater table only through the margin of surface water deliveries. While I cannot directly test this assumption, I believe it is plausibly true since allocations, to my knowledge, are not used for anything other than determination of surface water deliveries. The second assumption relates to the relevance of the instrument. Results from the first-stage are presented in table 3.3 and show that allocations are a strong instrument for deliveries. I present both the reduced-form (outcome regressed on allocations) and the instrumental variable results for each set of results.

Other threats to identification stem from regional time-varying unobservables that correlate with both changes in water allocations and changes in the depth to the groundwater table. The inclusion of local precipitation as a control is motivated by this concern. I assume that, conditional on a rich set of fixed effects and controls for localized weather shocks, time-varying unobservables that impact changes in the groundwater table are not correlated with surface water allocations. Given that annual allocation percentages are determined by an algorithm based on environmental conditions and reservoir levels, this is plausible to assume. Insensitivity of the treatment effect to

Table 3.3: Agricultural SW Deliveries: First-Stage Results

	(1)	(2)
Ag SW Allocation (AF/ crop acre)	0.588***	0.531***
	(0.0460)	(0.0540)
Harmful Degree Days		-0.000353
		(0.00172)
Growing Degree Days		0.000184***
		(0.0000432)
Annual Precipitation		-0.000461*
		(0.000202)
Observations	9,660	9,240
N Cluster	345	330
F Stat	163.6	79.07
Weights	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO
Time FE	✓	✓
Unit FE	✓	✓

Note: The table presents the first-stage effect of surface water allocations on surface water supplies. The dependent variable is agricultural surface water deliveries per crop acre in levels from 1993-2021. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the inclusion and exclusion of time-varying local weather shocks included in $\boldsymbol{X}_{it}$ lends support for this assumption.

Outcome 2: Domestic Well Failures

Changes in the depth to the groundwater table lead to domestic wells running dry. To estimate the effect of heat and surface water scarcity on domestic well failures, I use well-level panel data and again estimate an instrumental variable approach with two-way fixed effects using OLS,

$$\begin{aligned} Y_{it} &= \beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + \boldsymbol{B}'\boldsymbol{X}_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \\ SWD_{it} &= \gamma_1 SDA_{it} + +\gamma_2 HDD_{it} + \boldsymbol{\Gamma}'\boldsymbol{X}_{it} + \lambda_t + \alpha_i + \mu_{it} \end{aligned} \tag{3.8}$$

where Y_{it} is now a binary outcome indicating a reported well failure. The coefficient estimates of interest from this equation, β_1 and β_2, represent the the change in likelihood that a domestic well fails in a given year when surface water availability and extreme heat change, respectively. The independent variables, SWD_{it} and SWA_{it}, represent surface water deliveries and allocations in AF per acre, respectively. HDD_{it} reports the number of harmful degree days at well i in year t. The vector $\boldsymbol{X}_{it}$ controls for other localized weather shocks. Annual fixed effects, λ_t, control for statewide dynamic shocks, like statewide policy or state-level drought.

Identification of β_1 and β_2 as the causal impacts of surface water scarcity and heat on the likelihood of domestic well failure rests on a similar set of three assumptions. Regional time-varying factors that correlate with both domestic well failures and surface water allocations remain a threat to identification. To alleviate this concern, I again control for local weather shocks in $\boldsymbol{X}_{it}$. The other identifying assumptions concern the instrument for surface water deliveries. Like before, I assume allocations affect domestic well failures only through the margin of surface water deliveries and that allocations are a strong predictor of surface water deliveries.

Outcome 3: Agricultural Well Construction

The final outcome of interest is new agricultural well construction. I focus on well construction because it is the one observable mechanism that contributes to the reduction in groundwater tables. New agricultural wells represent the observable extensive-margin response that complements the unobservable intensive-margin response of increased pumping. To estimate the effects of drought and surface water curtailment on agricultural well construction, I estimate two different specifications using the panel that is constructed at the Detailed Analysis Unit by County (DAUCO) and annual level. First, using an instrumental variables approach with two-way fixed effects, I estimate equation 3.9:

$$
\begin{aligned}
Y_{it} &= \beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + \boldsymbol{B}'\boldsymbol{X}_{it} + \lambda_t + \alpha_i + \varepsilon_{it} \\
SWD_{it} &= \gamma_1 SDA_{it} + +\gamma_2 HDD_{it} + \boldsymbol{\Gamma}'\boldsymbol{X}_{it} + \alpha_i + \lambda_t + \mu_{it}.
\end{aligned} \tag{3.9}
$$

All variables are defined as before except now the variable Y_{it} measures the count of new agricultural wells where i signifies the DAUCO and t denotes the year between 1993 and 2020, and α_i represents unit fixed effects, which control for DAUCO-level time-invariant factors like area size and location. All regressions are weighted by crop acres, which identifies the weighted average treatment effect across California crop acres.

Because Y_{it} reports the non-negative count of new agricultural wells and suffers from overdispersion, I supplement this by deploying a control function approach with fixed effects estimated with Psuedo-Poisson Maximum Likelihood (PPML) (Wooldridge 2015). I estimate the Poisson model with equation 3.10, the preferred specification:

$$
\begin{aligned}
E[Y_{it}|SWD_{it}, \mathbf{X}_{it}, \alpha_i, \lambda_t] &= \exp\{\beta_1 S\hat{W}D_{it} + \beta_2 HDD_{it} + \boldsymbol{B}'\mathbf{X}_{it} + \alpha_i + \lambda_t + \phi\hat{\mu_{it}}\} \\
SWD_{it} &= \gamma_1 SDA_{it} + \gamma_2 HDD_{it} + \boldsymbol{\Gamma}'\boldsymbol{X}_{it} + \alpha_i + \lambda_t + \mu_{it}.
\end{aligned} \tag{3.10}
$$

This method also allows me to test for endogeneity of the regressor by including $\hat{\mu_{it}}$ in the second-stage. The coefficient on $S\hat{W}D_{it}$ indicates that for every one AF decrease in surface water deliveries, the number of new agricultural wells will change by $e^{\beta_1} - 1$ percent. Similarly, for every additional harmful degree day, $e^{\beta_2} - 1$ percent more agricultural wells will be constructed.

3.5 Results

Results from the estimation of equation 3.7 are reported in Table 3.4. Columns (1) and (2) report results from the reduced-form effect of per-acre allocations on the change in groundwater depth with and without controls for local weather. Columns (3) and (4) present IV results where allocations are used as an instrument for surface water deliveries. All specifications include time and well fixed effects. In the preferred specification in column (4), I further condition on local weather variables contained in $\boldsymbol{X}_{it}$.

The reduced-form results, which represent an estimate of the intent to treat, show that surface water allocations have a negative and significant impact on changes in the depth to the water table. The table shows that allocations are relevant to agricultural groundwater pumpers and affect the underlying groundwater table through changes in surface water deliveries. However, reduced-form results are attenuated because allocations are not perfectly correlated with surface water deliveries.

IV results in columns (3) and (4) demonstrate that allocation-induced changes in surface water deliveries and extreme heat have a negative and significant effect on the groundwater table. The preferred estimates in column (4) of Table 3.4 imply that a one AF reduction in SW deliveries leads to 3.75 ft decline in the groundwater levels. Results are stable to the inclusion of additional weather controls. I see that groundwater depth is also responsive to extreme heat, with groundwater levels declining by 0.04 ft for every additional harmful degree day. Even holding constant changes in surface water supplies, additional heat is leading to a reduction in the groundwater table. This is likely due to increased groundwater extraction through both intensive and extensive margin adjustments.

Table 3.4: Changes in Depth to the Groundwater (DTW)

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-2.263**	-1.627*		
	(0.807)	(0.750)		
Ag SW Deliveries (AF/ crop acre)			-4.953**	-3.753*
			(1.609)	(1.618)
Harmful Degree Days		0.0482*		0.0373*
		(0.0219)		(0.0169)
Observations	575,478	575,324	561,170	561,016
N Groups	98,097	98,077	83,789	83,769
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2021 at the monitoring well level. Columns (1) and (2) report results from the reduced-form OLS model. Columns (3) and (4) report the second-stage IV results, where Ag surface water allocations are used as an instrument. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This degradation of the groundwater stock, which manifests through changes in the depth to the water table, creates externalities for other users of that resource. In this context, the external costs imposed by groundwater pumpers who are adapting to changes in heat and surface water scarcity are borne by all neighboring users and future users of the groundwater. This externality disproportionately puts household users of groundwater at risk since domestic wells are generally drilled shallower on average and are more susceptible to well failure.

To explore this, I estimate a panel linear probability model, where *failure* is a $\{0, 1\}$ outcome variable in a given year for all domestic wells in California. Table 3.5 displays the results from the estimation of equation 3.8. Column (1) presents the reduced-form effect of per-acre allocations and heat on probability of a well failure with time and well fixed effects using data from 2015 to 2020. Column (2) includes local weather controls and includes 2014 in the sample.[10] Columns (3) and (4) show the same specification but now instrument for per-acre surface water deliveries with allocations, with column (4) showing the results from using the full sample of years 2014-2020. Across all specifications, extreme heat significantly increases the likelihood that domestic wells fail. The preferred specification in column (4) implies that an additional harmful degree day increases the probability that a well fails by 0.2%. That specification also displays that a 1 AF reduction in surface water per crop acre increases the likelihood of local domestic well failure by 5%. These estimates are large marginal effects relative to the weighted mean probability of well failure displayed in Table 3.2.

Table 3.5: Linear Probability of Reported Well Failure

	Reduced Form		IV	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-0.0156*	-0.0280		
	(0.00705)	(0.0156)		
Ag SW Deliveries (AF/ crop acre)			-0.0296**	-0.0557**
			(0.00986)	(0.0192)
Harmful Degree Days		0.00212*		0.00208*
		(0.000950)		(0.000908)
Observations	468,333	468,075	468,313	468,055
N Groups	78,084	78,041	78,064	78,021
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is a {0,1} outcome if a domestic groundwater reported a failure that year. The panel spans from 2015-2020 and is composed of all domestic groundwater wells with unique coordinates in California. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The final set of results explores one mechanism by which agricultural groundwater users are responding to heat and surface water scarcity: the construction of new wells. I start again

[10]Columns (1) and (3) use data from 2015 through 2020. The voluntary household system was introduced early in 2014 and may have not been a widely known reporting tool for households across the state. This could explain why the point estimates for surface water are smaller in magnitude and less precise when including 2014.

by showing the reduced-form effect of surface water allocations on new well construction in Table 3.6, using both OLS and PPML to account for the fact that the outcome of interest is a count variable. Columns (1) and (2) show the simple two-way fixed effect OLS results with and without local weather controls, respectively. Columns (3) and (4) show results from the PPML estimation, where the final specification conditions on local precipitation and growing degree days. Results in column (4) imply that a one AF decline per crop acre in California, all else equal, leads to approximately 24.2% increase in the annual number of new agricultural wells drilled. While every additional harmful degree day causes an approximate 0.9% annual increase in new agricultural wells.

Table 3.6: Construction of New Agricultural Wells: Reduced-Form

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-7.180**	-6.581*	-0.333*	-0.278*
	(2.665)	(2.596)	(0.131)	(0.124)
Harmful Degree Days		0.115**		0.00897***
		(0.0390)		(0.00202)
Observations	9,660	9,240	8,568	8,400
N Cluster	345	330	306	300
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

While Table 3.6 displays the response to an exogenous surface water allocation shock, surface water allocations may not represent actual scarcity. Producers and irrigation district may choose to receive more or less surface water throughout the year, complementing their allocations with additional deliveries from purchases from the spot market for example. The endogenous choice to adjust deliveries during a drought year may attenuate the reduced-form estimates in Table 3.6.

Table 3.7 reports the estimates of new agricultural well construction on surface water deliveries, where surface water deliveries are instrumented by allocations. Columns (3) and (4) are estimated using a control function approach with a linear first stage and PPML in the second stage.

As expected, the estimate on surface water deliveries is larger than the corresponding reduced-form estimate in Table 3.6 and implies that the extensive-adaptation response is approximately 46.2% increase in new agricultural wells.

Table 3.7: Construction of New Agricultural Wells: IV and Control Function

	IV		CF/PPML	
	(1)	(2)	(3)	(4)
Ag SW Deliveries (AF/ crop acre)	-13.06**	-12.38**	-0.690**	-0.620*
	(4.584)	(4.750)	(0.262)	(0.262)
Harmful Degree Days		0.111***		0.0128***
		(0.0329)		(0.00261)
$\hat{\mu}$			0.732*	0.767*
			(0.346)	(0.347)
Observations	9,660	9,240	8,568	8,400
N Groups	345	330	306	300
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses. Columns (3) and (4) standard errors are calculated using 500 bootstrap simulations, clustered at the DAUCO level.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

One concern is that farmers are simply moving their well drilling forward in time instead of increasing the total number of wells drilled. A concern with this kind of inter-temporal substitution is that this specification, which focuses only on the contemporaneous effect, would be overestimating the treatment effect. Tables 3.9 and 3.10 in the Appendix consider the dynamics of agricultural well drilling and provides evidence to suggest that the contemporaneous effect is capturing the bulk of the response, but the contemporaneous effect alone may err on the conservative side relative to the true cumulative effect.

In addition to drilling more wells, it could be that farmers are responding by drilling deeper wells. Table 3.13 in the Appendix considers the effect of surface water and temperature shocks on the drilled depth of newly constructed wells, both agricultural and domestic. Results suggest some evidence of this although estimates are imprecise.

Extensive and Intensive Margin Adaptation

Following equation 3.2, I use the point estimates from the empirical results to decompose the gross effect on depth to the groundwater into an extensive-margin response (more agricultural wells) and an intensive-margin response (more water per well). This exercise relates changes in groundwater levels (i.e., changes in water-occupied space) within an aquifer (DTW) to behavioral changes in the volume of groundwater pumped for agricultural use. I impose hydrologic aquifer characteristics unique to the Central Valley Aquifer as described in Table 3.8. Together, these values allow me to calculate the intensive-margin response by farmers, which is traditionally unobserved in this setting and characterize the relative contributions of these two margins.

I report the calculations from this exercise on an AF per crop acre basis such that they are consistent units as the primary measure of surface water in the empirical models. A one AF/acre reduction in surface water results in a 3.72 ft ($DTW'(s)$) decline in groundwater levels, or equivalently, 0.45 AF/acre additional groundwater extractions extractions ($DTW'(s)/\kappa$). Given the estimates of new agricultural wells drilled in table 3.7, I calculate that approximately 0.01 AF/acre of that effect results from new wells pumping the average amount, or 81,750 AF statewide. While 0.44 AF/acre of the gross effect is due to the intensification of existing wells, or 4,410,000 AF statewide.

In percentage terms, extensive margin adaptation by farmers accounts for about 1.8% (5.1%) of the effect on groundwater levels results from surface water curtailments (harmful degree days), while the majority of the gross effects results from intensifying the average amount of water pumped per well. The large difference, in percentage terms, between extensive and intensive margins is likely due to the high fixed costs associated with drilling new agricultural wells. New agricultural wells, however, likely increases the groundwater demand in years beyond the contemporaneous year. Whereas, intensive margin adjustments are isolated decisions in the contemporaneous year. Over the life of a groundwater well, the cumulative extensive margin effect may outweigh large single-year, intensive margin adjustment.

Understanding these mechanisms through which agricultural producers respond to weather shocks and the subsequent impacts can better inform policy aimed at conserving water resources. I show that farmers substitute at least 45% of the lost surface water with groundwater supplies when surface water curtailments are imposed. This helps mitigate the yield effects of the weather shocks,

Table 3.8: Parameter Values for Decomposition

Parameter	Value	Units	Description	Source
$DTW'(s)$	-3.72	ft	Gross change in DTW caused by a one AF/acre change in surface water	Table 3 Column 4
$DTW'(h)$	0.0373	ft	Gross change in DTW caused by one additional HDD	Table 3 Column 4
κ	8.33	unitless	Inverse aquifer yield coefficient	Department of Water Resources (2020)
$w'(s)$	-459	# of wells	Change in the number of new agricultural wells drilled due to a one AF/acre change in surface water	Table 6 Column 4 multiplied by the total annual average of new agricultural wells
$w'(h)$	12.8	# of wells	Change in the average number of new agricultural wells drilled due to one additional HDD	Table 6 Column 4 multiplied by the total annual average of new agricultural wells
q	178	AF/well	Average AF of groundwater pumped per well	Authors' calculation from Department of Water Resources (2020) and w
w	85,937	# of wells	Number of wells drilled in California	Well Completion Reports (see Data)
acres	9,989,648	# of acres	Total irrigated crop acres in California	2015 USDA Cropland Data Layer & Hagerty (2021)

Note: The table reports estimated and calculated values for parameters in the decomposition of intensive and extensive margin effects presented in equation 3.2.

but strains historically unregulated groundwater resources. I also show that farmers adapt through both the extensive and intensive margin to these shocks, implying that groundwater regulation must target both mechanisms of behavior – reducing excess pumping at the well-level and restricting the drilling of new wells–in order to be effective.

3.6 Discussion

The impacts of climate change depend on the extent to which individuals adapt. While climate adaptation by some may limit their own potential damages from extreme heat and precipitation variability, these adaptive measures may unintentionally impose costs on others. In this paper, I show that agricultural producers in California significantly adapt to added heat and reduced surface water through the channel of constructing new agricultural wells. I also show that local groundwater levels are responsive to these annual fluctuations in weather. These climate-induced changes deplete local groundwater resources, imposing externalities on other users of groundwater. Negative externalities arise for rural communities through the channel of domestic well failures and subsequent reductions in drinking water access.

These findings contribute to the knowledge of the impact of climate change in three ways. First, I show that producers in California spend approximately $37 million annually for every AF per crop acre reduction of surface water availability. While irrigation may mitigate agricultural yield and revenue damages, climate change still imposes a significant annual cost to irrigated agriculture. Second, adaptation strategies contribute additional burden on those less able to engage in adaptive behavior. These externalities of adaptation have traditionally been ignored in calculating the economic costs of climate change but should be taken into account for a more complete accounting of climate change damages. Importantly, in the context of California groundwater, these costs, measured by domestic well failures, disproportionately affect low socioeconomic communities. Results are relevant for policymakers seeking to implement environmental regulation.

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3.7 Appendix

This appendix discusses the dynamics of well construction and the robustness of the main findings to alternative modelling choices and falsification tests.

3.7.1 Dynamics of Well Construction

Tables 3.9 and 3.10 consider the dynamics of agricultural well drilling. In Table 3.9, I report the results from equation 3.9 but now supplemented with up to three lagged years of agricultural surface water deliveries. Columns (2) through (4) each add an additional lag. In these specifications, deliveries are instrumented with surface water allocations. Table 3.10 similarly considers the dynamic effects on new agricultural well construction but instead focuses on the reduced-form effect of surface water allocations with the Poisson transformation. This is because the control function approach outlined in equation 3.10 is incompatible with lagged variables that enter nonlinearly. A look at the coefficients on lagged surface water supplies across all specifications reveals no consistent pattern. The sum of the coefficients, which captures the effect of a single supply shock over time, are not statistically different from each other across specifications. This suggests that the contemporaneous effect is characterizing the most meaningful impact of year-to-year changes in water supplies on new agricultural well construction.

These results can be explained by the presence of two opposing forces at play. On the one hand, heat and surface water shocks may alter farmers' expectations about future climate conditions and water availability, causing them to drill more wells today and over the lifetime of their operations. Realizations of drought increase the incentive to drill by increasing the cost of delaying.

On the other hand, it may be the case that farmers are simply shifting forward in time the decision to drill a new well. A behavioral response that only consists of inter-temporal substitution would suggest that coefficients on lagged variables should take the opposite sign of the contemporaneous effect, because drilling a well today reduces the need to drill in the future. This in turn would cause the sum of the coefficients to attenuate as I add more lagged variables. Since I see no observable trend from the inclusion of the lagged variables, it suggests that neither of these forces are dominating. These two effects are working in opposite directions and cannot be teased out. Taken together, this pattern of results on lagged variables support the main results reported in Table 3.6. The vast majority of the effects of drought on well construction are concentrated in the first year. I proceed by focusing on the more parsimonious specification of equation 3.10 and retaining power with more observations.

Table 3.9: Lagged Agricultural Well Construction

	(1)	(2)	(3)	(4)
	New Ag Wells per DAUCO			
Ag SW Deliveries (AF/ crop acre)	-12.38**	-11.51**	-11.53*	-11.45*
	(4.750)	(4.450)	(4.582)	(4.537)
L.Ag SW Deliveries (AF/ crop acre)		-3.512	-2.999	-3.602
		(2.858)	(2.779)	(3.207)
L2.Ag SW Deliveries (AF/ crop acre)			1.377	3.089
			(2.355)	(2.505)
L3.Ag SW Deliveries (AF/ crop acre)				-4.109
				(2.853)
$\sum \beta_{delieveries}$	-12.38	-15.02	-13.15	-16.07
$p_{deliveries}$	0.00913	0.00877	0.0277	0.0355
Harmful Degree Days	0.111***	0.0981**	0.0971**	0.0897**
	(0.0329)	(0.0349)	(0.0318)	(0.0327)
L.Harmful Degree Days		0.0809*	0.0848*	0.0548
		(0.0397)	(0.0426)	(0.0390)
L2.Harmful Degree Days			0.0551*	0.0643**
			(0.0247)	(0.0239)
L3.Harmful Degree Days				0.0174
				(0.0237)
$\sum \beta_{hdd}$	0.111	0.179	0.237	0.226
p_{hdd}	0.000760	0.00484	0.00171	0.00302
Observations	9,240	8,910	8,580	8,250
N Cluster	330	330	330	330
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Other Weather	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Table reports regression results from the estimation of equation 3.9. The dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.7.2 Dynamics of Other Groundwater Outcomes

The effects of surface water reductions and heat could conceivably impact groundwater outcomes in future years as well. If more agricultural wells are drilled in the contemporaneous year, this extensive margin change may also result in additional groundwater extraction – and thus, a lower groundwater table – in future years as well. If dynamics are present, it may imply that the contemporaneous effect alone is a lower bound of the cumulative effect of surface water and heat shocks. Table 3.11 reports estimates of changes in groundwater depth (ΔDTW) regressed on lagged weather shocks.

In general, there appears to be no significant nor consistent pattern among the coefficients from previous years. On the one hand, the coefficients on previous year's surface water deliveries tend to be positive, meaning they somewhat offset the contemporaneous effect. On the other hand, the previous year's HDDs report a positive coefficient, meaning that the current year's heat alone underestimates the true impact. However, the standard errors on the lagged effects tend to be large, and therefore, I conclude that the effects of weather shocks on changes in groundwater depth tend to be isolated to the contemporaneous year.

Similarly, I explore the impacts of prior weather shocks on reported well failures in table 3.12. Columns 2 and 3 indicate that the effects of a one AF per acre surface water reduction may result in as much as a 32% increase in the probability of well failure. However, this is the opposite direction of the lagged effects of harmful degree days. I am hesitant to draw definitive conclusions from this table, however, since the panel only consists of five total years of well failure data.

3.7.3 New Well Depth

In addition to drilling more wells, it could be that farmers are responding by drilling deeper wells. Table 3.13 considers the effect of drought on the drilled depth of newly constructed wells, both agricultural and domestic. Columns (1) to (3) present results of the effect of surface water allocations and harmful degree days on well depth, conditional on time and unit fixed effects and weather variables. Columns (2) and (3) isolate agricultural and domestic wells, respectively. Columns (4) through (5) present the IV results where allocations are used as an instrument for deliveries. While noisy, the sign of the effects suggest that as surface water supplies decrease and heat increases, wells are drilled to a greater depth.

3.7.4 Falsification Tests

Lastly, I conduct two falsification tests of my primary model. First, table 3.14 reports the results of regression of new domestic well construction on agricultural surface water deliveries and harmful degree days. Since agricultural surface water allocations are solely related to the agricultural sector, I expect shocks to this variable to be unrelated to domestic well construction. Indeed, none of the coefficients report a significant effect on the new domestic well construction. Furthermore, additional HDDs do induce more domestic wells to be drilled, but the response is smaller in magnitude than for agricultural well construction. This supports that agricultural well drilling is due to reduced surface water for agriculture, and not some correlated factor with all types of well drilling more broadly. Further, this also shows that domestic households do not respond to heat to the same magnitude as agricultural groundwater users. Thus, this muted adaptation by domestic users suggests that they are more vulnerable than agricultural users to groundwater scarcity and are prone to well failures in the future.

I explore whether shocks in surface water supplies to other sectors, municipal and industrial, impact agricultural well drilling in table 3.15. These results indicate that municipal and industrial water supplies are actually positively correlated with agricultural well construction, which is opposite of the effect of agricultural surface water. None of these coefficients are significant, and again, supports that the results in table 3.6 and 3.7 are due to agricultural surface water and not another factor that is correlated with all sectors' water supplies.

Table 3.10: Lagged Agricultural Well Construction

	(1)	(2)	(3)	(4)
	New Ag Wells per DAUCO			
Ag SW Allocation (AF/crop acre)	-0.278*	-0.284*	-0.306*	-0.281*
	(0.124)	(0.130)	(0.126)	(0.137)
L.Ag SW Allocation (AF/crop acre)		0.0184	-0.0150	-0.0370
		(0.0500)	(0.0436)	(0.0495)
L2.Ag SW Allocation (AF/crop acre)			0.157	0.184*
			(0.0835)	(0.0814)
L3.Ag SW Allocation (AF/crop acre)				-0.0202
				(0.0715)
$\sum \beta_{deliveries}$	-0.278	-0.266	-0.164	-0.154
$p_{deliveries}$	0.0249	0.0481	0.235	0.338
Harmful Degree Days	0.00897***	0.00958***	0.00915**	0.00972**
	(0.00202)	(0.00261)	(0.00287)	(0.00323)
L.Harmful Degree Days		0.00331	0.00435	0.00190
		(0.00266)	(0.00250)	(0.00251)
L2.Harmful Degree Days			0.00447	0.00383
			(0.00254)	(0.00266)
L3.Harmful Degree Days				0.00521*
				(0.00240)
$\sum \beta_{hdd}$	0.00897	0.0129	0.0180	0.0207
p_{hdd}	0.00000911	0.000326	0.000125	0.000110
Observations	8,400	8,073	7,722	7,400
N Cluster	300	299	297	296
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.11: Lagged Changes in Groundwater Depth

	(1)	(2)	(3)	(4)
			ΔDTW	
Ag SW Deliveries (AF/ crop acre)	-3.754*	-3.807*	-4.785**	-4.650**
	(1.619)	(1.525)	(1.580)	(1.743)
L.Ag SW Deliveries (AF/ crop acre)		1.668	1.456	1.569
		(1.009)	(0.958)	(0.900)
L2.Ag SW Deliveries (AF/ crop acre)			0.141	-0.265
			(0.999)	(1.030)
L3.Ag SW Deliveries (AF/ crop acre)				-0.233
				(0.464)
$\sum \beta_{deliveries}$	-3.754	-2.139	-3.187	-3.579
$p_{deliveries}$	0.0204	0.118	0.0205	0.0346
Harmful Degree Days	0.0373*	0.0376*	0.0388*	0.0345*
	(0.0169)	(0.0168)	(0.0162)	(0.0152)
L.Harmful Degree Days		0.0109	0.0215	0.0301*
		(0.0106)	(0.0112)	(0.0146)
L2.Harmful Degree Days			-0.0129	-0.0230
			(0.0131)	(0.0131)
L3.Harmful Degree Days				-0.00683
				(0.0290)
$\sum \beta_{hdd}$	0.0373	0.0486	0.0474	0.0348
p_{hdd}	0.0273	0.0152	0.0279	0.214
Observations	560,931	421,251	321,384	246,159
N Cluster	282	277	269	260
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the change in the depth to the groundwater from the surface (ft) from 1994-2020 at the monitoring well level. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.12: Lagged Probability of Well Failure

	(1)	(2)	(3)	(4)
	Well Failure Reported			
Ag SW Deliveries (AF/ crop acre)	-0.0548**	-0.0397**	-0.178**	0.000778
	(0.0191)	(0.0131)	(0.0597)	(0.0277)
L.Ag SW Deliveries (AF/ crop acre)		-0.0677*	-0.177*	-0.0296
		(0.0265)	(0.0691)	(0.0278)
L2.Ag SW Deliveries (AF/ crop acre)			0.0257	-0.0216
			(0.0168)	(0.0122)
L3.Ag SW Deliveries (AF/ crop acre)				0.00908
				(0.00649)
$\sum \beta\_deliveries$	-0.0548	-0.107	-0.329	-0.0414
$p_{deliveries}$	0.00415	0.000413	0.00529	0.453
Harmful Degree Days	0.00205*	0.00157*	0.00142*	0.0000432
	(0.000899)	(0.000759)	(0.000634)	(0.0000781)
L.Harmful Degree Days		-0.00333*	-0.00187	0.000179
		(0.00166)	(0.00116)	(0.000168)
L2.Harmful Degree Days			-0.000906	-0.000166
			(0.000612)	(0.000161)
L3.Harmful Degree Days				0.0000875
				(0.000150)
$\sum \beta_{hdd}$	0.00205	-0.00176	-0.00135	0.000144
p_{hdd}	0.0228	0.106	0.364	0.745
Observations	476,748	476,748	397,290	317,832
N Cluster	342	342	342	342
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.13: New Constructed Well Depth

	Reduced Form			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
	Both	Ag	Domestic	Both	Ag	Domestic
Ag SW Allocation (AF/ crop acre)	-22.90	-23.14	-8.170			
	(18.16)	(21.67)	(7.699)			
Ag SW Deliveries (AF/ crop acre)				-37.03	-34.48	-14.14
				(29.10)	(32.23)	(14.34)
Harmful Degree Days	1.431*	2.592*	0.346	1.340*	2.449*	0.319
	(0.624)	(1.108)	(0.244)	(0.563)	(1.019)	(0.237)
Observations	144,917	31,042	114,034	144,890	30,955	113,863
N Groups	337	310	334	328	295	322
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓	✓	✓
DAUCO x Type FE	✓	✓	✓	✓	✓	✓
Other Weather	✓	✓	✓	✓	✓	✓

Note: Dependent variable is the depth (ft) of newly constructed wells from 1993-2020 at the well level. Columns (1) and (4) reports results for both agricultural and domestic wells, (2) and (3) for just agricultural wells, and (3) and (6) for just domestic wells. All regressions are weighted by the DAUCO crop acres and include year and DAUCO by well type fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.14: Construction of New Domestic Wells

	OLS		PPML	
	(1)	(2)	(3)	(4)
Ag SW Allocation (AF/ crop acre)	-1.534	-1.021	-0.0657	-0.0128
	(1.582)	(1.535)	(0.0783)	(0.0641)
Harmful Degree Days		0.0774		0.00950*
		(0.0477)		(0.00445)
Growing Degree Days		-0.00782		
		(0.00473)		
Annual Precipitation		0.00734**		0.000417**
		(0.00280)		(0.000139)
Observations	9,660	9,240	9,072	8,876
N Cluster	345	330	324	317
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new domestic wells per DAUCO from 1993-2020. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.15: Construction of New Agricultural Wells: Municipal and Industrial Surface Water

	OLS		PPML	
	(1)	(2)	(3)	(4)
M&I SW Allocation per Acre	19.71	23.36	1.407	1.459
	(28.88)	(28.91)	(1.300)	(1.257)
Harmful Degree Days		0.115**		0.0143***
		(0.0422)		(0.00287)
Growing Degree Days		0.000191		0.000472
		(0.00839)		(0.000636)
Observations	8,874	8,400	7,540	7,224
N Cluster	306	300	260	258
Weights	Crop Acres	Crop Acres	Crop Acres	Crop Acres
Cluster	DAUCO	DAUCO	DAUCO	DAUCO
Time FE	✓	✓	✓	✓
Unit FE	✓	✓	✓	✓
Other Weather		✓		✓

Note: Dependent variable is the count of new agricultural wells per DAUCO from 1993-2020. Independent variable is surface water allocated (AF per crop acre) for municipal and industrial use, as opposed to agricultural use. Columns (1) and (2) report the coefficients for the OLS model. Columns (3) and (4) report coefficients from a psuedo-poisson maximum likelihood model. All regressions are weighted by the DAUCO crop acres and include year and DAUCO fixed effects. Standard errors are clustered at the DAUCO level and are reported in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Chapter 4

Supply Chain Resilience and Extreme Events

Food supply chains have experienced severe disruptions in recent years, first due to the COVID-19 pandemic and then due to the conflict between Russia and Ukraine. These disruptions have motivated researchers and policymakers to assess the resiliency of food supply chains to extreme shocks and to search for policies to make them more robust to such events in the future (United Nations Food and Agriculture Organization 2021; U.S. Department of Agriculture 2022).

Extreme shocks to food systems can emanate from a variety of sources, including pandemics, geopolitical conflicts, and natural disasters. A key element linking possible extreme events is that they are likely to simultaneously impact food supply chains at successive stages. The COVID-19 pandemic, for example, caused short-run retail demand shocks for key staples, as consumers attempted to stockpile goods amidst fears of looming shortages, while the upstream production and processing stages experienced bottlenecks and reduced production due to processing plant shutdowns and inability to harvest some crops due to labor shortages (Martinez, Maples, and Benavidez 2020; Lusk and Chandra 2021).

The recent experiences have made building more resilient food supply chains that adapt quickly in the presence of extreme events a clear policy goal for much of the world. US policymakers have already introduced several measures intended to enhance the resilience of US food supply chains. They include intensified enforcement of competition laws, subsidizing entry of new processing firms, outlawing profiteering or "price-gouging" in response to severe market disruptions, and supporting geographic diversification of food systems. This paper seeks to evaluate the impacts of each of these policy interventions. Although substantial recent work has indicated the qualitative value of more resilient food supply chains, considerable debate remains regarding the optimal policy responses (Tukamuhabwa et al. 2015; Jiang, Rigobon, and Rigobon 2021) and the implications for stakeholders along the supply chain (Davis, Downs, and Gephart 2021).

Food supply chains have evolved through the quest for production efficiency and cost savings, but the common perception is that the most efficient supply chain structures may be the least resilient (Viswanadham and Kameshwaran 2013; Hobbs 2021; U.S. Department of Agriculture 2022),[1] and, thus, strategies to enhance resilience may reduce efficiency of supply chain operations during normal times. To date, this possible resilience-efficiency trade-off has been discussed (Hobbs 2021; Lusk, Tonsor, and Schulz 2021), but has not been subjected to rigorous analysis nor quantified. Providing this input to policymakers is a key focus of this paper. Although I study policies that have been adopted or discussed in the US and calibrate the model to US data, I expect that the results will have relevance for other economies grappling with supply chain resilience issues.

I develop a flexible model of a prototype food supply chain, which allows me to express key trade-offs between efficiency and resilience under a broad set of extreme shocks and forms of market competition. Ability to depict alternative competition scenarios is a key consideration because market concentration and intermediaries' market power have been cited repeatedly by policymakers as factors that inhibit supply chain resilience (The White House 2022; U.S. Department of Agriculture 2022).

A key innovation of the model relative to others is that I incorporate explicitly that extreme shocks will generally impact supply chains simultaneously at multiple stages, as was true with the onset of the COVID-19 pandemic. I simulate the correlated nature of market shocks by drawing shock variables for the vertical stages of the supply chain—farm production, processing and retailing, and consumption—from a multi-variate joint distribution. I show that shocks to farm supply, consumer demand, and processing capacity are more disruptive the greater their correlation.

I calibrate the model based on contemporary data and recent empirical research for the

[1]U.S. Department of Agriculture (2022) begins its report on agricultural competition by asserting "the pandemic exposed the risks and dangers created by many of today's production systems, which value hyper-efficiency over competition and resiliency" (p.2).

US to represent prototype supply chains for key staples. I then utilize Monte-Carlo simulations to examine the welfare impacts for supply chain participants of different extreme events under alternative supply chain structures and policy responses. Market efficiency of alternative supply chain structures is measured in terms of the mean economic surplus they generate across simulated market outcomes, while market resilience is measured in terms of the relative variance (coefficient of variation) under a large number of simulated shocks.

I utilize the calibrated model and simulation framework to study four policy proposals that have emerged in the resilience debate. First, I investigate the role of concentration and market power in the processing/retailing sector on resilience of supply chains in response to extreme shocks. On January 3, 2022, the Biden Administration announced plans for stricter enforcement of antitrust laws in the meatpacking industries. In addition, legislation known as the Meat and Poultry Special Investigator Act of 2022 has been introduced in the US Congress to give the US Department of Agriculture (USDA) authority to investigate competition issues in the meat and poultry industries. USDA has announced plans to partner with the US Department of Justice to enforce antitrust laws vigorously and to step up its own enforcement of competition under the Packers and Stockyards Act (U.S. Department of Agriculture 2022). Market power exercised by intermediaries is shown to raise prices to consumers and depress prices received by farmers (Crespi and MacDonald 2022), but its impacts on supply chain resilience are not well understood.

Second, given a baseline level of market power for market intermediaries, I study the impact of entry into the processing sector on market efficiency and resilience in the event of extreme shocks. As noted, subsidization of entry into meat processing is a key policy response being implemented in the US, with the USDA's Meat and Poultry Processing Expansion Program representing a key element of this overall commitment. Entry of processors spreads the shutdown risk across a greater number of plants and may reduce intermediaries' market power, but more processing facilities imply lower throughput per plant, generating higher costs in the presence of size economies.

Third, I study the ramifications of price controls imposed along the supply chain in response to significant market shocks. These policies take the form of anti-price-gouging laws, or *ad hoc* price controls imposed by politicians under emergency authority. While price limits impede intermediaries from exercising market power and prevent extreme price shocks to consumers, they may exacerbate shortages of products and limit market participants' abilities to adapt through a price mechanism to changing market conditions. I show that the impact of price controls depends importantly on the competitive conditions of markets. In settings where intermediaries' exercise significant market power, price caps lead to cause higher output and economic surplus compared to the flexible-price case.

Fourth, I study whether more geographically dispersed production enhances resilience. Production of many agricultural commodities in the US has become highly specialized geographically, which has undoubtedly caused efficiency gains as regions produce according to their comparative advantages. Proponents of more diverse and localized food production systems argue that spatial concentration leaves the food supply chain vulnerable to devastating shocks that impact an entire production region and that local food systems are more nimble and resilient (Thilmany et al. 2021; Raj, Brinkley, and Ulimwengu 2022). The simulations illustrate the trade-off between reduced volatility due to more dispersed production risk, and reduced production efficiency and market surplus associated with geographically dispersed production systems.

Overall, I find that, while some of these policies can reduce relative volatility of welfare outcomes for farmers and consumers, their impacts on resilience and efficiency depend critically on the structure and competitive conditions in the market. Policies aimed at increasing resilience must carefully assess the probabilistic nature of extreme events and the related efficiency trade-offs. This paper facilitates these discussions by providing a quantitative framework that enables the resilience-efficiency trade-offs of the major policy proposals to be assessed under extreme shocks.

4.1 Extreme Events

The COVID-19 pandemic and the Russia-Ukraine conflict in close succession and the disruptions they have caused have brought heightened awareness to the potential vulnerability of food supply chains to extreme events (Bellemare, Bloem, and Lim 2022). The urgency of investigating food supply chain resilience to such events is magnified by a general recognition that, moving forward, macro forces are likely to make countries increasingly vulnerable to such shocks (Marani et al. 2021). For example, the majority of emerging infectious diseases originate in wildlife animals and transmit through interactions among wildlife, domestic animals, and humans within rapidly changing environments and expanding contacts between humans and wildlife, accelerating the potential for

Event	Farm Supply	Consumer Demand	Processing Capacity
Pandemics	Negative: Shock to labor and other farm inputs	Positive: Stockpiling behavior in short-run Negative: Recession and mortality in long-run	Negative: Health-related plant shutdowns
Natural Disasters & Extreme Weather	Negative: reduced yields and livestock fatality	Positive: Stockpiling	No likely impact unless facilities are destroyed or damaged
Geopolitical Conflict	Negative: Reduced planting and harvesting	Positive: Stockpiling Negative: Recession and mortality in long-run	Negative: Potential destruction of facilities. Blocked transportation networks
Range of Impact	-[5%,15%][2]	+[40%, 75%][3]	-[20%, 40%][4]

Table 4.1: Shocks to the Food Supply Chain Under Extreme Events

pandemic events (Wolfe, Dunavan, and Diamond 2007; Jones et al. 2013; Allen et al. 2017). A consensus has also emerged that climate change is associated with increasing incidence and intensity of severe weather events, including extreme temperatures, extreme precipitation, and drought (Wuebbles et al. 2014; Cornwall 2016). Finally, the destructive capacity of geopolitical conflicts is exacerbated by modern conventional weaponry, as well as the risk of introduction of biological weapons onto the battlefield.

Table 4.1 outlines three categories of extreme events and their potential impacts on stages of the food supply chain. The magnitude of shocks will vary widely depending on specific contexts, and table 4.1 is meant to be illustrative, not exhaustive. I make no attempt to study the most extreme "extinction" events that could occur, such as nuclear conflict or asteroid or comet impact on the Earth. Such events are predicted to have long-lasting impacts such that coping with them would require massive stockpiling of food reserves, which is not considered in this model.

4.2 Model

Resilient food supply chains for the US and many other economies mean an ability to sustain food production and consumption without undue reliance on international trade because catastrophic events are likely to curtail trade due to disruptions in transportation networks and/or country bans imposed on exports and imports (Raj, Brinkley, and Ulimwengu 2022).[5] We, thus, consider a

[5]The Russia-Ukraine conflict provides ample examples of both trade effects. Ukrainian grain and oilseed exports are mainly transported by ocean vessel emanating from the Port of Odessa and were curtailed due to a blockade by

closed-economy model of a supply chain containing farm production, processing and retailing, and consumption.[6]

Given the concerns about the impact of competitive conditions within a supply chain on its resilience, it is important to work with a model that has flexibility to incorporate alternative forms of competition. I adapt and extend the flexible oligopoly/oligopsony market (FOOM) model to incorporate correlated shocks within the supply chain, economies of size in food processing/marketing, and production emanating from multiple regions.[7]

The model assumes fixed proportions in production throughout the supply chain in the sense that a given volume of the farm product is required to produce a unit of the consumer good. Given fixed proportions, the output produced at each stage of the supply chain can be equalized given appropriate measurement units and is denoted by Q.

To simplify exposition of the base model, I assume the food product is produced and processed in a single region ($R = 1$). The model is later extended to incorporate multiple production regions as a resilience-enhancing strategy. The inverse supply function of farmers in the production region is:

$$P^f(Q) = S(Q|X, \mu), \tag{4.1}$$

where X denotes supply shifters, and μ is a parameter to depict a supply shock.

Consistent with past supply-chain models, e.g., Gardner (1975), Schroeter (1988), Wohlgenant (1989), Holloway (1991), Sexton (2000), I assume an integrated processing-retailing sector.[8] A num-

Russian forces. Many countries curtailed trade with Russia under sanctions. Meanwhile, other countries imposed export restrictions due to rapidly rising prices for key commodities. Another contemporaneous example of export bans exacerbating food shortages and raising food prices is the escalation of world grain prices in 2007-2008 that led to restrictions or bans on grain exports in Argentina, India, Kazakhstan, Pakistan, Ukraine, Russia, and Vietnam (Mitchell 2008).

[6] In addition to the fact that catastrophic events are likely to disrupt international trade, a closed-economy specification also makes sense given the focus on the US and calibration to US data. Over 87% of food consumed in the US is produced domestically according to the USDA.

[7] This model framework emerged from the so-called "new empirical industrial organization" or NEIO, with key early contributions to the study of oligopoly power by Appelbaum (1982) and Bresnahan (1982). The framework was extended to an agricultural-markets context and to include intermediaries' oligopsony power by Schroeter (1988). Sheldon (2017) provides a recent review of contributions to food-market analysis based on the NEIO/FOOM model framework.

[8] An analytically equivalent approach is to assume a separate, competitive food retailing sector, which operates with constant unit costs.

ber of n homogeneous processors exist in the region. They may exercise buyer power over farmers and seller power over consumers. Consistent with the norm for most industries, processors may operate multiple plants, so total plants, denoted by N, equals or exceeds the number of processors: $N \geq n$.

Processors collectively face a national demand for the retail product.[9] Consumer demand for the processed product is:

$$P^r(Q) = D(Q|Y, \sigma), \tag{4.2}$$

where Y contains demand shifters, and σ is a parameter to depict shocks to demand.

Suppressing notation for shifters and shock variables, the objective function for a vertically integrated, profit-maximizing processor j choosing the output q_j is:

$$\max_{q_j} \pi_j = (P^r(Q) - P^f(Q))q_j - c^w q_j, \tag{4.3}$$

where $c^w q_j$ is the total variable cost for processor j. Fixed costs are irrelevant to the production decision and are omitted. I assume that all processors have access to the same technologies and, thus, this cost function is common among them. Further, consistent with prior research (Gardner 1975; Holloway 1991; Sexton 2000), I assume constant marginal costs, c^w, but allow c^w to be shifted up or down based on the plant number, N, to allow for possible economies of size, as I explain in the next subsection.[10]

Given that processors are homogeneous, optimization yields symmetric behavior in equilibrium (i.e., $q_j = q_k = q$). Taking the first-order condition and converting derivatives to elasticities, I

[9]This formulation is consistent with the idea that, although regional markets may exist for bulky and perishable farm products, final products are less bulky and perishable and easier to transport and, thus, have a broader geographic market than for procurement of the farm product.

[10]Each processor j that operates multiple plants, $N_j > 1$, must allocate its optimal farm-product purchases and processed product output, q_j^*, across its processing facilities. I do not model this allocation process explicitly, but assume plants are located optimally within the producing region. Hence, each plant operates with the same marginal costs, c^w, and produces an equal share, q_j^*/N_j, of the total firm output.

obtain the market equilibrium condition (see Appendix 4.5.1 for derivation):

$$P^r(1 - \frac{\xi}{\eta}) - c^w = P^f(1 + \frac{\theta}{\epsilon}), \tag{4.4}$$

where $0 \leq \theta \leq 1$ is the processor's buyer power parameter, $0 \leq \xi \leq 1$ is the processor's seller power parameter, $\eta > 0$ is the absolute demand elasticity evaluated at the market equilibrium, and $\epsilon > 0$ is the farm supply elasticity evaluated at the market equilibrium. The left-hand side represents the processor's perceived net marginal revenue (PMR) from selling an additional unit of the final product, while the right-hand side is its perceived marginal cost (PMC) of acquiring an additional unit of the farm product.

The model parameterizes both buyer and seller market power on the unit interval, with $\xi, \theta = 0$ denoting perfect competition, $\xi, \theta = 1$ denoting pure monopoly/monopsony, and $\xi, \theta \in (0, 1)$ denoting different degrees of oligopoly/oligopsony power. The model does not presuppose a particular form of market competition, but seeks to measure the implications of specific departures from perfect competition, which may arise due to unilateral power of the intermediaries, such as under Cournot-Nash competition, or from tacit or overt collusion.

4.2.1 Analytical Solutions

To obtain analytical solutions and enable simulation, I assign linear functions to the model. Suppressing the shock parameters in the functions, I let the farm supply and market demand functions be:

$$P^f(Q) = b + \beta Q, \tag{4.5}$$

$$P^r(Q) = a - \alpha Q, \tag{4.6}$$

where a and b capture the effects of the shifter variables for consumer demand and farm supply, respectively.

To capture potential economies of size in processing, I specify the marginal processing cost function as:

$$c^w = c^w(N). \tag{4.7}$$

I allow the marginal cost to be locally constant for small changes in firm-level output, but to be a function of the total number, N, of processing plants operating in the market. This specification is a convenient way to study processing efficiency because policy proposals involving processor entry or expanding production into multiple regions involve increasing N. Equilibrium output of each processing plant changes discretely as a function of N, given the farm supply function. Thus, $\frac{\partial c^w}{\partial N} > 0$ reflects economies of size (i.e., more active plants imply reduced output per plant and higher unit costs), and $\frac{\partial c^w}{\partial N} = 0$ represents constant returns to size. Diseconomies of size is not considered due to lack of empirical support.

In the risk-free and competitive world, the equilibrium condition is:

$$(a - \alpha Q) - c^w = b + \beta Q, \tag{4.8}$$

which yields the competitive equilibrium output of the industry:

$$Q^c = \frac{a - b - c^w}{\alpha + \beta}. \tag{4.9}$$

The equilibrium retail and farm prices are obtained by plugging Q^c into the consumer demand and farm supply functions, respectively.

Similarly, I find equilibrium output and prices under imperfect competition. For the linear model the first-order condition, equation 4.4 becomes:

$$(a - \alpha Q)(1 - \frac{\xi}{\eta}) - c^w = (b + \beta Q)(1 + \frac{\theta}{\epsilon}). \tag{4.10}$$

I can derive the market's risk-free oligopoly-oligopsony equilibrium output, farm price, and retail price by solving the system consisting of equations 4.5, 4.6, and 4.10:

$$Q^{oo} = \frac{a(1-\frac{\xi}{\eta}) - b(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}, \tag{4.11}$$

where $Q^c > Q^{oo}$ for all positive ξ and θ, and Q^{oo} decreases in ξ and θ. The output per processing firm is $q^{oo} = \frac{Q^{oo}}{n}$. The equilibrium retail price is $P^{r,oo} = a - \alpha Q^{oo}$, and the equilibrium farm price is $P^{f,oo} = b + \beta Q^{oo}$.

Given the parameterized model and equilibrium prices and output, the economic surplus measures for consumers, farmers, and processors are straightforward to derive. Consumer surplus (CS) equals $\frac{1}{2}(a - P^{r,oo})Q^{oo}$, producer surplus (PS) equals $\frac{1}{2}(P^{f,oo} - b)Q^{oo}$, and processor variable profits equals $(P^{r,oo} - P^{f,oo} - c^w)Q^{oo}$. The dead-weight-loss (DWL) from market power is given by $\frac{1}{2}(P^{r,oo} - P^{f,oo})(Q^c - Q^{oo}) - c^w(Q^c - Q^{oo})$.

4.2.2 Measure of Resilience

Researchers have used the variance or standard deviation of a variable or welfare measure of interest, like industry-level output or CS, to measure volatility under a given shock (e.g., Ma and Lusk (2021)). However, to compare the volatility of several random variables with different mean values, the coefficient of variation (CV), the standard deviation of a variable divided by its mean, is the most appropriate measure of relative dispersion (Curto and Pinto 2009).

CV provides a dimensionless measure of *relative* volatility that is widely used in economic risk assessments, like financial stability (Pinches and Kinney 1971; Ozkok 2015), socioeconomic inequality (Houthakker 1959; Braun 1988), and agronomic yield variability (Kravchenko et al. 2005). In the context of supply chain resilience, CV measures the relative dispersion of CS, PS, and intermediary profits under a set of extreme shocks to the system. It allows me to compare the volatility of welfare for supply-chain participants (producers, intermediaries, consumers), who have different average surplus measures, across different policy proposals and supply-chain structures.

4.2.3 Parameterization

To parameterize the model, I normalize the risk-free, competitive equilibrium industry-level output to 1.0. The corresponding equilibrium retail price on the national market is $a - \alpha Q^c$ and also normalized to 1.0. The corresponding demand elasticity at this equilibrium, η, hence equals $\frac{1}{\alpha}$, and $a = 1 + \alpha = 1 + \frac{1}{\eta}$.

On the supply side, the competitive farm equilibrium price is $f = 1 - c^w$, where c^w is a function of the number of processors, N, and characterizes the economies of size that a processing plant is able to obtain. This farm price is the farm share of the normalized retail value of a unit of the product under perfect competition. Total farm output is also 1.0. Thus, $\beta = \frac{f}{\epsilon}$ and $b = f(1 - \frac{1}{\epsilon})$, where ϵ is the farm price elasticity of supply at the competitive equilibrium.

As noted, allowing for the presence of economies of size in processing is critical in the model. Economies of size in food processing have been studied most extensively for the meatpacking industries, wherein size economies have been found to exist and to be substantial. Morrison Paul (2001a) shows that the cost function for US beef processing can be expressed approximately as $C(q) = mq^g$ where m is a multiplier, q is the output of a processor, marginal cost is $c(q) = gmq^{g-1}$, and $g = \frac{\partial \ln(C)}{\partial \ln(q)}$ is the cost elasticity of output with $0 < g < 1$ denoting size economies. Morrison Paul (2001a) reports estimates of $g \approx 0.95$ for US beef processing based on industry-level data.

Based on a plant-specific analysis of US beef processing, Morrison Paul (2001b) finds an almost identical estimate for g wherein cattle input and other variable inputs are allowed to change, but physical plant is fixed, an environment she terms the "intermediate run" case and nearly identical to the setting I simulate. MacDonald and Ollinger (2000) also report a nearly identical cost elasticity estimate for US hog processing. Ollinger, MacDonald, and Madison (2005) found greater size economies for US poultry, with the cost elasticity estimates for chicken ranging from 0.88 to 0.93. Even greater size economies were found for turkey processing.

To adapt these size economy estimates to the model structure, I express marginal processing costs as $c^w(N) = cN^{\gamma}$, where $\gamma \geq 0$. I equate this expression to marginal cost in Morrison Paul (2001a) to solve for γ. Here $\gamma = 0$ denotes constant returns to size, while $\gamma > 0$ indicates the presence of economies of size – the marginal cost increases as the number of active plants rises, or as the per plant equilibrium output falls. Given that the equilibrium output per homogeneous plant is $q_j = \frac{1}{N}$, which falls in N, the cost function is defined as:

$$mg(\frac{1}{N})^{g-1} = cN^{\gamma}. \tag{4.12}$$

Parameter	Description	Value	Source
η	|Demand elasticity|	0.7	(Okrent and Alston 2011)
ϵ	Supply elasticity	1	(Chavas and Cox 1995)
f	Farm share	0.3	(USDA-ERS)
g	Cost elasticity of output	0.95	(Morrison Paul 2001a,b; MacDonald and Ollinger 2000)
γ	Economies of size parameter	$1-g$	Authors' calculation
ξ,θ	market power parameters	0, 0.15, 0.3	(Sexton and Xia 2018)
N	Total number of processing plants	40	Garrido et al. (2021)

Table 4.2: Baseline Parameter Values for Simulation

Letting $c = mg$, the equation for γ simplifies to (see online Appendix 4.5.1 for derivation):

$$\gamma = 1 - g. \tag{4.13}$$

Equilibrium solutions to the model then depend on six parameters (η, ϵ, f, g or γ, ξ, and θ) that are all pure numbers and describe the market structure, and three exogenous shock variables to the supply chain. I assigned base values for these parameters by drawing upon the empirical literature for US meat supply chains. These base values and sources are displayed in table 4.2.

4.2.4 Correlated Shocks

Destructive events such as a natural disaster, war, or a pandemic that impact labor supplies may negatively impact both farm supplies and available processing capacity (Wahdat and Lusk 2022). These events also simultaneously and positively shock demand due to consumers attempting to stockpile goods.[11] However, to date the literature on food supply chain resilience has not incorporated the correlated nature of shocks due to extreme events (Davis, Downs, and Gephart 2021).

To illustrate how extreme events introduce correlated shocks between retail and processing stages, figure 4.1 displays weekly percentage changes from average in beef slaughter and retail sales in 2020 following onset of the COVID-19 pandemic in the US. The shaded area reflects the initial

[11] As table 4.1 notes, extreme events may eventually manifest as negative demand shocks if they result in a significant increase in mortality and/or cause economic recession. The analysis focuses on the shorter-term impacts, wherein positive demand shocks due to consumer stockpiling are likely. The framework can readily be adapted to studying the impacts of correlated negative demand shocks, along with negative supply shocks and processing plant shutdown risk.

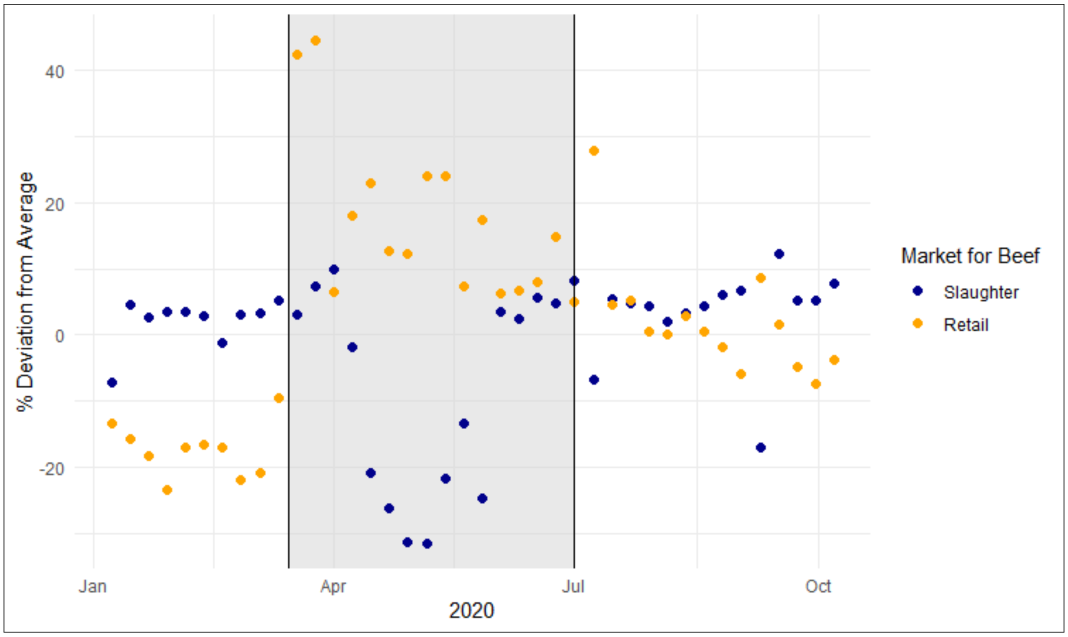


Figure 4.1: Weekly beef slaughter and retail sales relative to average.
Source: Retail beef sales are from USDA Economic Research Service. Slaughter data are originally from USDA Agricultural Marketing Service and USDA National Agricultural Statistics Service and provided by Livestock Marketing Information Center.
Note: Authors' calculation. The shaded region shows the large deviations from the average in the weeks immediately after the first COVID-19 cases in the US in March 2020.

weeks of the COVID-19 outbreak in the US, mid-March through the end of June. The initial weeks of the pandemic induced panic buying and hoarding of available supplies up to 45% beyond normal retail sales. At the same time, slaughter dropped as much as 32% below average because processing plants were forced to stop operations due to employee illnesses or local ordinances.

Multi-variate joint distributions (or copula) allow for random variables drawn from differing distributions with dependant structures. Copulas are commonly used in quantitative finance for portfolio risk-management, where the volatility of individual investments that compose a portfolio are correlated with each other (Fan and Patton 2014). For supply chain analysis of extreme events, copulas allow for random draws from a positive half-normal parallel demand shock (σ), negative half-normal parallel supply shock (μ), and binomial processor shutdown shock (N').

Table 4.1 informs the parameterization of these distributions according to the possible magnitudes of extreme events in percentage terms. The mean and variance of the half-normal distributions are specified by a single scale parameter, θ_H^i for $i = \{D, S\}$, in the set of expressions below. Here, the half-normal parameter θ_H^D corresponds to a mean 20% shift in demand (i.e., mean of $\sigma = 0.5$

is 20% of $a = 1 + \eta = 2.43$), and θ_H^S implies a 30% shift in farm supply (i.e., mean of $\mu = 0.1$ is a third of f). After parallel shifts, demand and supply curves have new intercepts $a' = a + \sigma$ and $b' = b + \mu$, respectively. The binomial shutdown shock determines the number of processing plants that remain active, N', from a total number of plants, N. On average, 75% of the plants remain in operation after an extreme event in the simulation model.

$$\begin{aligned} \sigma &\sim H(\theta_H^D = 2) \\ \mu &\sim H(\theta_H^S = 10) \\ N' &\sim B(N, 0.75) \end{aligned} \tag{4.14}$$

The magnitude of shocks vary across extreme events, but the values chosen here are emblematic of recent experiential evidence.[12] The densities of each shock for the baseline simulations are presented in figure 4.2.

Given distributions of shocks, I then draw 100,000 sets of shocks from a multi-variate joint distribution, in essence creating 100,000 extreme events. The dependant nature of these shocks are defined by a 3 by 3 covariance matrix, where the off-diagonal elements specify the degree of correlation, ρ, between each stage's shock.

To illustrate the role of correlation between shocks, I simulate over the off-diagonal elements of the covariance matrix for $\rho \in [0, 0.5]$. Figure 4.3 displays simulation outcomes for a supply chain with moderate market power ($\xi = \theta = 0.15$) for alternate values of ρ. For this illustrative simulation, all off-diagonal elements are simply equal to ρ, but these elements are fixed at differing baseline values for the policy simulations. The vertical axis measures percentage changes in CV relative to the independent-shocks setting. Increasing the correlation among shocks increases CV of all welfare measures. Intuitively, a stronger correlation between a and b increases the variance of CS and PS, but has little effect on their means.[13] In the baseline, I allow $\text{cor}(\sigma, \mu) = 0.25$, $\text{cor}(\sigma, N') = -0.50$,

[12]The choice of shock distributions, by construction, influences the baseline level of volatility in market outcomes. Importantly, however, the simulations hold constant the distribution of shocks across simulations and measure the final outcomes as percentage changes relative to a baseline. While a separate choice of shock parameters may lead to different baseline levels of volatility, they do not meaningfully alter the simulated percentage change effects of marginal changes in market structure.

[13]The mean values of CS and PS increase slightly in ρ because the positive demand shift tends to dominate the correlated negative shift in farm supply.

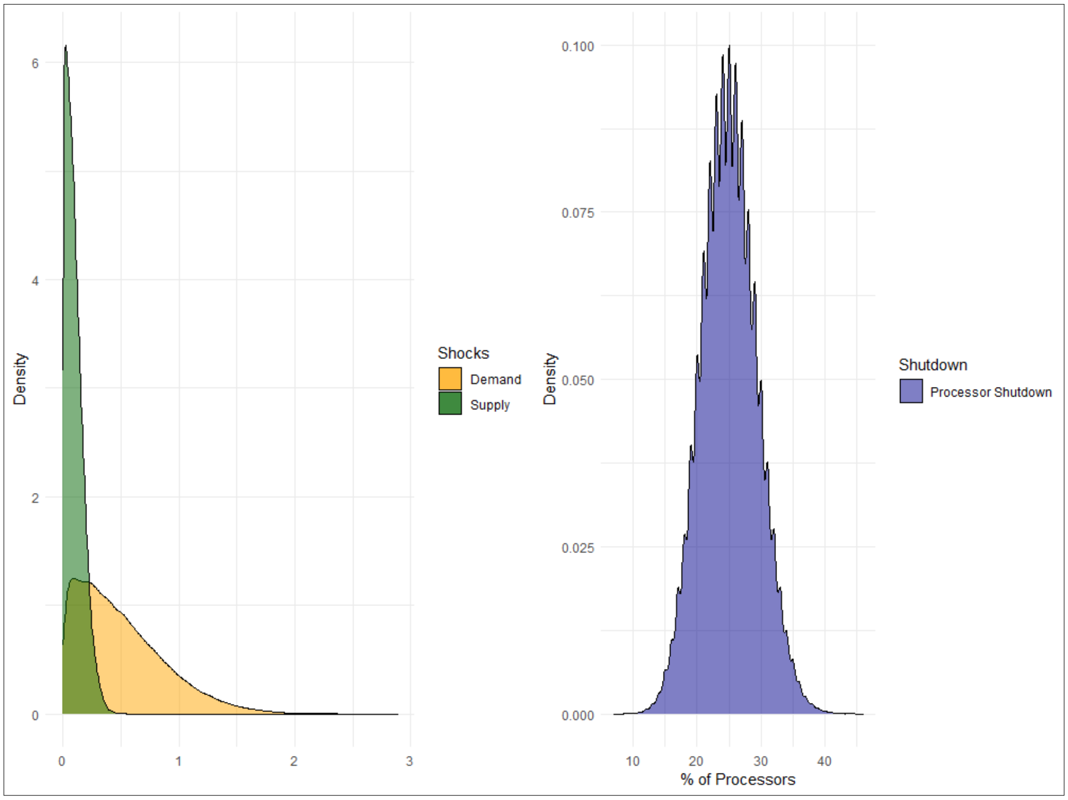


Figure 4.2: Density of shocks from a multi-variate joint distribution.

Note: Left panel displays the density of 100,000 draws from half-normal distributions for the supply and demand shocks. Right panel displays the density across 100,000 draws from a binomial distribution, where 25% of plants shut down on average.

and $\text{cor}(\mu, N') = 0.10$.[14]

4.2.5 Post-Shock Equilibrium

When processing plants experience a shutdown shock (i.e., N falls to N'), I assume that the market power parameters stay unchanged in the short run, i.e., market power is related to n, not N. At the same time, consumer demand and farm supply curves shift. I assume that operational plants can adjust farm-product acquisitions and processed product outputs to respond to the new consumer demand $(a' - \alpha Q)$ and farm supply $(b' + \beta \frac{N}{N'} Q = b' + \beta' Q)$ functions after shocks occur.[15]

Given the new demand and supply function intercepts and supply function slope, the new

[14]These values are informed by weekly data from the beef supply chain from 2019-2020 and reflect that shutdowns and stockpiling are likely to be highly correlated, supply shifts and demand shifts moderately correlated, and supply shifts and processor shutdowns slightly correlated. The results are not sensitive to the choices of these correlation values.

[15]For example, additional farm supplies can be called forth by bringing product from storage or accelerating harvesting. Processing throughput can be expanded by operating a Saturday shift, as occurred in beef processing during the COVID-19 pandemic.

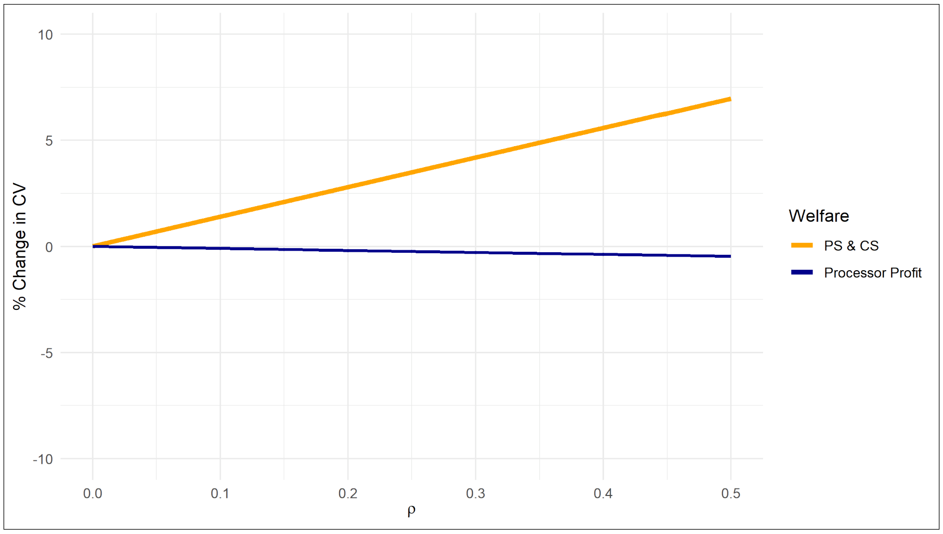


Figure 4.3: Correlation between shocks at different supply chain stages.

Note: Authors' creation from numerical simulation. Figure displays the implications of increasingly correlated shocks at different supply chain stages. The vertical axis measures percentage changes in CV of producer, consumer, and processor surplus under correlated shocks relative to independent shocks. Welfare outcomes are calculated using the post-shock equilibrium defined in equation 4.15.

industry output is:

$$Q^{oo'} = \frac{a'(1-\frac{\xi}{\eta}) - b'(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta'(1+\frac{\theta}{\epsilon})}. \tag{4.15}$$

Per plant output is $\frac{Q^{oo'}}{N'}$. Equilibrium prices and welfare measures are computed accordingly.

4.3 Simulations

I study four widely discussed policy responses intended to protect consumers and farmers by reducing supply chain volatility in response to market shocks: 1) reducing intermediary market power, 2) subsidizing the entry of processors, 3) limiting retail price increases through anti-price-gouging laws, and 4) creating regional diversification of production capacity.

I simulate each policy proposal and report its impact on mean economic surplus and the relative volatility of surplus (i.e., CV) for farmers, consumers, and market intermediaries. I present the results for the latter three policy interventions for three alternative levels of processor market power: perfect competition ($\xi = \theta = 0$), moderate market power ($\xi = \theta = 0.15$), and high market power ($\xi = \theta = 0.3$) to reflect different market structures in key agricultural industries.[16]

The simulation outcomes are summarized in the following figures. In each figure, the vertical axis tracks percentage changes in the mean welfare measures and their CV as market parameters (e.g., market power parameters ξ and θ) change. The percentage changes along the vertical axis are computed relative to the baseline scenario that is depicted as the leftmost parameter value for each simulation. Online Appendix 4.5.2 explains mathematically why the mean surplus and CV curves follow particular patterns and why the curves for CS and PS tend to follow the same pattern. Though the mathematics determining the patterns may be somewhat complicated, numerical simulations and outcomes depict the market resilience and efficiency impacts as I explain below.

4.3.1 Reducing Intermediary Market Power

The economic welfare implications of market power in the food and agriculture sector have long been a focus for agricultural economists (Sexton and Xia 2018; Crespi and MacDonald 2022). However, little is known about the resiliency impacts of intermediary market power. Figure 4.4 shows the impacts of market power in the range $\xi = \theta \in [0, 0.3]$ on resilience measured in terms of CV (left panel) and mean economic surplus (right panel) based on 100,000 simulations for each value of $\xi = \theta$.

The right panel displays the well-understood result that, as intermediary market power decreases, consumers and producers gain economic surplus and processors lose profits. Less understood, however, is that CV for consumers' and farmers' surplus also decreases as the intermediary market power falls, as does CV of processors' profits. Both the standard deviation of surplus and its mean value for farmers and consumers rise as the level of processor market power drops, but mean surplus rises faster than the standard deviation, causing CV to fall.[17]

These results are the first demonstration that, in the presence of correlated economic shocks,

[16] Although the market power parameters are not tied to a particular form of competition, it is useful to relate them to non-cooperative Cournot competition, where $\xi = \theta = 0.15$ corresponds approximately to the market power generated by 6–7 symmetric Cournot competitors and to a Hirschman–Herfindahl (HHI) index of approximately 1,500, a value that the US Department of Justice regards as moderately concentrated in its Merger Guidelines. $\xi = \theta = 0.3$ corresponds to Cournot competition involving 3 or 4 symmetric firms, and an HHI index in the range of 2,500 to 3,300, which would be considered as highly concentrated by the DOJ under the Merger Guidelines. Notably four-firm oligopoly-oligopsony corresponds roughly to the market structure for the US beef and pork industries (U.S. Department of Agriculture 2022).

[17] Intermediaries with market power rationally pass on less of a demand or supply shock to farmers and consumers than would occur in a perfectly competitive market because they internalize a portion of the impact their output decision has on the farm price and consumer price. Conversely, perfect competitors treat these prices as given.

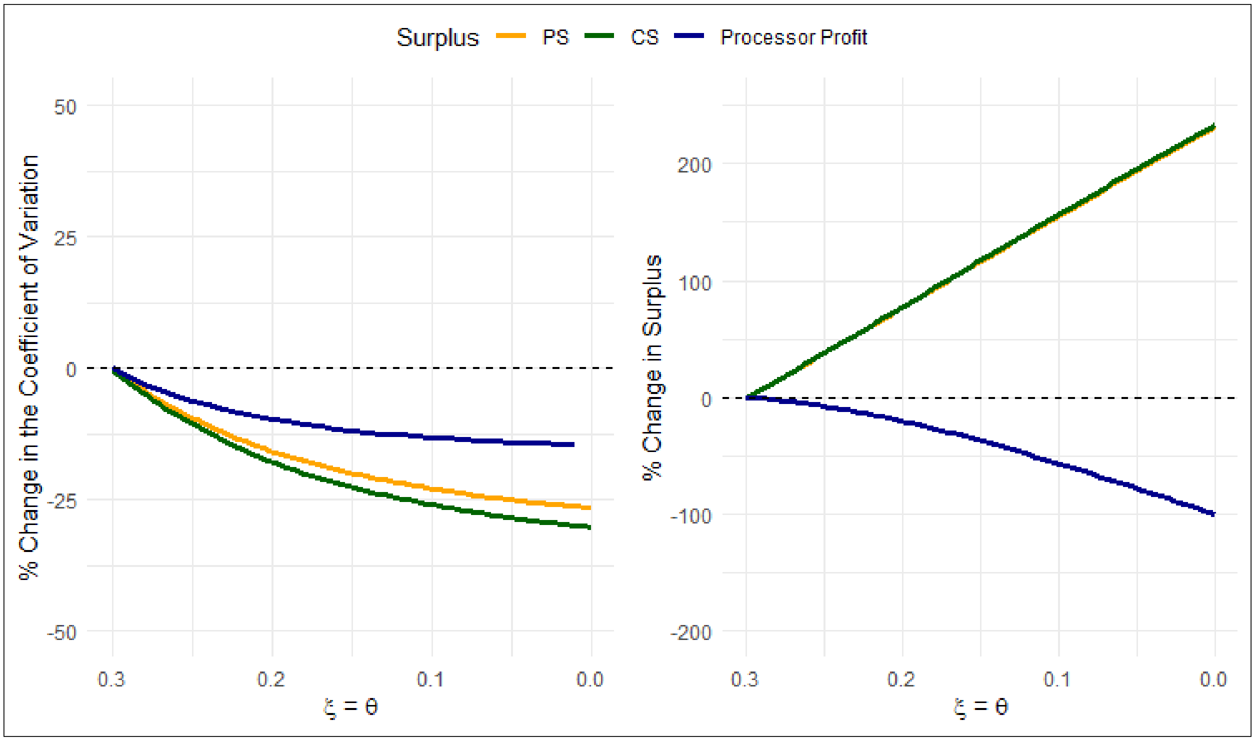


Figure 4.4: Impacts of decreasing intermediary market power on market surplus and resilience.

Note: Authors' creation from numerical simulations. The vertical axis measures the percentage changes in CV (left panel) and mean surplus (right panel) relative to the high market power setting ($\xi = \theta = 0.3$). The left panel displays the reliance gains from competition, and the right panel shows that producer and consumer surplus increase, and processor profit declines as market power decreases.

consumers and farmers benefit from both higher average economic surplus and reduced variability of surplus from policies that induce more competitive supply chains. Thus, policies designed to increase competition among market intermediaries may represent "win-win" outcomes for consumers and farmers.

4.3.2 Entry of Processors

One of the primary policy responses in the US to the COVID-19 pandemic and disruptions caused in the meat supply chains is a USDA initiative which provides $500 million to support entry of new firms into meat and poultry processing (U.S. Department of Agriculture 2021).[18] The objectives of this policy are to increase competition in local regions and to reduce bottlenecks in meat processing

[18]While meat processing has received the most intense scrutiny due to allegations of anti-competitive behavior, other segments of food supply chains have received similar critiques. In early 2022, for example, USDA launched an investigation into the fertilizer, seed, and food retail markets as a result of heightened prices (U.S. Department of Agriculture 2022).

under shutdown risks.

The potential resiliency improvements from processor entry in the model are twofold. First, additional processing plants disperse shutdown risks over a larger number of operations, thus diversifying the risk of losing processing capacity and reducing variance in industry output. Second, additional processors potentially increase competition among processors, which, as figure 4.4 demonstrates, increases average surpluses to farmers and consumers and decreases the CV of those surpluses.

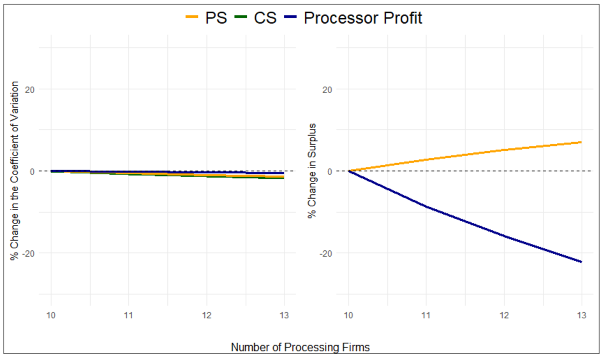
The main focus of the US policy is to support entry of small-scale processors. Given the model framework, I simulate entry by processors that are symmetric with the incumbent processors. A limitation of this approach is that it cannot capture the aspects of small-scale processing and local/regional food systems that remained resilient amidst the COVID-19 pandemic.[19] On the other hand, this approach tends to errs in favor of a policy to stimulate entry because entrants in the model have the same marginal cost as incumbent processors, whereas small-scale entrants will have higher unit costs in the presence of economies of scale. Symmetric entrants also expand market competition in the model in ways that small-scale entrants may be unable to accomplish in reality.[20] Counterbalancing the enhanced resiliency and reduced market power from adding processors is that per plant throughput declines for all plants as more plants are added for a given farm supply function, meaning that processing plants are less able to exploit the available economies of size.

I simulate adding processors for each of the three market competition scenarios and assume that market power parameters are dependent on n, reflecting symmetric, non-cooperative Cournot competition among processors, such that $\xi = \theta = \frac{1}{n}$. Each processor operates $\frac{N}{n}$ plants, where N is equal to 40 in the baseline in accordance with table 4.2. Therefore, as n increases, the total number of processing plants simultaneously increases, dispersing the risk of plant shutdown.

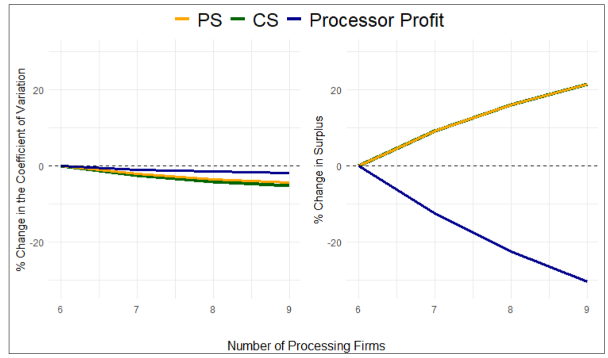
The nearly competitive scenario begins with $n = 10$ processors and sequentially introduces entering processors to reach $n = 13$. Processor market power is less consequential in these settings, ranging from $\xi = \theta = 0.08$ for $n = 13$ to $\xi = \theta = 0.10$ for $n = 10$. Similarly, moderate market

[19]Thilmany et al. (2021) argue that such systems involve shorter supply chains, with greater connectivity among supply-chain participants. These factors, they argue, enable participants in these supply chains to respond nimbly and flexibly to supply-chain disruptions.

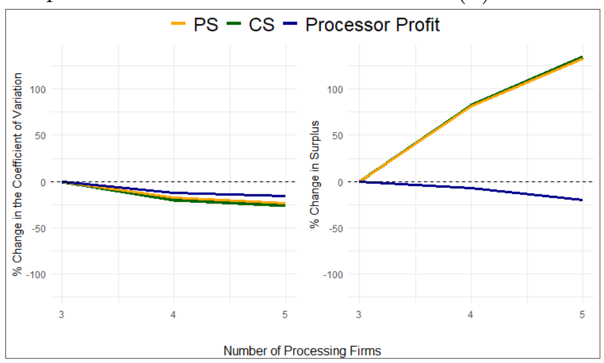
[20]For example, small food processors may only serve local or regional markets, leaving national concentration largely unaffected. Online Appendix 4.5.3 depicts simulations for the case where processor entry does not affect processor market power, isolating the impacts of entry on plant shutdown risk and plant economies of scale.



(a) Nearly Competitive



(b) Moderate Market Power



(c) High Market Power

Figure 4.5: Impacts of processor entry on average market surplus and resilience.

Note: Authors' creation from numerical simulations. Vertical axis measures the percentage changes in CV (left panels) and mean surplus (right panels) relative to the baseline number of processors for each scenario.

power is reflected by $n = 6$ ($\xi = \theta = 0.17$) to $n = 9$ ($\xi = \theta = 0.11$) and high market power by $n = 3$ ($\xi = \theta = 0.33$) to $n = 5$ ($\xi = \theta = 0.20$). For each value of n, I simulate 100,000 correlated shocks to demand, supply, and processing capacity.

Figure 4.5 reports simulation outcomes, with panels (a), (b), and (c) depicting the results for near perfect competition, moderate market power, and high market power, respectively. Similar to figure 4.4, lower levels of market power (larger n) are associated with smaller CV of market surplus. Additionally, mean CS and mean PS overlap and rise as market power diminishes. The resilience and efficiency improvements are greater for small values of n. That is, there are decreasing returns from adding n. Thus, stimulating entry is most effective in enhancing resilience, when it is done in markets with low n or high market power *ex ante*. Online Figure 4.10 further shows that these resilience and efficiency improvements are mostly attributed to the reduced market power effect. When market power is held constant, the economies of size penalty from reduced throughput per plant unequivocally reduces average welfare outcomes for all agents. Thus, the efficacy of policies to induce processing plant entry hinge importantly on whether such entry reduces processor market power.

4.3.3 Anti-Price-Gouging Laws

About two-thirds of US states have price-gouging laws that engage during natural disasters or declared emergencies and that limit increases in retail prices during such episodes (Morton 2022). These laws were triggered in a number of jurisdictions in response to the COVID-19 pandemic. Price caps may also be imposed on an *ad hoc* basis under emergency powers that political leaders often have.

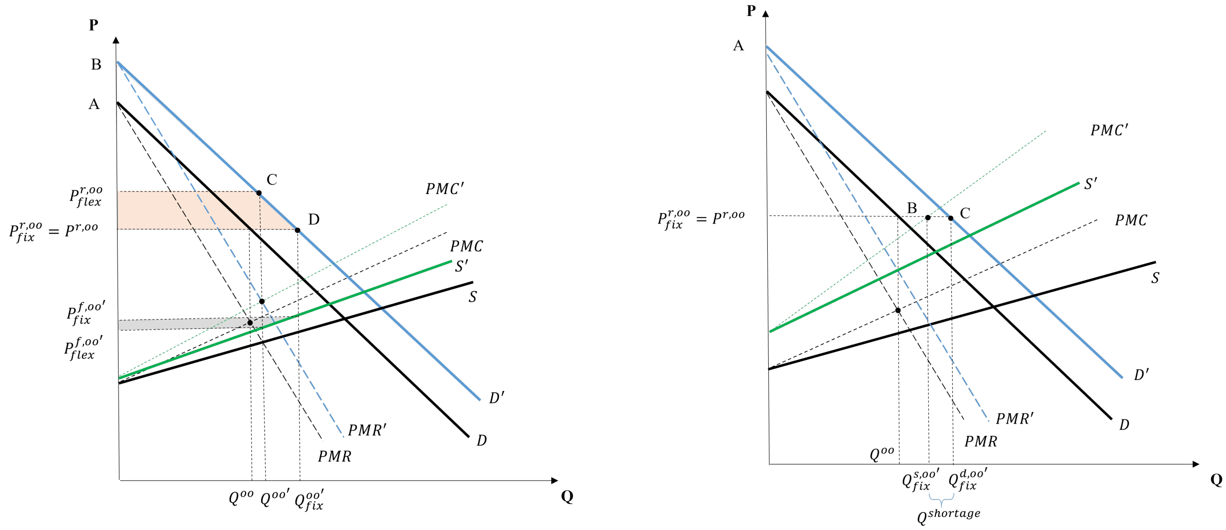
A key unanswered question, however, is how such anti-price-gouging laws impact supply chain resilience. When price is not allowed to signal market conditions and equilibrate the available supply with demand, shortages may ensue, and available products may not be allocated to the highest-valued consumer. Counterbalancing this effect is the fact that price ceilings do eliminate sellers' ability to exercise market power over a range of prices and, thus, may lead to increased industry output and higher CS and PS.

To illustrate the impact of anti-price-gouging laws, consider the case where retail prices are fixed at the risk-free (pre-shock) level: $P^{r,oo} = a - \alpha Q^{oo}$ as specified in equation (4.2).[21] Allowing for flexible prices, the new equilibrium quantity produced post-shock, $Q^{oo'}$, is given by equation (4.15) and yields the flexible retail price $P^r(Q^{oo'}) = P^{r,oo}_{flex}$. The impact of capping the retail price at the pre-shock level, $P^{r,oo} = P^{r,oo}_{fix}$, is illustrated by two cases described in figure 4.6.

In Case 1 (left panel), the price ceiling, $P^{r,oo}_{fix}$, intersects the new demand curve, D', at $Q^{oo'}_{fix}$, before it intersects the post-shock PMC curve, PMC'. For all $Q \leq Q^{oo'}_{fix}$, $PMR(Q) = P^{r,oo}_{fix} > PMC'$. For any output larger than $Q^{oo'}_{fix}$, $PMR(Q) < PMC'$. Therefore, the processors produce $Q^{oo'}_{fix} > Q^{oo'}$ and charge the ceiling price, $P^{r,oo}_{fix}$. No shortage is created by the price ceiling. Both CS and PS increase relative to the flexible-price case, with the gain to consumers (producers) indicated by the pink (gray) shaded areas.

In Case 2, $P^{r,oo}_{fix}$ intersects (PMC'), at point B, before it intersects D'. Processors maximize

[21] Anti-price-gouging laws may also be applied to farm prices. Online Appendix 4.5.4 studies the case of price fixed at the farm level.



Case 1

Case 2

Figure 4.6: Fixing the post-shock retail price at the pre-shock level.

Note: Authors' creation. Case 1 illustrates a market setting wherein a price-ceiling eliminates seller power and does not cause a market shortage. Case 2 illustrates a post-shock equilibrium where the price ceiling does create a market shortage, with quantity demanded exceeding quantity supplied at the fixed price.

profits by producing quantity $Q^{s,oo'}_{fix}$, while consumers demand $Q^{d,oo'}_{fix}$, resulting in a market shortage equal to $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$.[22]

Given a shortage, the market could clear in various ways. For example, product could be allocated based on queues, and secondary markets could possibly reallocate product from low- to high-demand consumers. However, secondary resale markets for foods subject to shortage did not occur with any frequency in the US during the COVID pandemic, nor were consumer queues common. Rather, available products were allocated seemingly at random based on when shelves were restocked and consumers happened to arrive at stores.

We, thus, assume that the quantity supplied, $Q^{s,oo'}_{fix}$, is randomly allocated among all consumers who are willing to purchase at $P^{r,oo}_{fix}$. Consumer surplus is then computed by:

$$\frac{Q^{s,oo'}_{fix}}{Q^{d,oo'}_{fix}} \int_0^{Q^{d,oo'}_{fix}} \left(D'(Q) - P^{r,oo}\right) dQ. \tag{4.16}$$

Failure of product to be allocated to the consumers who value it most represents a welfare loss from

[22]Both cases depicted in figure 4.6 show post-shock output increases relative to the pre-shock equilibrium. Output may decrease depending on the magnitude of shocks and extent of processor market power. Online Appendix 4.5.4 discusses it.

fixed prices that offsets the benefit in reducing processor oligopoly power.

Anti-price-gouging laws typically allow some flexibility in prices post-shock.[23] We, hence, incorporate a continuum of price flexibility in the simulations from the pre-shock level, $P^{r,oo}$ by setting price $\bar{P}^{r,oo} = P^{r,oo}(1+\omega)$ for $\omega \geq 0$. Smaller values of ω denote a tighter price ceiling. For sufficiently large values of ω, the price ceiling will not bind. I present simulation results in figure 4.7 for $\omega \in [0, 0.60]$, where $\omega = 0.60$ allows sufficient price flexibility that the ceiling does not bind in the model, while $\omega = 0$ represents no flexibility and price is fixed at the pre-shock level.

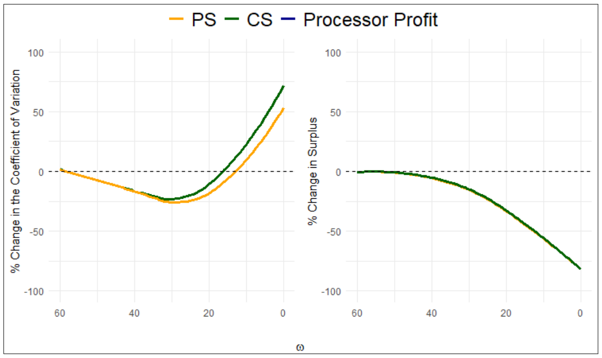
The three panels reflect both of the two possible cases of price ceilings illustrated in figure 4.6. Panel (a) depicts a perfectly competitive market, so $\bar{P}^{r,oo}$ represents Case 2 across all values of ω. Mean CS and PS are increasing in ω, while processor profits are zero for all ω under perfect competition.[24] Larger values of ω are associated with reduced volatility of welfare. More stringent price ceilings (i.e., $\omega < 15\%$) however, increase CV for both consumers and producers, reducing resilience. CS and PS also fall due to the induced shortages they create, resulting in a "lose-lose" scenario.

Panel (b) illustrates a supply chain with moderate market power. Here, Case 1 emerges and yields higher values for CS and PS for all but the most stringent price ceilings. These benefits are maximized when $\omega \approx 15\%$. As the price ceiling becomes stricter, a mix of Cases 1 and 2 holds across the 100,000 simulations. CV of CS and PS also have a nonlinear relationships with ω. The resilience improvement is maximized at $\omega = 0$ with the CV reduced by 30% from the flexible-price level. For $\omega > 20\%$, the relative volatility for CS and PS is higher than the flexible-price level. A "win-win' outcome can be achieved for ω ranging from about 0.05 to 0.15.

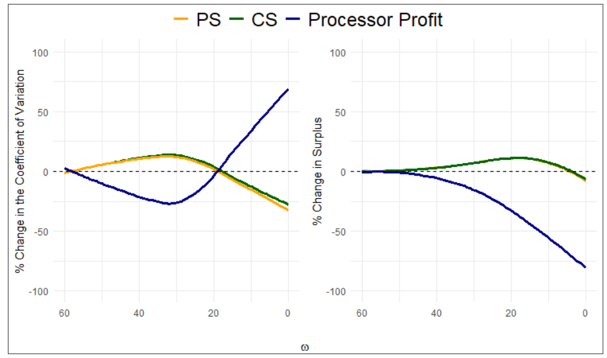
Panel (c) depicts a higher level of processor market power and the predominance of Case 1. Price ceilings increase CS and PS the most in these settings because of the market-power-reducing effect. The increase in CS and PS is greatest for the most stringent price ceilings. However, the CV of CS and PS is larger over most of the range of ω. For example, at $\omega = 20\%$, CV of CS and PS is greater by upwards of 40% compared to the market with no price restriction. Thus, under

[23] California's Penal Code Section 396, for example, prohibits price increases by more than 10% after an emergency declaration or 50% above the seller's cost to produce the good or service.

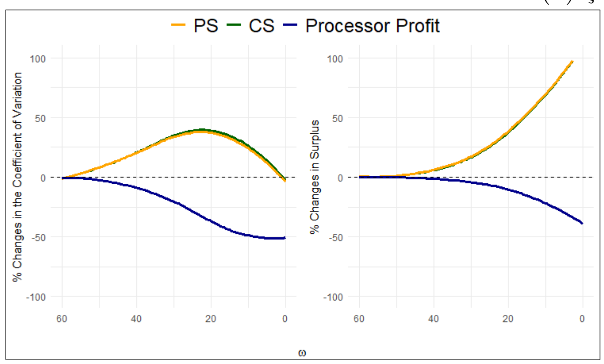
[24] Under perfect competition, a binding price ceiling leads to welfare losses for both producers and consumers due to the shortage that necessarily occurs in the competitive case and restricting both farm production and consumption below the surplus-maximizing levels. See more discussion in online Appendix 4.5.4. For example, allowing prices to increase by no more than 10% lowers average CS and PS by about 35%.



(a) $\xi = \theta = 0$



(b) $\xi = \theta = 0.15$



(c) $\xi = \theta = 0.3$

Figure 4.7: Impacts of anti-price-gouging laws on market surplus and resilience.

Note: Authors' creation from numerical simulations. Vertical axis measures the percentage changes in CV (left panels) and mean surplus (right panels) relative to a fully flexible price. The impacts of price ceilings are highly non-linear and depend critically on market structure. Processor profit is omitted from panel (a) because it is zero in each instance.

higher intermediary market power, anti-price-gouging laws benefit producers and consumers most by transferring surplus to them from intermediaries, but they do not improve the resilience of supply chains. A win-win outcome for producers and consumers can, however, be achieved as ω approaches zero.

Figure 4.8 illustrates the effects of binding price ceilings on market shortages under different market competition scenarios. The vertical axis measures shortage as the difference between the normalized quantity demanded and the quantity supplied at the fixed price. Despite the fact that price is more stable and seller power is essentially eliminated with a strict anti-price-gouging law, such a law does not necessarily improve farmer and consumer welfare or reduce the volatility of CS and PS. Market shortages created by these laws are more severe, the more competitive the underlying market structure. Anti-price-gouging laws are most likely to increase CS and PS the less competitive is the market, but in these cases, as figure 4.7 demonstrates, the laws often increase the

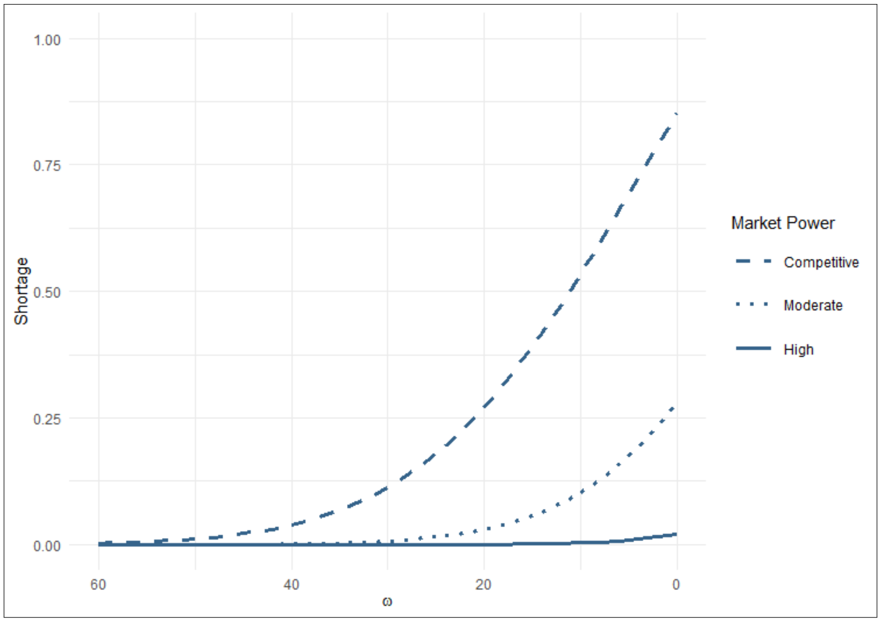


Figure 4.8: Market shortage with a price ceiling with different levels of market power.
Note: Authors' creation from numerical simulations. The vertical axis measures the difference between normalized quantity demanded and quantity supplied under the level of price ceiling. The horizontal axis indicates the tightness of the price ceiling; smaller ω is, tighter the ceiling. The curves show that a price ceiling introduced in a competitive market induces a greater shortage compared to the same ceiling implemented in an imperfectly competitive market.

volatility of producer and consumer returns as measured by CV.

Although I have simulated an anti-price-gouging law for a single supply chain, in reality they paint with a "broad brush." They generally apply to all food and drink products, as well as a variety of other products deemed as necessities, regardless of the competitive structure. The efficacy of these laws, thus, depends importantly on overall competitive conditions of food markets within the implementing jurisdiction and the stringency with which price increases are restricted.

4.3.4 Regional Diversity of Farm Production

Agricultural production in the US has become increasingly geographically concentrated as regions produce according to their comparative advantages. Distributing agricultural production and processing across geographically diverse regions and emphasizing localized food systems has been proposed as a resilience strategy (Raj, Brinkley, and Ulimwengu 2022) because supply shocks in one region may not impact other regions and geographically diversified food systems may be able to adapt more nimbly to extreme shocks than concentrated systems (Thilmany et al. 2021; U.S. Department of Agriculture 2022).[25]

Although diversifying production of key commodities across multiple regions may enhance the supply chain's resilience to some shocks, it will likely come at a cost of reduced production efficiency (Sexton 2009). To explicate this trade-off in the simplest way, I examine the marginal change of expanding from a single production and processing region to two regions. To ensure analytical solutions, I assume that each region has the same number of plants, and the plants belong to the same group of symmetric processors. It follows that the two regions have the same buyer power and seller power. Marginal processing costs are thus $c^w = c \times (RN)^\gamma$, where $R > 1$ denotes the number of production regions.

The retail market remains national as in the baseline case, with demand as specified in equation (4.2). I assume that no farm product is transferred between production regions, thereby allowing local plants in different regions to face different supply functions:

$$\begin{aligned} P_1^f(Q_1|X_1, \mu_1) &= b_1 + 2\beta Q_1 \\ P_2^f(Q_2|X_2, \mu_2) &= b_2 + 2\beta Q_2, \end{aligned} \tag{4.17}$$

where subscript 1 refers to the base region of farm production and 2 refers to the new region.[26]

Solving the two-region system, I obtain the equilibrium total output (see online Appendix 4.5.1 for details):

$$\tilde{Q^{oo}} = \frac{a(1-\frac{\xi}{\eta}) - \bar{b}(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}, \tag{4.18}$$

where $\bar{b} = \frac{b_1+b_2}{2}$. Plugging $\tilde{Q^{oo}}$ into the first-order-conditions, I obtain the pre-shock regional equilibrium output:

$$\tilde{Q_i^{oo}} = \frac{a(1-\frac{\xi}{\eta}) - \bar{b}(1+\frac{\theta}{\epsilon}) - c^w + \frac{\alpha(1-\frac{\xi}{\eta})}{\beta}(\bar{b} - b_i)}{2\alpha(1-\frac{\xi}{\eta}) + 2\beta(1+\frac{\theta}{\epsilon})}, \tag{4.19}$$

[25] A specific contemporary U.S. example is the Local Food Purchase Assistance Cooperative Agreement Program, authorized through the American Rescue Plan, which invests $400 million for government purchases of locally produced and processed foods.

[26] When $b_1 = b_2 = b$ (here b is the supply function's intercept in the baseline setup) and if c^w is the same as in the baseline, each region produces exactly one half of the equilibrium output in the one-region scenario, Q^c, and regions have the same supply elasticity under perfect competition.

where $i = 1, 2$. The term, $\frac{\alpha(1-\frac{\xi}{\eta})}{\beta}(\bar{b} - b_i)$, in the numerator is the deviation from half of the industry output or $\frac{Q_i^{oo}}{2}$. Intuitively, the larger b_i or the more costly it is to produce farm outputs in region i, the less the region produces in equilibrium. If $b_2 > b_1$, the new region produces less than the incumbent region due to higher production costs.

The two regions face independent supply shocks (μ_1, μ_2) and the same demand shock at the national level in the simulations. The supply function of region 2 has an intercept equal to $b + k$ where $k = f \times 0.23 = 0.069$, reflecting production costs that are 23% higher than the first region due to the cost inefficiencies of local production found by Sexton (2009). Each region also faces independent shutdown risks among its plants, so that N_i' plants remain active in region i. As a result, PS differs across regions and equals $\frac{P_i^f \tilde{Q_i^{oo}}}{2} = \beta_i' \tilde{Q_i^{oo}}^2$. When $b_2 > b_1$, $PS_2 < PS_1$.

The post-shock equilibrium output equals:

$$\tilde{Q^{oo'}} = \frac{a'(\beta_1' + \beta_2')(1 - \frac{\xi}{\eta}) - B(1 + \frac{\theta}{\epsilon}) - (\beta_1' + \beta_2')c^w}{\alpha(\beta_1' + \beta_2')(1 - \frac{\xi}{\eta}) + 2\beta_1'\beta_2'(1 + \frac{\theta}{\epsilon})}, \tag{4.20}$$

where $\beta_i' = \beta \frac{N}{N_i'}$ and $B = b_1'\beta_2' + b_2'\beta_1'$. Region i's output is found from the first-order-condition of the region given $Q^{oo'}$:

$$(a' - \alpha Q^{oo'})(1 - \frac{\xi}{\eta}) - c^w = (b_i' + 2\beta_i' Q_i^{oo'})(1 + \frac{\theta}{\epsilon}). \tag{4.21}$$

The simulation results are presented in figure 4.9. Surpluses decline for all agents and market power values. There are resilience benefits for producers, but consumers' CV rises. When market power is high, for example, the decrease in mean CS is as much as 15% and that of PS is close to 10%, while the decrease in CV for PS is about 10% and CV for CS rises by 5%. Consumers suffer from higher relative volatility because mean CS falls faster than the variation of CS. The divergent trends in the CV for CS and PS imply additional trade-offs among stakeholders associated with this policy. In general, regional diversification of production does not represent a favorable policy option if production efficiency in the new region declines as indicated here. The only benefit is reduced CV of PS from spreading the production risk across multiple regions. Consumers do not benefit because less efficient production implies higher prices and more volatility in CS.

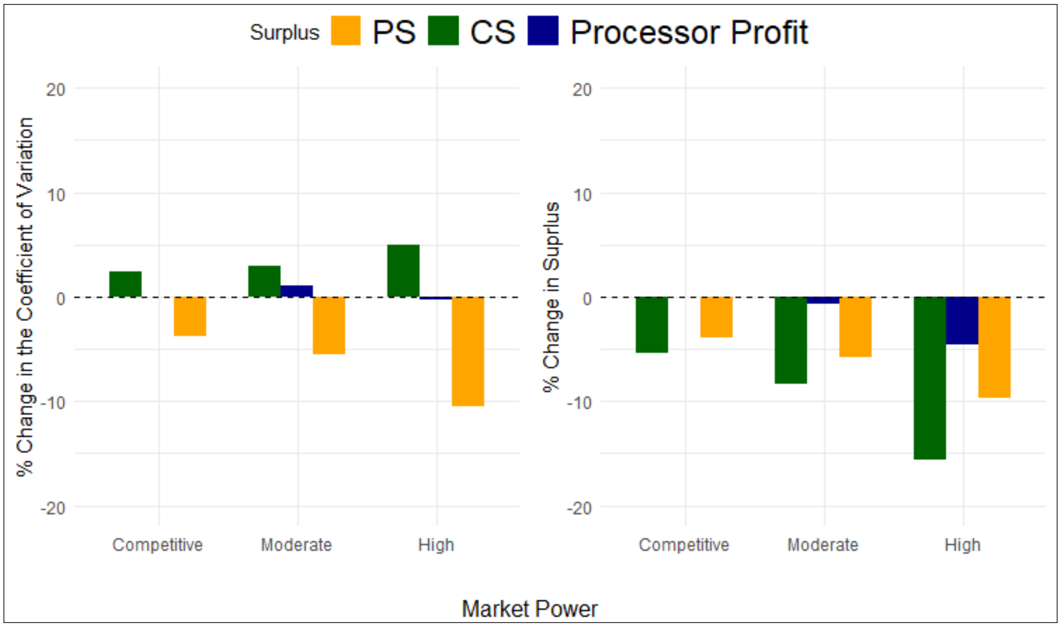


Figure 4.9: Impacts of adding a production region to market surplus and resilience.
Note: Authors' creation from numerical simulations. The vertical axis measures the percentage changes in CV (left panel) and mean surplus (right panel) due to moving from a single production region to two. The results show resilience benefits to producers, but not consumers. Mean surplus declines for all agents. Processor profit is omitted from the competitive case because it is zero in each instance.

4.4 Conclusion

Experiences of coping with food supply chain disruptions due to COVID-19 and the Russia-Ukraine conflict, as well as the recognition that extreme events are likely to become more common moving forward, have spurred interest in food supply chains and policies to improve supply-chain resilience. This paper has studied the efficiency and resilience impacts of four of the most prominent strategies being discussed or implemented in the US.

The supply-chain model allows for any representation of market competition ranging from perfect competition to pure monopoly/monopsony in the processing stage. This model flexibility is important in studying market resilience because market power of intermediaries has often been blamed for supply chains' lack of resilience, and strategies to enhance food markets' competitiveness have been at the forefront of policy discussions. A key innovation of the model framework is its recognition that extreme events are likely to introduce correlated shocks within a supply chain. I show that market disruptions from extreme events are more severe the greater the correlation of positive shocks to consumer demand and negative shocks to farm supply and processing capacity.

An essential contribution of this work is the quantification of the impacts of proposed policies on resilience under extreme shocks, as measured by the coefficient of variation of market surplus earned by each group of supply-chain participants, and market efficiency, as measured by the average market surplus achieved under the policy for each participant. The efficiency-resilience trade-off is crucial to policy evaluation because the popular belief is that the quest for efficiency has caused supply chains to become less resilient.

Results of the simulation analysis yield key insights regarding the proposed policies. Policies designed to stimulate competition among market intermediaries have the potential to yield win-win outcomes for farmers and consumers by transferring market surplus to them and reducing the variability of returns under extreme shocks.

Stimulating entry of processors is most effective in supply chains with high market power. Farmers and consumers benefit from significantly higher market surplus and lower variability of surplus in these settings. Benefits of entry are much more limited in settings that are already highly competitive or if entrants are unable to reduce the exercise of market power by incumbent processors.

The impacts of anti-price-gouging laws also depend critically on the competitive conditions of impacted supply chains. In competitive markets, restrictive price caps can be highly damaging, reducing consumer and producer surplus due to restricted production, creating shortages at the restricted price, and increasing the relative variability of surplus. The laws can be effective when imposed in less competitive markets, where they can increase market output instead of causing shortages. However, these laws generally reduce resilience to consumers and producers under extreme shocks, creating a trade-off between efficiency and resilience. Because anti-price-gouging laws apply widely in emergency situations, their overall efficacy in food markets hinges on competitive conditions across the full spectrum of markets where the laws would apply.

Diversifying production into multiple regions is unlikely to be beneficial regardless of market competition conditions if production in new regions is less efficient than in the incumbent regions. In all competitive settings considered, regional diversification reduced market surplus for all participants due to inefficiencies created in shifting production to less efficient regions and raising processing costs due to reduced exploitation of size economies. Regional diversification produced generally small and mixed effects on relative variability of returns, reducing variability for producers and increasing it for consumers.

A key finding is that widely discussed resilience policies in the US are most effective in supply chains with high levels of processor market power. They are generally less effective, or even harmful, in competitive or nearly competitive supply chains. Despite popular belief that important US food supply chains such as meats exhibit high processor market power, empirical research, much of it now somewhat dated and subject to methodological critiques, has generally found small values for θ and ξ (Sexton and Xia 2018). New studies of competitive conditions in key food supply chains represent a critical research need.

Though I focus on welfare impacts of policies under extreme shocks, three out of the four policies studied impact supply chains during normal times, while anti-price-gouging laws only activate during emergencies. Impacts of the three policies on normal-time surplus for producers, consumers, and processors follow the same patterns indicated by the simulations with supply-chain shocks. Specifically, more competitive supply chains, whether due to stricter enforcement of antitrust laws or subsidization of entry by new processing firms, also increase surplus for farmers and consumers during normal periods and provide the added benefit of being more resilient to extreme events. However, diversifying production into new, less-efficient regions reduces market surplus for all supply-chain participants in normal periods, while producing mixed results for resilience under extreme events.

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4.5 Appendix

4.5.1 Equation Derivations

In this appendix, I derive the first order conditions (FOC) and the marginal cost function in the Model section. Given the objective function and assuming that plants are of the same size in equilibrium:

$$\max_q \pi \equiv (P^r(Q) - P^f(Q))q - c^w q. \tag{4.22}$$

To solve the function, I take the FOC with respect to q, obtaining:

$$P^r - P^f + \frac{\partial P^r}{\partial q}q - \frac{\partial P^f}{\partial q}q - c^w = 0. \tag{4.23}$$

Rearranging the terms produces:

$$P^r(1 + \frac{\partial P^r}{\partial q}\frac{1}{P^r}q) - c^w = P^f(1 + \frac{\partial P^f}{\partial q}\frac{1}{P^f}q). \tag{4.24}$$

Further rearranging the terms generates:

$$P^r(1 + \frac{\partial P^r}{\partial Q}\frac{Q}{P^r}\frac{\partial Q}{\partial q}\frac{q}{Q}) - c^w = P^f(1 + \frac{\partial P^f}{\partial Q}\frac{Q}{P^f}\frac{\partial Q}{\partial q}\frac{q}{Q}). \tag{4.25}$$

Denote the inverse of absolute demand elasticity, $|\frac{\partial P^r}{\partial Q}\frac{Q}{P^r}|$, by $\eta > 0$, and the inverse of supply elasticity, $\frac{\partial P^f}{\partial Q}\frac{Q}{P^f}$, by $\epsilon > 0$. The term, $\frac{\partial Q}{\partial q}\frac{q}{Q}$, is denoted by $0 \leq \xi \leq 1$ $(0 \leq \theta \leq 1)$ and is the seller (buyer) power parameter.

Similarly, I rewrite the equation:

$$P^r(1 - \frac{\xi}{\eta}) - c^w = P^f(1 + \frac{\theta}{\epsilon}). \tag{4.26}$$

Plugging in the linear demand and supply function, I find equation 4.10 in the main text.

To solve the two-region problem, I conduct a similar procedure with two FOCs that resemble equation 4.10:

$$(4.27)\qquad \begin{aligned}(a-\alpha Q)(1-\frac{\xi}{\eta})-c^w &= (b_1+\beta Q_1)(1+\frac{\theta}{\epsilon})\\ (a-\alpha Q)(1-\frac{\xi}{\eta})-c^w &= (b_2+\beta Q_2)(1+\frac{\theta}{\epsilon}),\end{aligned}$$

where the subscript indices the region and $Q_1+Q_2=Q$. Solving the system of equations simultaneously, I find the equilibrium total regional outputs $\tilde{Q^{oo}}$ as in equation 4.18. Plugging $\tilde{Q^{oo}}$ to the system of equations above, I find regional equilibrium outputs as specified in equation 4.19.

The derivation of the marginal cost function, $c^w(N)=cN^\gamma$, is worth some illustration, too. Given equation 4.12 that $mg(\frac{1}{N})^{g-1}=cN^\gamma$, the general expression for γ is:

$$(4.28)\qquad \gamma=(1-g)+\frac{\ln\frac{mg}{c}}{\ln N}.$$

In Morrison Paul (2001a), the total cost is a function of the plant-level output, q, and expressed as $C(q)=mq^g$ with $g\in(0,1]$. The cost elasticity of plant-level output *per se* is independent from the output.

Similarly in this setup, γ captures the cost elasticity with respect to the number of plants, N. The number of plants determines the equilibrium plant-level output under perfect competition. Thus, γ captures the cost elasticity of plant output and should not be a function of N. To make γ independent from N, I let $\ln\frac{mg}{c}=0$ or $\frac{mg}{c}=1$. Thus, I obtain equation 4.13 in the main text.

4.5.2 Coefficient of Variation and Mean Welfare Measures

This appendix develops the mathematics for the CV and mean values of PS and CS. I start with the mean CS. Recall from the Model section that the pre-shock CS equals $\frac{(a-P^{r,oo})Q^{oo}}{2} = \frac{\alpha}{2}(Q^{oo})^2$ where

$$Q^{oo} = \frac{a(1-\frac{\xi}{\eta}) - b(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}. \tag{4.29}$$

Shocks change a, b, β, and N and result in a new industry equilibrium output $Q^{oo'}$:

$$Q^{oo'} = \frac{a'(1-\frac{\xi}{\eta}) - b'(1+\frac{\theta}{\epsilon}) - c^w}{\alpha(1-\frac{\xi}{\eta}) + \beta'(1+\frac{\theta}{\epsilon})}, \tag{4.30}$$

where $\beta' = \frac{N}{N'}\beta$. The corresponding CS, CS', can be computed as $\frac{\alpha}{2}(Q^{oo'})^2$.

Under shocks, the percentage change in the mean CS is determined by the percentage change in the industry output as a particular parameter changes (e.g., as market power increases in figure 4.4). For the same reason, changes in the mean post-shock PS are also determined by changes in the industry output. Thus, in most figures, the curves of changes in the mean post-shock CS and mean post-shock PS overlap.

The two curves deviate slightly in figure 4.5 because of a rounding issue for integers in computing $\beta' = \frac{N}{N'}\beta$ that enters $Q^{oo'}$. Given different values of N, the simulated $\frac{N}{N'}$ differ. In general, $\frac{N}{N'}$ declines in N.

The curves of changes in the mean post-shock CS and mean post-shock PS curves in figure 4.9 also deviate because PS is not computed using the total industry output as CS is; PS is computed using two regional outputs, respectively, and then adding up the two regional PS values.

CV equals the standard deviation divided by the mean of CS under shocks. Formally, CV of CS equals:

$$\frac{\sqrt{\sum_{i=1}^{I}(CS_i' - \bar{CS'})^2\delta_i}}{\bar{CS'}} = \sqrt{\sum_{i=1}^{I}(\frac{CS_i'}{\bar{CS'}} - 1)^2\delta_i}, \tag{4.31}$$

where I is the number of simulation iterations, δ_i is the probability of each CS_i', and the δ_i add up to one. The mean of post-shock CS, $\bar{CS'}$, equals $\sum_{i=1}^{I} CS_i'\delta_i$.

Intuitively, the larger the deviation of CS_i' relative to pre-shock CS, the larger is $\frac{CS_i'}{\bar{CS'}}$. Therefore, CV increases in the relative magnitude of the CS pre and post the shocks. Given the parameter values, CV for CS increases in $\frac{CS'}{CS}$, which is proportional to $\frac{Q^{oo'}}{Q^{oo}}$, if $\frac{CS'}{CS} > 1$. If $\frac{CS'}{CS} < 1$, CV decreases in $\frac{CS'}{CS}$.

In the baseline simulations, $\frac{CS'}{CS} > 1$ and $\frac{Q^{oo'}}{Q^{oo}} > 1$ is the typical case where CV increases in $\frac{Q^{oo'}}{Q^{oo}}$ and hence increases in the ratio of:

$$R = \frac{a'(1-\frac{\xi}{\eta}) - b'(1+\frac{\theta}{\epsilon}) - c^w}{a(1-\frac{\xi}{\eta}) - b(1+\frac{\theta}{\epsilon}) - c^w}\frac{\alpha(1-\frac{\xi}{\eta}) + \beta(1+\frac{\theta}{\epsilon})}{\alpha(1-\frac{\xi}{\eta}) + \beta'(1+\frac{\theta}{\epsilon})}. \tag{4.32}$$

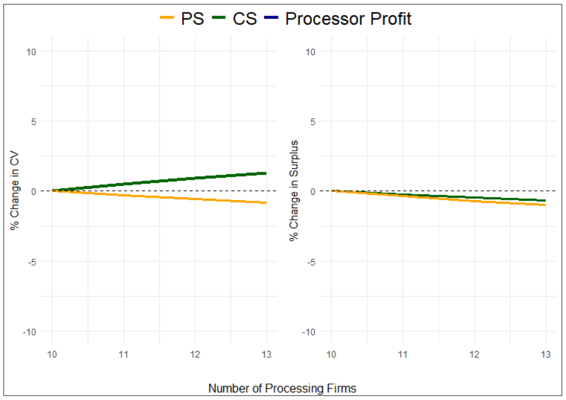
Taking first derivatives and given baseline parameter values, one can show, with complex mathematics, that R rises in ξ if $a' > a$ (i.e., a positive demand shock) and $\beta' > \beta$ which echoes figure 4.4. The complexity of analytical expressions supports the use of simulations as employed in the main body of this study.

Similarly, given that the post-shock PS equals $\frac{\beta}{2}(Q^{oo'})^2$, one can show that CV of PS is determined by $\frac{\beta' PS'}{\beta PS}$. Because $\beta' = \frac{N}{N'}\beta$, $\frac{\beta' PS'}{\beta PS}$ moves with $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}}$. The relative resilience of post-shock CS and post-shock PS follow the same pattern as long as $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}} > 1$ and $\frac{Q^{oo'}}{Q^{oo}} > 1$. If $\sqrt{\frac{N}{N'}}\frac{Q^{oo'}}{Q^{oo}} < 1$ and $\frac{Q^{oo'}}{Q^{oo}} > 1$, the patterns of CV for CS and PS differ.

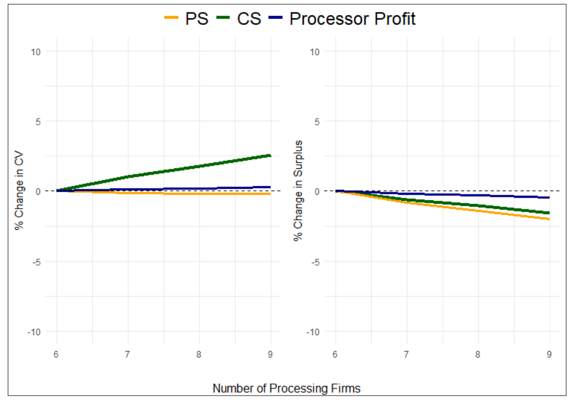
4.5.3 Processor Entry with No Market Power Effect

In the main text, I study processor entry for a setting where entry reduces processor buyer and seller power. Another possibility is that entry, especially by small-scale processors, does not impact the market power of incumbent firms. Figure 4.10 depicts impacts on CV and mean surplus for this case.

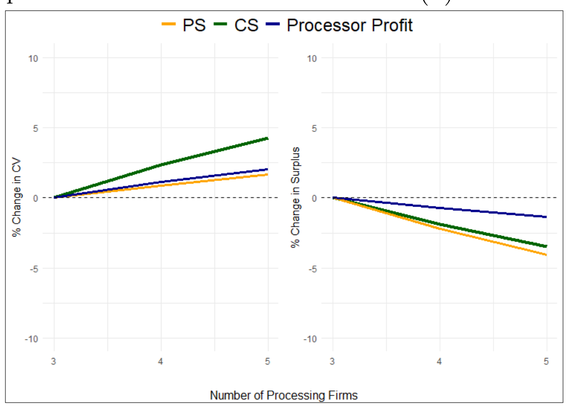
When market power is held constant, the economies of size penalty from entry unequivocally reduces average welfare outcomes for all agents. There is a small resilience gain for producers when the market power is low (i.e., N is large). The CV for PS decreases, when N is large because the variance of PS falls faster than the mean PS. The variance of PS decreases due to spreading production shocks over a larger number of plants. These results show that the resilience and efficiency improvements in figure 4.5 largely depend on the reduced market power effect of processor entry.



(a) Competitive



(b) Moderate Market Power



(c) High Market Power

Figure 4.10: Impacts of adding processors with constant market power on market surplus and resilience.

Note: Authors' creation from numerical simulations. Vertical axis measures the percentage changes in CV (left panels) and mean surplus (right panels) relative to the baseline number of processors for each scenario.

4.5.4 Anti-Price-Gouging Laws: Additional Cases

For both cases in figure 4.6 in the main text, the output supplied under a fixed price is larger than the pre-shock equilibrium output, Q^{oo}. I now illustrate a different case in figure 4.11 where output at the price cap is smaller than the pre-shock equilibrium output. Here, sellers have limited market power, and the fixed price, $P^{r,oo}$, intersects the new PMC curve ($PMC^{'}$) at output $Q^{s,oo'}_{fix} < Q^{oo}$. The market shortage is $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$. The welfare impacts of the shortage under random allocation of limited supply are the same as those discussed in Price-Gouging section.

Second, I discuss the impact of a price ceiling imposed on the farm price instead of on the retail price. Figure 4.12 depicts this case. Absent an anti-price-gouging law, equilibrium output occurs where $PMR^{'}$ intersects $PMC^{'}$ at output $Q^{oo'}$, with farm price $P^{f,oo'}$. However, under anti-price-gouging, the farm price ceiling is set at the pre-shock level, $P^{f,oo}$.

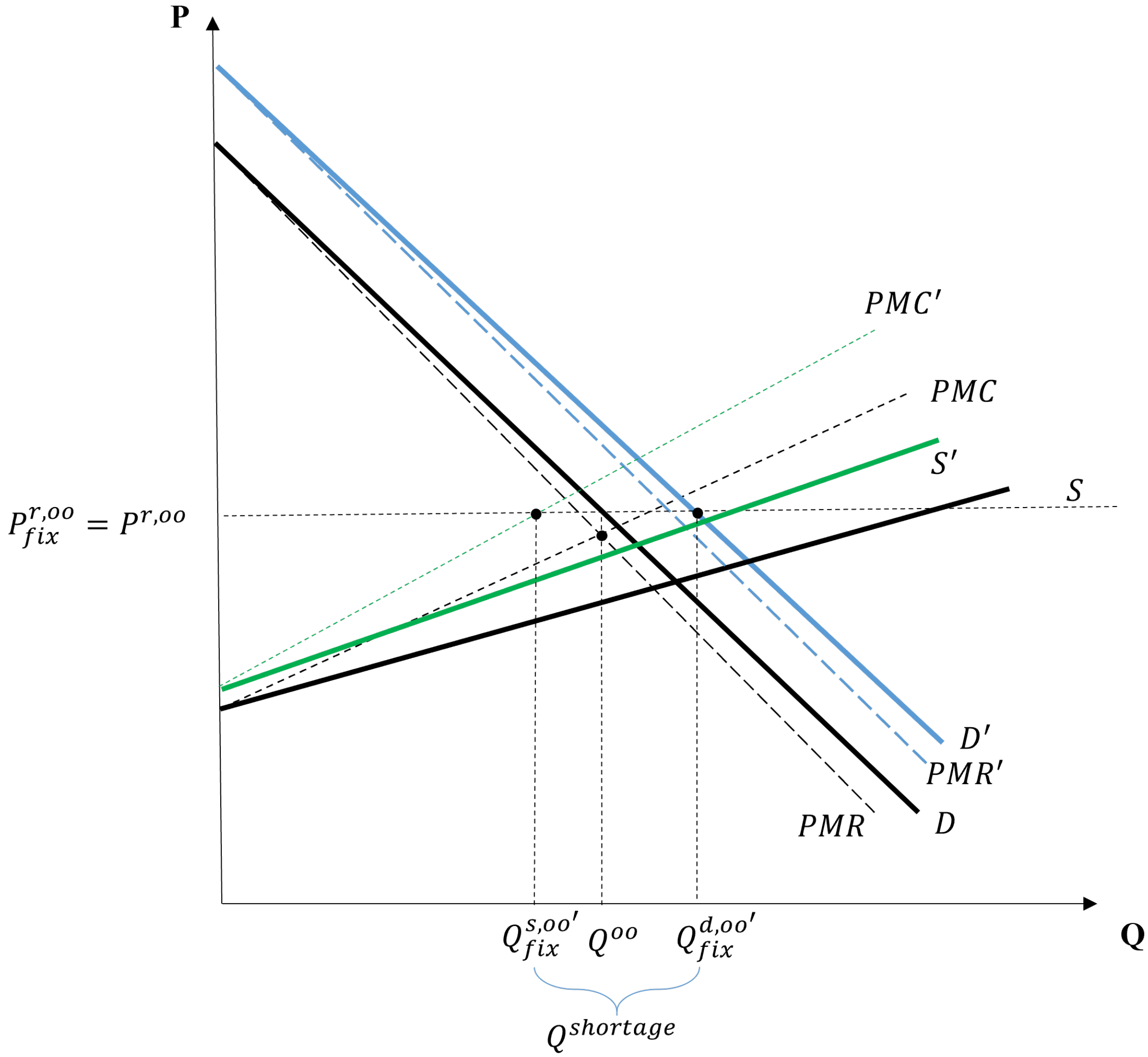


Figure 4.11: Fixing the retail price under limited seller power

Portions of the post-shock supply curve, $S^{'}$, above $P^{f,oo}$ are no longer attainable. The price ceiling, $P^{f,oo}$, thus, represents the processors' PMC for purchasing farm outputs. Processors demand $Q^{d,oo'}_{fix}$ at this price, but suppliers only provide $Q^{s,oo'}_{fix}$. The market shortage is $Q^{d,oo'}_{fix} - Q^{s,oo'}_{fix}$.

Finally, the effect of retail price stickiness under no seller or buyer power is illustrated in figure 4.13. Though it shares much similarity with the cases under imperfect competition, there is no incentive for the processor to reduce the output for higher prices to begin with. As a result, imposing the fixed retail price would unambiguously result in a smaller equilibrium output and a shortage of supply. The processor produces Q prior to the shocks and charges P. Post the shocks, the price is fixed at $P_{fix} = P$. This price meets the new supply curve, S', at Q^s_{fix} which is strictly smaller than Q_{flex}. The shortage of supply is $Q^d_{fix} - Q^s_{fix}$. Note that this case applies even if there is buyer power in the market because the key driver for a shortage is the lack of seller power.

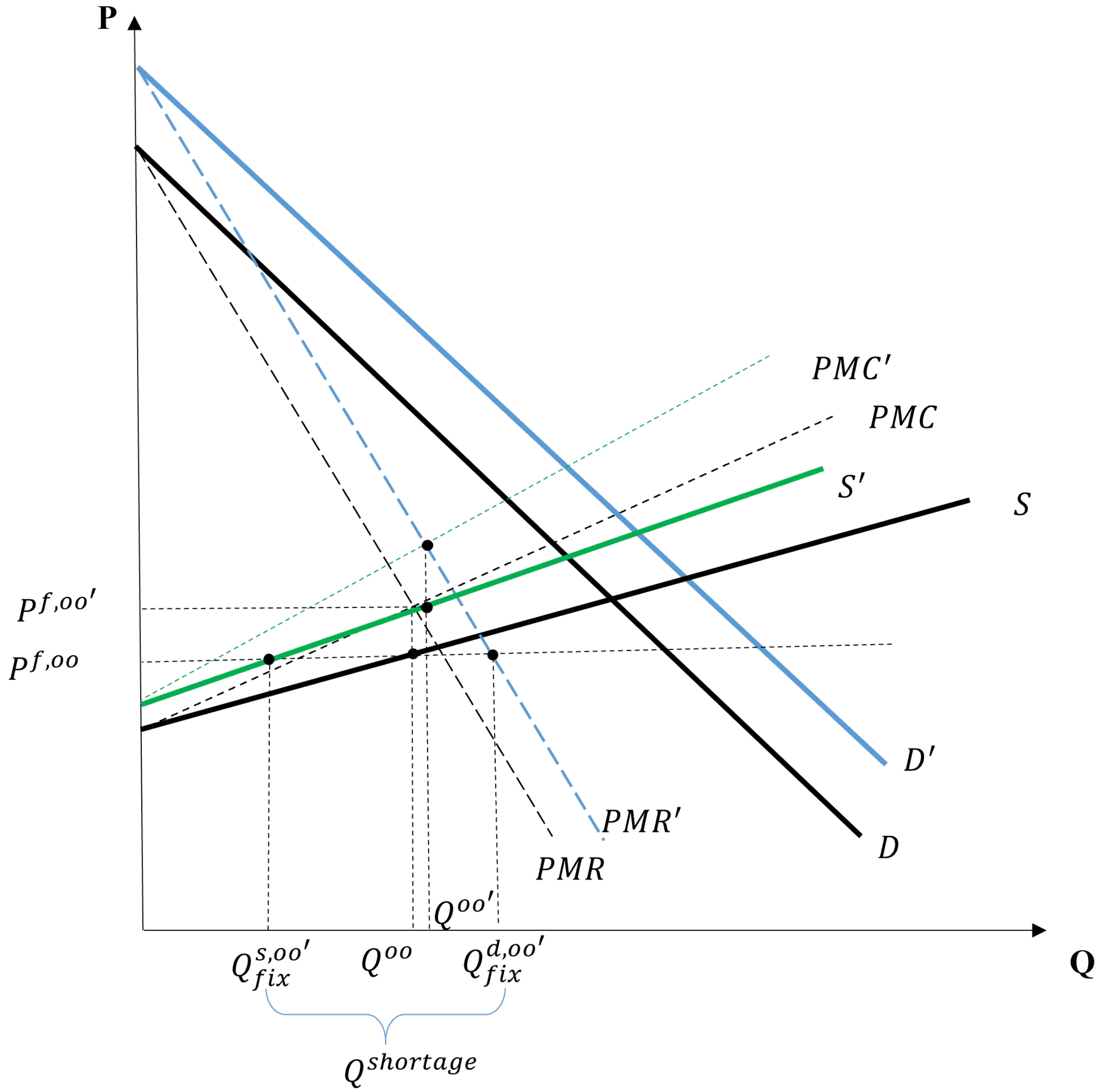


Figure 4.12: Fixing the farm price under imperfect competition

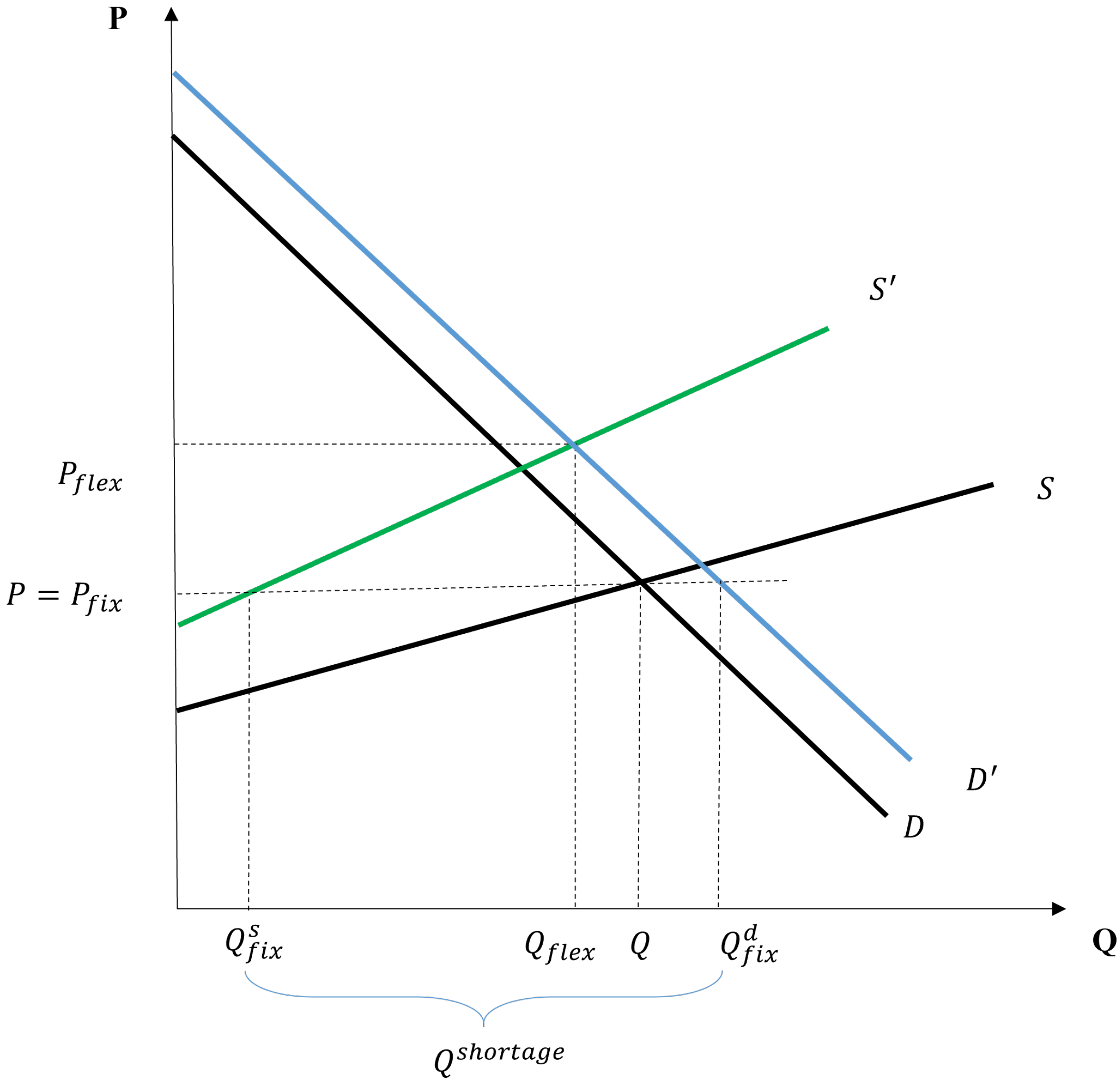


Figure 4.13: Fixing the retail price under perfect competition