Three Essays in Environmental Economics

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ABSTRACT

The first chapter of this dissertation analyzes how policy uncertainty affects electric utility investment rates. Policy can either positively or negatively impact firm profits, as seen in the difference between subsidies and taxes. Using a real option theoretical model, I show how uncertainty over these two types of policies can have positive or negative impacts on investment rates. Empirical results using investment data for electric utilities provide evidence in support of differential effects of uncertainty. I find a positive effect of policy uncertainty on electric utility investment rates using my preferred measure of policy uncertainty. This suggests that policies applicable to electric utilities negatively impact their profits, such as taxes.

The second chapter experimentally tests whether individuals behave according to real option theory when considering low-probability high-severity outcomes. Individuals often make important decisions under uncertainty with severe outcomes, such as choosing medical treatments. I find that university student research participants behave according to directional predictions real option theory in low-probability high-severity contexts. However, participants' willingness to pay for information deviates from real option theory predictions. In these contexts, such as a low probability lifesaving medical procedure, individuals would wait too long or gather too much information than real option theory predicts. In the context of public policy, these types of scenarios would cause voter preferences to deviate from the optimal timing of policy according to real option theory.

The third chapter examines whether power plants respond to the Clean Air Interstate Rule and Cross State Air Pollution Rule by switching fuel types, retiring polluting boilers, or installing new pollution control technology. The results suggest that recent regulations achieved emissions reductions by changing the composition of pollution control technology without causing boiler retirements. I find evidence that plant managers switch fuel type in response to sulfur dioxide regulation. I find that boilers are more likely to install dry type technologies and selective noncatalytic reduction technology in response to regulation. These two categories of technologies can be classified as relatively cheap and less effective than their counterparts.

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CHAPTER I
POLICY UNCERTAINTY AND ELECTRIC UTILITY INVESTMENT

ABSTRACT

I investigate the effect of policy uncertainty on energy investments using a theoretical model based on real option theory and firm-level data on electric utility investments. Consistent with real options theory, a growing body of research finds policy uncertainty deters investment (e.g., Gulen & Ion 2016, Baker et al. 2016). This previous research does not distinguish between uncertainty over "carrot" policies, such as subsidies, and "stick" policies, such as taxes. This is problematic for environmental policy which uses both types of policies and evidence shows different responses to these types of policies (e.g. van Soest, 2005; Ye, et al. 2022). My real option theoretical model shows uncertainty over these two types of policies has differential effects on firm investments. This finding adds to the literature about the differential effects of taxes and subsidies (Requate, 2005). I test the implications of the model for electric utilities using firm-level data on quarterly capital investment. I construct two measures of electric utility-specific policy uncertainty using counts of newspaper articles that discuss electric utility-relevant policy. The empirical analysis, combined with the theoretical findings, reveals two results. First, increases in volatility over policy activity correspond to an increase in utility investment consistent with utilities expecting future policies to be "sticks." Second, popular newspaper-based measures of policy uncertainty might not be an accurate proxy for uncertainty defined in real options theory. These insights illustrate an overlooked difference between taxes and subsidies as a regulating mechanism for environmental policy.

1.1 INTRODUCTION

In this paper, I investigate how policy uncertainty affects energy investments differently between types of policy instruments. A growing body of research finds policy uncertainty deters investment (e.g., Gulen & Ion, 2016; Baker et al., 2016). This previous research does not distinguish between uncertainty over "carrot" policies, such as subsidies, and "stick" policies, such as taxes. This is problematic for environmental policy which uses both types of policies and evidence shows different responses to these types of policies (e.g. van Soest, 2005; Ye, et al. 2022). I develop a real option model to show the theoretical basis for differential effects of types of policy uncertainty. I test the implications of this model with firm-level data on electric utility investments.

I develop a theoretical model based on real option theory that accommodates two types of policy. "Carrot" policies positively affect a firm's profits, and "stick" policies negatively affect a firm's profits. This key difference in assumptions relative to other models, means that "carrot" policies scale firm profits directly and linearly but "stick" policies inversely scale profits nonlinearly. The model shows uncertainty over "carrot" policies increases investment and uncertainty over "stick" policies decreases investment. To test the implications of my model, I construct a theoretically consistent measure of electric utility-specific policy uncertainty using text analysis of newspaper articles. To construct this measure, I create a policy index that measures the level of policy activity (first moment) by calculating the proportion of newspaper articles that discuss electric utility-specific policy. Then I estimate the policy uncertainty index (second moment) by estimating the stochastic volatility of the policy index. This policy uncertainty index, which I refer to as statistical policy uncertainty, corresponds to the real option definition of uncertainty – the statistical volatility in a random variable such as price or demand (Dixit & Pindyck, 1994).

The theoretical model shows uncertainty over "carrot" policies and "stick" policies impact firms' investment differently. Relative increases in uncertainty over "carrot" policies results in lower capital investments, and relative increases in uncertainty over "stick" policies increases capital investments. Intuitively, compared to "stick" policies happening with certainty, firms would rather have uncertainty over "stick" policies. When considering policies such as taxes, firms would rather there be some reasonable chance that the policy would not occur. In this scenario, firms would invest more in large capital projects simply because expected profits are higher than if the stick policy would occur with certainty. I apply the model to the electric utility industry, which is characterized by frequent regulation and large irreversible capital investments. I empirically document a positive effect of statistical policy uncertainty on electric utilities' capital investment. This result is consistent with theoretical results that uncertainty over "stick" policies can increase investment. According to these results, electric utilities expect policies to more often be "sticks" rather than "carrots" during our study period.

I compare statistical policy uncertainty to the predominant measure of policy uncertainty in the empirical literature. Baker, et al.'s (2016) widely used method of measuring policy uncertainty calculates the proportion of newspaper articles that explicitly discuss uncertainty and relevant policies. I refer to Baker, et al.'s (2016) method as direct policy uncertainty as they capture direct references to uncertainty over policies. Both statistical policy uncertainty and direct policy uncertainty might affect electric utility investments. Direct policy uncertainty can be thought of as uncertainty over current, specific policies passing Congress. In contrast, statistical policy uncertainty can be thought of as uncertainty over future, undefined policies. These two measures of policy uncertainty are summarized in Table 1. As an application of my model, I empirically estimate the effect of these two measures of policy uncertainty on electric utilities' capital investments using firm-level data on quarterly capital investment. I focus on electric utilities because they typically make large irreversible investments and are subject to many regulations. Examining trends in investment rates over time in Figure 1, electric utility investment rates have recently started to fall. [1] This further motivates exploring potential explanations of this recent trend through the lens of policy uncertainty. I find evidence that electric utilities react to both direct policy uncertainty and statistical policy uncertainty. Interestingly, these two types of uncertainty have opposing effects on investment. Statistical policy uncertainty increases investment, but direct policy uncertainty decreases investment. This could be explained by differences in firm expectations of current policy uncertainty around specific policies (direct policy uncertainty) and future policy uncertainty over non-specific policies (statistical policy uncertainty). For example, the difference between a utility's response to uncertainty over

[1] All figures and tables can be found at the end of the chapter.

the Inflation Reduction Act passing Congress and general uncertainty over future carbon emission regulations. The empirical results suggest that direct policy uncertainty and statistical policy uncertainty capture distinct information to which electric utilities respond.

A positive effect of policy uncertainty stands in contrast to the existing literature. Real options investment models have come to a consensus that higher uncertainty deters investment as there is value for firms to delay investment until the uncertainty is resolved (Bernanke, 1983; Pindyck, 1991; Dixit, 1989; Bloom, Bond, and Van Reenen, 2007). The prior empirical literature on policy uncertainty cites these classic real options investment models as a theoretical basis for the negative effect of policy uncertainty on investment (Baker, Bloom, & Davis, 2016; Gulen & Ion, 2016). Research outside of the real option literature has found positive effects of uncertainty on investment by making assumptions about strategic behavior (Kulatilaka & Perotti, 1998), risk preferences (Abel & Blanchard, 1986), or market structure (Oi, 1961). Empirically, few have found positive effects of uncertainty on investment, and those who do attribute these results to strategic behavior (Vo & Le, 2017; Wu et al., 2020). The differential effects of policy instruments are well documented in the environmental policy literature (Requate, 2005). This paper extends the literature by providing a theoretical basis for the differential effects of policy uncertainty and documenting empirical evidence that corroborates the model.

I present a theoretically consistent approach to measuring policy uncertainty which connects popular text-based measures of policy uncertainty to the real option literature. Researchers have estimated implied uncertainty (Bloom, 2009; Dew-Becker &

Giglio, 2023), or direct measures of uncertainty through newspapers (Baker, Bloom, & Davis, 2016), earnings calls (Hassan et al., 2019; Sautner et al., 2023), surveys of managers (Bloom et al., 2022), and social media such as Twitter (Baker et al., 2021). When considering a policy uncertainty index as a second-moment statistic, volatility over a random variable, some researchers have also directly measured a policy index, the random variable itself (Noailly et al., 2022; Palikhe et al., 2023). I improve upon these previous iterations by directly measuring a policy index (random variable) and statistically estimating the policy uncertainty index (second moment statistic). This method is consistent with real options theory which focuses on future uncertainty while the other text analysis measures focus on all uncertainty which makes it difficult to compare the empirical findings to theory.

This paper shows that “stick” policy uncertainty does not behave the same as other types of uncertainty. Although most policy uncertainty discourages investment, this paper shows that policymakers need not always be worried about the uncertainty that their actions induce. Further, I show that two types of policy uncertainty affect firms’ investment decisions: current policy uncertainty around specific policies (direct policy uncertainty) and future policy uncertainty over non-specific policies (statistical policy uncertainty). Policymakers create uncertainty in industries through both avenues, but the differences are not well understood.

1.2 LITERATURE REVIEW

Baker, Bloom, and Davis’ (2016) seminal work enabled many researchers to examine the effect of policy uncertainty on macroeconomic and microeconomic outcomes through newspaper text analysis. Using dictionary-based methods, research has empirically shown a negative relationship between policy uncertainty and firm investment rates (e.g. Baker, Bloom, & Davis, 2016; Gulen & Ion, 2016; Kang, Lee, & Ratti, 2014). Other alternative data-driven text analysis techniques have produced similar impacts of policy uncertainty deterring investment (Larsen, 2017; Kalamara et al., 2020). Before using newspaper articles to proxy for levels of uncertainty, empirical research suggested that higher levels of political uncertainty suppressed investments by identifying periods of general political uncertainty (Handley & Limao, 2015). For example, presidential elections tend to suppress investment as uncertainty over future policies increases during that period (Jens, 2017; Julio & Yook, 2012). Previous research has measured different types of uncertainty such as financial uncertainty, economic uncertainty, interest rate uncertainty, worldwide uncertainty, etc. (Cascaldi-Garcia et al., 2020; Ahir et al., 2022). Other research has examined the effect of policy uncertainty on various dependent variables of interest, such as green investments (Cui et al., 2023) and energy generation (Gowrisankaran et al., 2022). The environmental economics literature has just begun to utilize some of these text-based forms of data (Dugoua et al., 2022). Despite the differences Requate (2005) found in types of policy instruments, empiric measurements of policy uncertainty have not differentiated among types of policies. I extend this literature by differentiating policy uncertainty between "carrot" policies, such as subsidies, and "stick" policies, such as taxes.

Researchers have employed creative solutions to address the challenges of measuring policy uncertainty. Researchers have estimated implied uncertainty (Bloom, 2009; Dew-Becker & Giglio, 2023), or direct measures of uncertainty through newspapers (Baker, Bloom, & Davis, 2016), earnings calls (Hassan et al., 2019; Sautner et al., 2023), surveys of managers (Bloom et al., 2022), and social media such as Twitter (Baker et al., 2021). When considering the policy uncertainty index as a second-moment statistic, some researchers have also directly measured a policy index as a first-moment statistic (Noailly et al., 2022; Palikhe et al., 2023). I improve upon these previous iterations by directly measuring a policy index (first moment) and statistically estimating the policy uncertainty index (second moment). This method combines two previous methods of direct measurement and statistical estimation, producing a measure theoretically consistent with the real options literature.

An empirical consensus on the effect of uncertainty on investment has not been reached. Van Vo and Le (2017) find evidence that in competitive markets firms increase their research and development investments during periods of high uncertainty. Wu et al. (2020) find that Australian firms exhibit a positive relationship between policy uncertainty and investment rates. They speculate that Australian firms might be behaving competitively since Australia did not endure the same economic turmoil as other countries in recent years. Although these results are few and far between, there exists some prior empirical evidence that policy uncertainty could increase investment. However, explanations of these empirical results speculate about firm behavior and do not provide any theoretical basis for their empirical results in those specific contexts.

The theoretical literature produces mixed results concerning the effect of uncertainty on investment rates as well. Pástor and Veronesi (2013) find a negative effect of policy uncertainty on stock prices using a general equilibrium model. Kulatilaka and Perotti (1998) argue that investment should grow in the face of higher uncertainty as firms act strategically to gain an advantage in non-competitive market structures. Oi (1961) shows that uncertainty decreases price stability and could increase return on investment due to increased potential profits. Abel and Blanchard (1986) posit that uncertainty leads risk-seeking investors to increase investment due to potentially large gains. Much of the research finding potential positive effects of uncertainty on investment rates relies on assumptions about market structure and competitive behavior. Real options investment models have come to a consensus that higher uncertainty deters investment as there is value for firms to delay investment until the uncertainty is resolved (Bernanke, 1983; Pindyck, 1991; Dixit, 1989; Bloom, Bond, and Van Reenen, 2007). These theories apply generally to a firm's investment decisions without making restrictive assumptions about market structure and competitive behavior. The theoretical model presented in this paper uses a real options investment model framework and finds that both positive and negative effects of policy uncertainty are consistent with the theoretical results under certain modeling assumptions.

The empirical results focus on the electric utility industry which is relatively capital-intensive and policy uncertainty should have a large impact on investment decisions. Prior research examined other types of uncertainty such as the impact of fuel price volatility on power plants' investment decisions and innovation (e.g. Stokey, 2016; Kellogg, 2014; Maghyereh & Abdoh, 2020). Dorsey (2019) found a negative effect of uncertainty around a specific policy (Cross State Air Pollution Rule) on power plants' investment decisions on a specific type of investment, abatement technology. Wang et al. (2023) found the uncertainty of the size of subsidies decreased green investments in China. Similarly, Fabrizio (2013) found a negative effect of uncertainty around the Renewable Portfolio Standards on power plant investments. Palikhe et al. (2023) broadly examined the effect of policy uncertainty on environmental firms and found a negative effect. However, no research has leveraged a broad measure of policy uncertainty in the electric utility industry.

1.3 THEORETICAL MODEL

I expand on a real options investment model from Dixit and Pindyck (1994) which finds a negative impact of uncertainty on investment. Like other real options investment models, Dixit and Pindyck's (1994) model defines uncertainty as volatility over the level of a random variable, such as demand. The original model assumes that the random variable is positively related to the firm's profit such as with demand uncertainty. This means their model can naturally apply to volatility over the level of policy activity when policy positively affects firm profits, such as "carrot" policies. I extend the original model by relaxing the assumption that random variable positively affects firm profits, allowing for uncertainty over "stick" policies. By generalizing Dixit and Pindyck's (1994) model, the effect of volatility in the level of policy activity can produce negative or positive effects on firm investment rates. When policy activity positively affects firm profits and the level of policy activity is increasing sufficiently quickly, I recover the original Dixit and Pindyck (1994) results that volatility over the level of policy activity deters firm investment. However, when policy activity negatively affects firm profits and the level of policy is increasing sufficiently slowly or decreasing, the model produces a novel result where volatility in the level of policy activity increases firm investment.

Consider a price-taking firm that is making an irreversible investment into capital, K, which costs κ. After the fixed cost of investment, there is no additional variable cost of capital. The firm does not use labor in the production process. Let profit flows be

$$\pi = Y^{\beta} * P * H(K) \quad (1)$$

where Y is a measure of the level of policy activity, $\beta \in \{-1,1\}$ is a measure of the effect of the policy activity on firm profit, P is the price of the output, and $H(K)$ is the production of the firm as a function of the level of capital, K.

The model results rely on this assumption of the interaction between policy activity and firm profits, so it is worth examining further. When $\beta = 1$, profits linearly increase as policy activity increases: $\frac{\partial \pi}{\partial Y} = P * H(K)$. This assumes there is constant profitability of "carrot" policies, such as subsidies. In other words, giving firms a fifth subsidy will increase their profits just as much as the first subsidy. When $\beta = -1$, profits nonlinearly decrease with policy activity: $\frac{\partial \pi}{\partial Y} = -\frac{1}{Y^2} * P * H(K)$. We consider the firm representative of an industry. For most industries, such as electricity generation, the industry is too integral to the economy for regulators to cause all firms to shut down. If firms still exist in the industry, then $\pi > 0$ otherwise they would shut down. This is consistent with the relationship between "stick" policies and profit. Increasing the number of "stick" policies decreases profits but will never cause the representative firm to become unprofitable. These assumptions mean that my results do not apply to uncertainty over all variables that negatively affect profits. For example, costs are typically modeled as additively separable in the profit function and my results do not apply.

The term Y^{β} can thus be thought of as a policy function that measures the long-run effect of policy activity on a firm's profits. When $\beta = 1$, increases in policy activity increase firm profits, as in the original Dixit and Pindyck (1994) model (i.e., carrots). For example, agricultural and defense policy is often characterized by production subsidies, price supports and production contracts that are beneficial to incumbent firms. However, when $\beta = -1$, increases in policy activity decrease firm profits, which was previously not examined (i.e., sticks). For example, many environmental policies are characterized by pollution taxes and regulations. Alternatively, β may represent different regulatory approaches to an industry. Consider the electricity industry. Historically, policy efforts to reduce pollution emissions from the electricity industry have focused on taxing pollution emissions or imposing technology standards such as smokestack scrubbers on fossil-fuel generators. Electric utilities would expect policy of this type to negatively affect their profit, and we could feasibly expect $\beta = -1$. More recently, the strategy to reduce greenhouse gas emissions from the electric utility industry has relied on subsidies for renewable electricity generation. Policy activity of this type could increase profits for electric utility companies that can easily increase electricity generation from renewables, and we could feasibly expect $\beta = 1$. Allowing the policy function to both increase and decrease in the level of policy activity acknowledges that the absence of policy activity (i.e. a period where these is little debate and passage of relevant bills) may be beneficial or detrimental to a firm depending on how policymakers have interacted with the industry in the past.

I am primarily interested in how uncertainty over the level of policy activity affects firm investments. For example, consistent debate over climate policy may be less detrimental to firm investment than stop-start policy debates that follow the pendulum swings of elections. Firms know the current level of policy activity with certainty. However, firms do not know what the level of policy activity will be in the future. Assume that Y behaves stochastically and follows a Geometric Brownian Motion

$$dY = \alpha Y dt + \sigma Y dz \tag{2}$$

where α is the drift term, σ^2 is the volatility, and dz is an incremental Weiner Process. The Geometric Brownian motion assumption implies that policy activity is a log-normally distributed random variable with expected value $E(Y) = Y_0 e^{\alpha t}$ and variance $Var(Y) = Y_0^2 e^{2\alpha t}\left(e^{\sigma^2 t} - 1\right)$. I prefer assuming a log-normal distribution since policy activity is non-negative, positively skewed, and multiplicative. Positive skew implies that regulation has increased over time. Multiplicativity implies that the effect of policies build on one another. When $\alpha > 0$, then the expected level of policy activity is increasing over time. When $\alpha < 0$, then the expected level of policy activity decreases over time. The volatility in policy activity, represented by σ, captures the degree of uncertainty over future levels of policy activity. As σ tends to 0, there is little uncertainty over the policy process and firms can accurately predict the impact of future policy. A firm may experience an unexpected decrease in profits due to a downward shock in carrot policy activity of an upward shock in stick policy activity.[2]

It is worth highlighting how these assumptions differ from previous real option theoretical models. Dixit and Pindyck (1994) also consider uncertainty over variables that negatively affect profit, such as costs. However, in their treatment of these cases, they assume that $\frac{1}{Y}$ follows a Geometric Brownian Motion where Y is defined as the variable that negatively affects profit. They retain their result that uncertainty decreases investment in these cases. Applying this approach to "carrot" and "stick" policies implies the level of policy activity evolves differently conditional on the type of policy. Since "carrot" policies positively affect profit, then we assume that Y follows a Geometric Brownian Motion, where Y is the level of "carrot" policy activity. However, since "stick" policies negatively affect profit, we must assume that $\frac{1}{Y}$ follows a Geometric Brownian Motion, where Y is the level of "stick" policy activity. Instead, in this paper, I assume that the level of policy activity, Y, follows a Geometric Brownian Motion for both "carrot" and "stick" policies. This assumption leads to the divergence of my results compared to Dixit and Pindyck (1994).

[2] It may also be the case that the does not know whether it will be subject to a carrot or stick policy at the next instant in time (i.e., β is also uncertain). I argue that such shifts between carrots and sticks occur less frequently than changes in policy activity and are thus a less impactful form of uncertainty. Nevertheless, I acknowledge the possibility that β may also be uncertain and leave this for future work.

Consider the firms' investment problem. They wish to choose the level of capital to maximize their current stream of profits and the discounted expected value of future profits less any additional investment in capital. The Bellman equation is

$$W(K,Y) = \max_{K'} Y^{\beta} PH(K)dt + e^{-\rho dt}\{E[W(K',Y+dY)] - \kappa(K'-K)\} \quad (3)$$

where K' is the level of capital in the next period and $K' \geq K$. That is, the firm cannot decrease the amount of capital that they have, and in this sense the capital investment is irreversible. Taking the derivative of the Bellman equation with respect to K' gives us the condition for optimal capital investment.

$$e^{-\rho dt}\{E[W_K(K',Y+dY)] - \kappa\} = 0 \quad (4)$$

We see that if the expected marginal value of incremental capital is greater than the marginal cost, then the firm will invest in new capital. Thus if $W_K(K,Y) \geq \kappa$, then the firm invests, and if not then $K' = K$.

Consider when the firm will not invest in new capital. This gives a boundary condition that characterizes when the firm will choose to invest in additional capital. Note that if $W_K(K,Y) \geq \kappa$, then the firm will invest in additional capital until $W_K(K,Y) = \kappa$. That is, the firm is not constrained to only invest in one additional unit of capital, but rather they could invest in many units in one period and then no units in the next few periods.

When the firm does not invest in capital, then the Bellman equation becomes

$$W(K,Y) = Y^{\beta} PH(K)dt + e^{-\rho dt}\{E[W(K,Y+dY)]\} \quad (5)$$

Rewriting equation (5) in terms of firm profit gives the following differential equation characterizing the value of investing for the firm.

$$0 = \pi + W'(\pi)\left(\beta\pi\alpha + \frac{1}{2}\beta(\beta-1)\pi\sigma^2\right) + \frac{1}{2}W''(\pi)(\beta^2\pi^2\sigma^2) \quad (6)$$

$$-\rho W(\pi)$$

The solution of this differential equation gives the value of investing for the firm.

$$W(K,Y) = A_1\left(Y^\beta PH(K)\right)^{\eta_1} + \frac{Y^\beta PH(K)}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)} \quad (7)$$

where

$$\eta_1 = \frac{1}{2} - \frac{\alpha}{\beta\sigma^2} + \sqrt{\left(\frac{\alpha}{\beta\sigma^2} - \frac{1}{2\beta}\right)^2 + \frac{2\rho}{\sigma^2}} \quad (8)$$

From equation (4), we know the boundary condition of inaction is such that $W_K(K,Y) = \kappa$. The smooth-pasting condition states that the partial derivative of $W_K(K,Y)$ with respect to Y is equal to the derivative of κ with respect to Y. This smooth-pasting condition is then $W_{KY}(K,Y) = 0$. Solving these two conditions using equation (7), gives a relationship between policy activity, Y, and capital, K that is the boundary condition of inaction for the firm. Specifically, when

$$Y > \left\{\left(\frac{\eta_1}{\eta_1 - 1}\right)\frac{\kappa}{PH'(K)}\left[\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)\right]\right\}^{\frac{1}{\beta}} \quad (9)$$

the firm invests in more capital until equation (9) holds with equality. Otherwise, the firm makes no investment in capital.

Note that when $\beta = 1$, increases in policy activity increase firm profit, and we recover the boundary condition found in Dixit and Pindyck (1994):

$$Y = \left(\frac{\eta_1}{\eta_1 - 1}\right)\frac{\kappa}{PH'(K)}[\rho - \alpha] \quad (10)$$

Assuming diminishing marginal product of capital, $H"(K) < 0$, the boundary condition exhibits a positive relationship between Y and K. This can most easily be seen in Dixit and Pindyck's (1994, p. 362) figure. The barrier or boundary presented in the left panel of Figure 1, shows the values of Y and K such that the marginal value of capital is equal to the marginal cost of capital. The area below the boundary shows when the firm will not invest in capital. For a fixed level of capital, as the level of policy activity, Y, evolves stochastically over time, the level of policy activity might increase sufficiently to hit the barrier or boundary condition. When the boundary condition is satisfied, then we can think of the firm immediately increasing its level of capital until they are in the region below the boundary condition once again.

Now let us examine the novel scenario where $\beta = -1$, which means increases in policy activity hurt firm profit. Equation (9) then becomes:

$$Y = \left(\frac{\eta_1 - 1}{\eta_1}\right) \frac{PH'(K)}{\kappa[\rho + \alpha - \sigma^2]} \tag{11}$$

Assuming diminishing marginal product of capital, $H"(K) < 0$, the boundary condition exhibits a negative relationship between Y and K illustrated in the right panel of Figure 1. The area where firms will not invest in more capital now lies above the boundary condition. When Y decreases sufficiently, the boundary condition is met, and the firm immediately invests in more capital until they are in the area above the boundary.

The original Dixit and Pindyck (1994) model assumes that the level of policy activity positively affects firm profits or $\beta = 1$. Since higher profits increase the value of a capital investment, intuitively the firm makes investments when the level of policy activity increases sufficiently. The model also accommodates firms for which the level of policy activity negatively affects profits, or $\beta = -1$. Intuitively, if policy activity hurts firm profits, then the level of policy activity must decrease sufficiently for firms to invest in more capital.

1.3.1 INVESTMENT RATE

I derive the firm's investment rate to find the effect of volatility on the firm's investment decision. The model presented above results in a barrier control problem where firms invest in capital until a boundary condition is met. This results in lumpy investments where the firm can increase its capital by large amounts in a short time but then not invest in any more capital for a long period. That is, firms invest in more capital when $W_K(K, U) \geq \kappa$ until $W_K(K, U) = \kappa$ at which point firms make no further investments until the level of policy activity changes sufficiently. As in Dixit and Pindyck (1994), I estimate an investment rate, defined as $\frac{\dot{K}}{K}$, resulting from these lumpy investments.

To find an analytic solution, I make further assumptions about the functional form of the production process. Let $H(K) = K^\theta$ be Cobb-Douglas where $0 < \theta < 1$. Then $H'(K) = \theta K^{\theta-1}$.

First, consider the novel case where $\beta = -1$. Equation (11) can be rewritten as

$$YK^{1-\theta} = \bar{M} \qquad (12)$$

where $\bar{M} = \left(\frac{\eta_1 - 1}{\eta_1}\right)\frac{P\theta}{\kappa[\rho+\alpha-\sigma^2]}$ is a constant given model parameters. When $YK^{1-\theta} \leq \bar{M}$ then the firm increases investment, increasing $YK^{1-\theta}$ until $YK^{1-\theta} = \bar{M}$. When $YK^{1-\theta} >$

$\bar{M}$ then the firm does not invest in new capital. When the level of capital does not change, then $YK^{1-\theta}$ follows the same Geometric Brownian Motion as Y. Let $M = YK^{1-\theta}$, and $m = \ln\left(YK^{1-\theta}\right)$. Then m follows an Arithmetic Brownian Motion so long as the firm does not invest in new capital.

$$m = \left(\alpha - \frac{\sigma^2}{2}\right)t + \sigma W_t \tag{13}$$

Assume that $\alpha < \frac{\sigma^2}{2}$ for the distribution of m to exist. Note that if $\alpha \geq \frac{\sigma^2}{2}$ then m does not hit the barrier in the long run. That is, the level of policy activity is increasing too quickly such that firms will never invest in new capital.

To derive the investment rate, consider the scenario where a firm will invest in new capital. A firm invests in new capital when m falls to hit the boundary condition. The probability that m hits the boundary condition is equal to the probability that m is sufficiently close to the boundary times the probability that m decreases causing it to hit the boundary condition. The probability that m is sufficiently close to the barrier is $-dh\left(\frac{2\alpha}{\sigma^2} - 1\right)$ where $dh = \sigma\sqrt{dt}$. The probability that m decreases is $\frac{1}{2}\left[1 - \frac{-\left(\frac{2\alpha}{\sigma^2}-1\right)\sqrt{dt}}{\sigma}\right]$.

So, the probability that a firm will invest in new capital is equal to $-dh\left(\frac{2\alpha}{\sigma^2} - 1\right)\frac{1}{2}\left[1 - \frac{-\left(\frac{2\alpha}{\sigma^2}-1\right)\sqrt{dt}}{\sigma}\right]$.

Next, consider the size of the investment when a firm does invest in new capital. The mathematical derivation is shown in the Appendix, but the change in capital when m decreases and hits the barrier is

$$\frac{dK}{K} = dk = \frac{dh}{1-\theta} \tag{14}$$

Finally, the investment rate is the product of the probability that m is sufficiently close to the barrier, the probability that m decreases and hits the barrier, and the magnitude of investment. Converting this into an investment rate gives

$$\frac{\dot{K}}{K} = \left(-\alpha + \frac{\sigma^2}{2}\right)\left(\frac{1}{1-\theta}\right) > 0 \tag{15}$$

which will be positive provided $\alpha < \frac{\sigma^2}{2}$. When $\alpha \geq \frac{\sigma^2}{2}$ then the investment rate is equal to 0. That is, the level of policy activity never falls low enough for firms to invest in new capital. Intuitively, the firms face too much negative policy activity which hurts their profits and deters them from investing. Finally, I examine the effect of the volatility of policy activity on the firm's investment rate. Consider the partial derivative:

$$\frac{\partial \frac{\dot{K}}{K}}{\partial \sigma} = \sigma\left(\frac{1}{1-\theta}\right) > 0 \tag{16}$$

When policy activity is negatively related to the firm's profit, the investment rate increases with more volatility over the level of policy activity.

When $\beta = 1$ I recover Dixit and Pindyck's (1994) result for firms that benefit from policy activity. Assume that $\alpha > \frac{\sigma^2}{2}$, to ensure that policy activity increases enough to hit the barrier and cause firm investment. Similarly calculating the investment rate as above, Dixit and Pindyck (1994) find the investment rate to be

$$\frac{\dot{K}}{K} = \left(\alpha - \frac{\sigma^2}{2}\right)\left(\frac{1}{1-\theta}\right) > 0 \tag{17}$$

which will be positive provided $\alpha > \frac{\sigma^2}{2}$. When $\alpha \leq \frac{\sigma^2}{2}$, then firms do not invest in any new capital, and the investment rate is 0.

To find the effect of volatility on the investment rate, take the partial derivative of equation (17) with respect to σ:

$$\frac{\partial \frac{\dot{K}}{K}}{\partial \sigma} = -\sigma\left(\frac{1}{1-\theta}\right) < 0 \tag{18}$$

When policy activity benefits firms, then volatility decreases investment rates.

1.3.2 DISCUSSION

The theoretical model presented above predicts that policy uncertainty, measured as the volatility in policy activity, can increase investment rates under certain circumstances. It highlights the difference between types of policies: “carrots” or policies that benefit firms and “sticks” or policies that hurt firm profits. Empirical studies cite real options investment models as a theoretical basis for the negative effect of uncertainty on investment rates (e.g. Baker, Bloom, & Davis, 2016; Gulen & Ion, 2016). As I have just shown, since policy activity can be either “carrots” or “sticks,” the theoretical model accommodates both positive and negative effects of policy uncertainty on investment rates. Further, real options investment models that focus on risk defined as the volatility in policy activity provide no theoretical guidance on the impacts of text-generated measures of policy uncertainty provided in the empirical research which are unable to distinguish between risk and uncertainty or notions of current and future risk.

The theoretical model provides predictions under the four different scenarios based on values of β conditional on how policy activity evolves, α.

When $\alpha > \frac{\sigma^2}{2}$ and $\beta = 1$, the model produces identical results to Dixit and Pindyck (1994) where policy uncertainty negatively impacts investment rates. In this scenario, firms expect future non-specific policies to positively affect their profits, or policies to be "carrots." However, positive expectations for policies are not sufficient in this model. The level of policy must be growing sufficiently fast to induce investments.

When $\alpha > \frac{\sigma^2}{2}$ and $\beta = -1$ or $\alpha < \frac{\sigma^2}{2}$ and $\beta = 1$, policy activity causes firms to halt all investments. In the first scenario, firms expect policy activity to negatively impact their profits and the level of policy activity is growing quickly. This lowers a firm's expected profits, and they halt all investment. In the second scenario, firms expect policy activity to positively impact their profits, but the level of policy activity is growing too slowly or even decreasing over time. Similarly, this lowers a firm's expected profits, driving its investment rate to zero.

Lastly, when $\alpha < \frac{\sigma^2}{2}$ and $\beta = -1$, firms expect "stick" policies and the policy level increases slowly or decreases over time. In this scenario, uncertainty drives the level of policy down due to the asymmetric effect of volatility. Mathematically, volatility will result in larger drops in policy activity when the level of policy activity is high compared to relatively smaller increases in policy activity. Even though there is an equal probability that policy activity will increase or decrease, the magnitude of the decrease is larger than the magnitude of the increase. This asymmetric effect of volatility encourages firms to invest more since policy negatively affects their profits. Intuitively, consider the choice between two scenarios: a tax policy implemented with certainty, and a tax policy implemented with some uncertainty. In expectation, firms would rather have uncertainty over the “stick” policy since there is a chance it will not be implemented. The higher expected profits under policy uncertainty translate into a higher investment rate.

It is plausible that firms would expect future non-specific policies to be either “carrots” or “sticks” depending on the industry, time period, regulatory body, or other factors. The key results of the theoretical model show that statistical policy uncertainty could have a positive or negative effect on firm investments. Ultimately, this is an empirical question.

1.4 EMPIRICS

Now that I’ve developed the theoretical model that predicts a positive effect of policy uncertainty, I turn to an application of my model showing how policy uncertainty affects the electric utility industry. First, I create two measures of policy uncertainty for the electric utility industry using newspaper text analysis. First, I create a policy index for the electric utility industry which measures the level of policy activity through newspaper text analysis. I derive a measure of the statistical policy uncertainty by estimating a stochastic volatility model using the policy index. Then I use Baker, Bloom, and Davis’s (2016) methods to create a direct policy uncertainty index for the electric utility industry. The direct policy uncertainty index measures current policy uncertainty: uncertainty over current policies passing and how those policies affect firms. The difference between these two measures is summarized in Table 1. Next, I present the data and models used to empirically estimate the effect of these two measures of policy uncertainty on electric utility investment rates. Finally, I present the empirical results that find evidence that policy uncertainty can have a positive effect on firm investment and suggest that the two measures of policy uncertainty both affect firm investment in different ways.

The difference between direct policy uncertainty and statistical policy uncertainty is highlighted by how each index is generated. I favor the statistical policy uncertainty index as it is consistent with the real option theory definition of uncertainty. Direct policy uncertainty measures a different type of uncertainty which has been favored by the empirical literature. In interpretation, the direct policy uncertainty measure captures every type of uncertainty related to a policy. It captures uncertainty over the legislative process including passing into law, uncertainty over the implementation of a specific regulation, uncertainty over the impact of the regulation on specific outcomes, and uncertainty over the future landscape of regulations among others. However, statistical policy uncertainty describes a specific type of uncertainty which is well-defined in the real option theory literature. Statistical policy uncertainty is the variation in the discussion of relevant policies. I interpret this as the uncertainty over the regulatory landscape. Periods of consistent strict regulations do not cause higher levels of uncertainty since electric utilities can form accurate expectations. However, when policymakers drastically increase or decrease their discussion of policies, uncertainty increases since utilities' expectations do not match the regulatory landscape.

1.4.1 ELECTRIC UTILITY POLICY UNCERTAINTY

In this section I present the newspaper text-based measures of policy uncertainty specific to the electric utility industry. Little data exists about industry-level policy uncertainty, so I utilize a text analysis of newspaper articles. Following Palikhe et al.

(2022) I create a policy index to measure the level of policy activity for electric utilities based on Baker et al.'s (2016) method. This measure uses media coverage in newspapers to generate a measure of discussion about policies specific to electric utilities. I use the policy index to estimate a monthly measure of statistical policy uncertainty. Second, I create a measure of direct policy uncertainty following Baker et al. (2016). Gentzkow et al. (2019) credit this approach as being among the most influential text analysis applications in economics. Baker et al. (2016) established the validity of their approach through a human audit of 12,000 articles to ensure that their methods appropriately captured relevant newspaper articles. Academic researchers used the economic policy uncertainty index in a wide range of contexts (Gulen & Ion, 2016; Wu et al., 2020), and the media have referenced the publicly available index numerous times, further emphasizing its practical use.

Baker et al. (2016) use a dictionary-based method to construct their economic policy uncertainty index. They identify a set of keywords that they search for in the database of all newspaper articles. This approach requires prior knowledge of relevant industry policy keywords as compared to other data-driven techniques (Calomiris & Mamaysky, 2019). Data-driven techniques outperform dictionary-based methods in the context of predicting observables such as stock prices. However, dictionary-based methods are justified when there is no directly observable information on the latent variable of interest such as policy uncertainty. Further, results from data-driven methods are often highly correlated with dictionary-based methods (e.g. Calomiris & Mamaysky, 2019).

I construct the electric utility policy index by identifying five sets of search criteria listed in Table 2. An article must contain one keyword from each of these five sets of search criteria to be counted by the index. The first set identifies articles economic in nature. I exclude any articles which include words in the second set, ensuring articles discuss policies as in Palikhe, et al. (2023). The third set of keywords relate to the regulating body for electric utilities. The fourth set of keywords guarantees that news coverage is relevant to the electric utility industry. The last set of keywords identifies specific policy topics to ensure that articles are reporting on policies specific to the electric utility industry.

I conduct all searches in the Newsbank database which contains over 4,400 newspapers across the United States. The database contains large regional newspapers with over one million articles each such as the Orlando Sentinel, the Star-Ledger, Houston Chronicle, the Seattle Times, and Chicago Sun-Times. Newsbank includes thousands of smaller local newspapers as well as national-level newspapers such as USA Today. Between 1985 and 2022, the database contains over 340 million U.S. news articles on which I conduct the searches.

After obtaining a monthly count of newspaper articles matching the search criteria, I normalize the data into an index. First, I divide the count of relevant articles by the total number of articles in the Newsbank database for that month which gives the proportion of newspaper articles discussing relevant policy. Next, I normalize this value, by dividing by the mean proportion of newspaper articles discussing policy between 1985 and 2009 and multiplying by 100. Formally, the electric utility policy index is calculated by the following:

$$P_t = \frac{\left(\frac{x_t}{a_t} * 100\right)}{\frac{\sum_1^{300} \frac{x_s}{a_s}}{300}} \tag{19}$$

where x_t is the number of newspaper articles satisfying the search criteria in month t, a_t is the number of all newspaper articles in month t, and in the denominator, time period 1 starts in January 1985, and time period 300 corresponds to December 2009. The resulting time series index measures newspaper coverage of electric utility policy from 1985 to 2022 relative to the average level of newspaper coverage from 1985 to 2009. A value of 125 in a given month means the proportion of electric utility policy-relevant articles is 1.25 times the average proportion of electric utility policy-relevant articles from 1985 to 2009.

I use the utility policy index to create a measure of statistical policy uncertainty. Let P_t be the policy index in time t which is a measure of the level of policy activity. I define statistical policy uncertainty to be the estimated latent time-varying volatility process from a stochastic volatility model assuming an AR(1) process. This captures the instantaneous variance of the time series in a more sophisticated way by taking into account both trends and one period changes. Formally,

$$P_t = e^{\frac{V_t}{2}} \epsilon_t \tag{20}$$

$$V_t = \mu + \phi(V_{t-1} - \mu) + \sigma\eta_t \tag{21}$$

Where ϵ_t and η_t are i.i.d. standard normal white noise, V_t is the latent time-varying volatility process with initial stationary distribution $V_0|\mu, \phi, \sigma \sim N\left(\mu, \frac{\sigma^2}{(1-\phi^2)}\right)$. Values of V_t are estimated using the stochvol package in R (Hosszejni & Kastner, 2021). After estimating the underlying parameters, values are simulated 10,000 times and the median value is taken as the measure of statistical policy uncertainty, V_t. V_t is interpreted as the log standard deviation of the policy index. A 1 unit increase in V_t, from 3 to 4, is interpreted as in increase in the standard deviation of the policy index by 34.5 points.

I also construct a direct policy uncertainty index to which I compare the theoretically consistent measure. Rather than excluding the uncertain keywords, the direct policy uncertainty index includes any articles that mention “uncertain,” “uncertainties,” or “uncertainty.” This means that the articles in both the policy index and direct policy uncertainty index are disjoint sets. That is, if an article shows up in the policy index, then it cannot show up in the direct policy uncertainty index by construction.

Figure 3 shows the utility-specific direct policy uncertainty index with the scale on the left-hand side. The index shows some notable distinct spikes from policy uncertainty. In January 2001, amidst rising gas prices, President George Bush was criticized for a lack of a national energy policy. In response to this, the White House adopted recommendations from the National Energy Policy Development Group in May 2001.[3] In April 2006, the Senate energy committee met with firms, scientists, and

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[3] https://georgewbush-whitehouse.archives.gov/news/releases/2001/06/energyinit.html

environmentalists to discuss greenhouse gas regulation. The fall of 2008 marked the presidential election during the Great Recession, meaning a great deal of policy uncertainty as voters wanted both lower energy prices and policy addressing climate change as seen in the Newsbank articles. In December 2009, while the United Nations Climate Change Conference took place, discussion in the United States turned toward the recent expansion of natural gas as a cost-effective and relatively clean alternative to coal-fired power plants. President Obama spoke about plans for energy security in March 2011 and Congress discussed a policy to increase fees on inactive oil and gas leases after media coverage highlighted the number of inactive federal leases. The Presidential election in 2012 also caused spikes in policy uncertainty when candidates discussed their ideas for addressing climate change and energy independence. These examples show that the index identifies policy-specific uncertainties that relate to utilities.

The utility policy index shown in Figure 3 with the scale on the left-hand side includes several peaks worth mentioning. May 2001 marked the initial implementation of the White House's energy policy. After periods of high energy policy uncertainty, those uncertainties were resolved as the federal government began implementing specific policies. Newspaper coverage of the Northeast blackout in August 2003 caused a minor spike in the policy index as experts weighed in with their policy recommendations. The index shows a clear uptick in December 2007 with the passage of the Energy Independence and Security Act. The American Clean Energy and Security Act of 2009 was passed in the House in June 2009 but was never passed in the Senate. This peak also corresponds to an increase in the policy uncertainty index in contrast to the Energy

Independence and Security Act which was successfully signed into law with little uncertainty. There was a modest uptick in the utility policy index during the presidential election in August 2012 as newspaper coverage turned to candidates' ideas on energy policy. June 2013 marked President Obama's last Climate Action Plan which outlined a set of initiatives intended to reduce greenhouse gas emissions. When paired with the utility policy uncertainty index, the utility policy index completes the picture of policy uncertainty highlighting when bills are passed with varying degrees of certainty. Further, the policy index gives evidence that the utility policy uncertainty index uniquely captures periods of high uncertainty.

A few specific events highlight the difference between statistical policy uncertainty and direct policy uncertainty. In December 2019, investment in natural gas production fell in response to uncertainty over climate change regulation, causing an increase in direct policy uncertainty. However, statistical policy uncertainty largely did not change. The policy index largely remained constant, indicating that discussion of these policies remained constant over this time period. In March 2017, the Trump administration rolled back carbon regulations, increasing direct policy uncertainty. Statistical policy uncertainty largely remained unchanged. Similarly, in August 2018 the Trump administration froze Obama administration fuel economy standards. This caused an increase in direct policy uncertainty but not statistical policy uncertainty. These periods suggest that the landscape of future policy was predictable during these times, but current policies were uncertain. Finally, in October 2010 statistical policy uncertainty increased while direct policy uncertainty remained relatively low. During this time newspapers began discussing a wide range of policy goals including renewable energy, fuel efficiency mandates, and biomass energy generation. This increased discussion caused a spike in the statistical policy uncertainty measure as the future regulatory landscape became more uncertain. However, when looking at the modest uptick in the direct policy uncertainty measure, none of the discussion focused on current policies. These specific events highlight a key difference between these two measures. Statistical policy uncertainty measures a very specific type of future uncertainty, whereas the direct policy uncertainty measure captures all types of uncertainty. This means any changes in direct policy uncertainty can be rationalized ex-post by identifying specific events.

1.4.2 DATA AND MODEL

Now I turn to firm-level data and the empirical model specification. Publicly listed U.S. firm-level data comes from the same Compustat dataset used by Baker, Bloom, and Davis (2016), updated to 2022 data. The dataset contains revenue, capital expenditures, physical assets, cash flows, and Standard Industrial Classification (SIC) codes, but the investment rate is the primary dependent variable of interest. The investment rate is defined as capital expenditure in quarter t divided by the stock of physical capital in quarter $t-1$. Physical capital is defined as net plant, property, and equipment which includes facilities and machines accounting for depreciation. Following Gulen and Ion (2016), I winsorize investment rates for the top and bottom 5%. I define electric utilities using the Standard Industry Classification for the electric services industry (SIC code 491) which includes power plants and electricity companies. The unbalanced panel data includes 165 utility firms with an average of 54.3 observations per firm for a total of 8,961 quarterly observations. The average investment rate for utility firms is 0.025 with a standard deviation of 0.02. While the panel of all firms includes data from 1985 to 2021, utility firm data only begins in 2001. Descriptive statistics and data definitions are presented in Table 3. Figure 1 shows trends in quarterly average investment rate for electric utilities from 2001 to 2022. Investment rates rose until 2008 after which dropping to a low in 2010. Investment rates recovered to a maximum in 2012 and have since fallen over time. This highlights the variability in investment rates in the data and the recent trend in falling investment.

I merge the firm-level investment data with the policy, direct policy uncertainty, and statistical policy uncertainty indices. Since the indices are measured at a monthly time scale, I aggregate them up to a quarterly measure by taking the average over the three months in the quarter.

I consider a model most directly comparable to the real option theoretical model following regression specifications from Baker, Bloom, and Davis (2016) and Gulen and Ion (2016). The dependent variable is the investment rate as defined previously. To ease interpretation, I take the natural log of the policy uncertainty index, policy index, and volatility. This gives the following specification:

$$\frac{\mathrm{CAPXY_{it}}}{K_{i,t-1}} = \alpha_1 \ln(PU)_t + \alpha_1 \ln(P)_t + \alpha_2 \ln(V)_t + \beta X_{it} + \delta M_t + \gamma_i + \theta_t + \epsilon_{it} \quad (22)$$

Where $\frac{\mathrm{CAPXY_{it}}}{K_{i,t-1}}$ is the investment rate for firm i in quarter t, $\ln(PU)_t$ is the natural log of the direct policy uncertainty index in quarter t, $\ln(P)_t$ is the natural log of the policy index in quarter t, V_t is the statistical policy uncertainty in quarter t, X_{it} is a vector of firm-specific control variables, M_t is a vector of macroeconomic control variables, γ_i is firm-level fixed effects, and θ_t is a vector of time controls including year, fiscal quarter, and calendar quarter fixed effects. The firm-specific control variables include sales growth and the ratio of cash flow to assets. The macroeconomic control variables include real GDP growth, consumer confidence, and the leading economic index from the Federal Reserve. Real GDP growth and the leading index come from FRED. The measure of consumer confidence comes from the University of Michigan's Consumer Sentiment survey. Errors are clustered at the firm and year level to account for heteroskedasticity. Descriptive statistics and data definitions are presented in Table 3.

When focusing on a particular sector, such as the electric utility industry, concerns about the endogeneity of the policy uncertainty index arise. When firms decrease their investments, it is possible that policy responds to this change in investment and induces higher levels of policy uncertainty. This higher level of policy uncertainty could help or hinder the firms. Due to limitations in addressing endogeneity, results should be interpreted as an illustration of theoretical predictions rather than causal effects.

1.4.3 RESULTS

The first column of Table 4 shows the results from the regression specification with statistical policy uncertainty. I find a statistically significant effect that statistical policy uncertainty increases firm investment. Column 2 includes the policy index as an added robustness check. Column 3 includes both statistical policy uncertainty and direct policy uncertainty. It might be the case that each of these measures captures similar information, so we might expect individual effects to no longer be significant. However, I find that both these measures of policy uncertainty have a statistically significant effect in opposite directions. The column 4 of Table 4 adds the policy index as well, showing the results are stable across different specifications and measures of policy uncertainty. The column 5 of Table 4 shows the results from Ordinary Least Squares estimation of the regression specification most closely comparable to Baker et al.'s (2016) results. There is some evidence that direct policy uncertainty decreases firm investment rates in the electric utility industry; however, the results are not statistically significant. The last column of Table 4 adds the policy index as an additional control. As Palikhe et al. (2023) argue, measures of direct policy uncertainty might capture changes in overall newspaper coverage of the topic rather than increases in uncertainty. When adding this additional control, the effect of direct policy uncertainty decreases investment rates at a statistically significant level. This matches previous empirical results that direct policy uncertainty has a negative effect on investment rates.

I now examine the economic significance of these results. From quarter 1 of 2014 to quarter 2 of 2014, the statistical policy uncertainty index increased by 7.13, one of the largest increases during my observations. Taken in conjunction with my results, this translates into an increase in capital investment of $70.24 million on average. Relative to the average investment, this signifies an increase of 27.4% in investment. During this same period, the direct policy uncertainty index increased by 82 points. This translates into a decrease in investment of $12.27 million on average, or 5% relative to the average investment. From quarter 3 of 2008 to quarter 4 of 2008, the direct policy uncertainty index increased by 192 points, one of the largest increases during my observations. This translates into a decrease in investment of $19.13 million or 7.5% relative to the average investment. During this same period, the statistical policy uncertainty index increased by 0.11, translating into an increase in investment of $1.11 million or 0.4% relative to the average investment.

These results highlight a few aspects of the theoretical model previously developed. There is evidence that both direct and statistical policy uncertainty affect firm investment rates. There is evidence that direct policy uncertainty as measured by news coverage has a negative effect on investment in the electric utility industry. This result mirrors previous empirical results using similar measures of direct policy uncertainty. Statistical policy uncertainty, which is directly seen in the theoretical model, was found to have a positive effect. This result is theoretically consistent with my model when firms expect stick policies, or policies that negatively impact their profits. These results also highlight the difference between measures of policy uncertainty. Direct policy uncertainty appears to have negative effects on firm investment rates regardless of the type of policy. However, statistical policy uncertainty can have positive or negative effects on investment rates. This empirical evidence is consistent with the theory, meaning the type of policies over which there is uncertainty (carrots or sticks) changes firms' responses to uncertainty.

I consider some potential interaction effects between policy uncertainty and firm characteristics. In Table 5, I report results allowing for the effect of policy uncertainty measures to change depending on the level of firm revenue. Larger firms might be more sensitive to changes in policy uncertainty or account for the positive effect of statistical policy uncertainty. The magnitude of the effect of statistical policy uncertainty increases in this specification, but the qualitative results do not change. Direct policy uncertainty still negatively affects investment rates, and statistical policy uncertainty increases investment rates.

Finally, I consider the effect of economic policy uncertainty on electric utility investment rates. The investment data includes all capital investment data from pollution abatement technology to corporate offices. This means changes in investment might capture responses to electric utility policy uncertainty and general economic policy uncertainty. I replicate Baker, et al.'s (2016) economic policy uncertainty index and generate an equivalent economic policy index and statistical economic policy index. Table 6 shows the effects of economic policy uncertainty on electric utility investment rates. I find no effect of the direct economic policy uncertainty on investment, but statistical economic policy uncertainty increases investment rates. This suggests that electric utilities view economic policy as "sticks" rather than "carrots" during this period as well. However, this highlights that investments included in the data include both unique capital investments in electric utilities such as electric generators and general investments such as corporate offices. I would expect both general economic policy uncertainty and electric utility specific policy uncertainty to have an impact on investments.

1.5 CONCLUSION

Periods of high policy uncertainty have real impacts on firm-level investment decisions. However, previous empirical research has not distinguished between types of policies raising concerns that results may reflect the predominate type of policy used in an industry rather than the effect of uncertainty. Using a tightly coupled mix of theory and empirics, this paper shows the type of policies over which there is uncertainty matters when considering firms' investment rates. Uncertainty over carrot policies, such as subsidies, causes a decrease in investment rates. However, uncertainty over stick policies, such as taxes, causes an increase in investment rates, which is counter to previous empirical evidence. These theoretical results do not replace the prior literature but generalize their framework. Empirically, I find evidence of a novel positive effect of statistical policy uncertainty on electric utility investment rates. This result is theoretically consistent with my model assuming that utilities expect policies to be "sticks" during this time.

Further, the theoretical results highlight the difference between direct policy uncertainty and statistical policy uncertainty. The former has been commonly used in empirical literature since Baker et al. (2016). However, the latter has been the traditional definition used by real option investment models such as Dixit and Pindyck (1994). The empirical evidence suggests that these firms in the electric utility industry respond to both these types of policy uncertainty. I find that direct policy uncertainty decreases utility investment rates, but statistical policy uncertainty increases investment rates. These results begin a larger conversation about the nuances of how firms react to policy uncertainty.

One parameter in the theoretical model informs the expected effect of policy uncertainty on investment rates. The firm's expectations about the effect of policy on their profit, β in the model, in combination with the drift of the level of policy activity, α, determine the effect. When firms expect a policy to positively affect profit and the level of policy activity is increasing sufficiently over time, then the model produces the standard results that policy uncertainty deters investment. However, when firms expect a policy to negatively impact their profit and the level of policy activity is decreasing or increasing at a sufficiently small rate, then the model produces a novel result that policy uncertainty increases investment rates. Ultimately, these parameters boil down to an empirical question about firms' expectations about the effect of policy and how the level of policy activity changes over time. This highlights future opportunity to use earning calls transcripts to capture firm sentiment regarding policies.

The empirical results suggest that electric utility firms expected policy to negatively affect them over the relevant period. Newspaper articles discussed regulations such as greenhouse gas regulation in April 2006 and increased fees for oil and gas leases in March 2011, providing anecdotal evidence that policies were "stick" regulations. This produces another testable hypothesis that this paper does not address, but future work could measure firms' expectations to further corroborate the theoretical model. The empirical model might suffer from endogeneity as well. If policymakers react to low levels of investment in electric utilities, then this might induce higher levels of uncertainty. The results serve as an application of theoretical predictions rather than causal effects.

To give further credibility to the results, there are a few areas for future work. First, future research could explicitly create policy uncertainty measures for both types of policies: “carrots” and “sticks.” This would allow an analysis of how these types of uncertainties affect investment rather than using the regression results to imply what type of policy firms were experiencing. Further, future work could examine different types of investment rates. Compustat gives broad capital expenditures without specifying the types of investments that are being made. Other datasets, such as the Federal Energy Regulatory Commission Form 1, give more investment information specific to utilities. This would allow analysis of what types of investments respond to changes in policy uncertainty.

These results suggest a new understanding of how firms respond to policy uncertainty. When considering policy uncertainty in the real option context, consistent discussion of policies reduces future uncertainty. Policy makers could effectively reduce policy uncertainty by keeping an open dialogue, rather than unexpectedly starting policy discussions. However, if uncertainty is an inherent part of the regulatory process, then an argument could be made for “stick” policies. I’ve primarily considered the implications for the electric utility industry, but these results could apply to other sectors as well. If we expect agricultural or defense sectors to primarily receive “carrot” policies, such as subsidies, then policy uncertainty would decrease firm investment. Policy makers should carefully consider the specific context and potential reactions by the regulated firms when analyzing how policy uncertainty might impact investments.

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APPENDIX

Table 1: Policy Uncertainty Measure Descriptions

Policy Uncertainty Measure	Description
Direct Policy Uncertainty	Policy uncertainty as measured by text analysis of newspaper articles mentioning uncertainty, following Baker, Bloom, and Davis (2016). This measure attempts to directly measure policy uncertainty by counting articles that discuss relevant policies and include words relating to uncertainty.
Statistical Policy Uncertainty	Policy uncertainty as measured by estimating the stochastic volatility of the level of policy activity. First, I construct a text analysis measure of newspaper articles mentioning relevant policies, the policy index. Next, eI estimate the latent time-varying volatility process from a stochastic volatility model assuming an AR(1) process using the policy index.

Table 2: Electric Utility Policy Uncertainty Newspaper Article Search Terms

Keyword Group	Search Criteria
Economic	"economic" or "economy"
Uncertainty	"uncertain" or "uncertainty" or "uncertainties"
Regulatory Body	"Congress" or "legislation" or "regulation" or "regulatory" or "White House" or "policy" or "Federal Energy Regulatory Commission" or "Nuclear Regulatory Commission" or "public utility commission"
Industry	"electricity" or "electric" or "utilities" or "power plant" or "energy industry" or "energy sector"
Policy	"energy policy" or "energy tax" or "energy subsidy" or "carbon tax" or "cap and trade" or "cap and tax" or "pollution controls" or "environmental restrictions" or "clean air act" or "clean water act" or "greenhouse gas regulation" or "climate change regulation" or "mercury air toxics standards" or "coal ash" or "energy efficiency" or "smart grid" or "carbon capture and storage" or "renewable energy tax credit" or "renewable energy production tax credit" or "net metering" or "electrification" or "carbon pollution" or "emissions regulations" or "carbon emissions" or "modernization" or "grid security" or "energy security" or "air pollution" or "smog"

Table 3: Descriptive Statistics

Variable	Description	Mean	Standard Deviation
Investment Rate	Capital expenditures in the previous quarter divided by stock of physical capital as measured by plant, property, and equipment, winsorized, multiplied by 100 so values are interpreted as percentages	2.57	2.02
Policy Index (P)	Direct measure of policy activity using newspaper article text analysis.	184.80	111.14
Direct Policy Uncertainty (PU)	Direct measure of policy uncertainty using newspaper article text analysis following Baker, Bloom, and Davis (2016).	223.16	201.38
Statistical Policy Uncertainty (V)	Estimated statistical volatility of the Policy Index.	7.68	0.95
Real GDP growth	Real GDP growth from FRED.	0.50	1.34
Consumer Sentiment Index	University of Michigan's Consumer Sentiment survey which summarizes consumer perception of economic conditions.	84.12	10.97
Leading Index	Predicted six-month growth rate for the coincident index which measures economic conditions.	0.82	0.82
Cashflow	Ratio of cash flow to assets for a firm in a quarter.	0.02	0.52
Sales Growth	Growth of revenue for a firm from last quarter.	0.01	0.24

Table 4: Policy Uncertainty and Firm-level Investment

Dependent Variable: Firm Investment Rate	(1)	(2)	(3)	(4)	(5)	(6)
Statistical Policy Uncertainty (V)	0.113**	0.100**	0.146***			0.111**
	(0.045)	(0.043)	(0.049)			(0.044)
Direct Policy Uncertainty (ln(PU))			-0.134**	-0.060	-0.155**	-0.168***
			(0.055)	(0.050)	(0.063)	(0.064)
Policy Index (ln(P))		0.047			0.280***	0.151
		(0.079)			(0.105)	(0.093)
Cashflow	0.167***	0.167***	0.167***	0.166***	0.166***	0.167***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Sales Growth	0.486**	0.485**	0.486**	0.475**	0.476**	0.484**
	(0.199)	(0.199)	(0.199)	(0.198)	(0.197)	(0.199)
Real GDP growth	-0.025	-0.024	-0.052	-0.014	-0.039	-0.057
	(0.046)	(0.045)	(0.047)	(0.047)	(0.048)	(0.048)
Consumer Sentiment Index	-0.012***	-0.012***	-0.012**	-0.014***	-0.016***	-0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Leading Index	-0.021	-0.020	-0.001	-0.046	-0.011	0.007
	(0.046)	(0.046)	(0.047)	(0.049)	(0.048)	(0.048)
Constant	1.752***	1.697***	2.042***	2.791***	2.264***	1.936***
	(0.575)	(0.614)	(0.587)	(0.507)	(0.572)	(0.611)
Firm FE	YES	YES	YES	YES	YES	YES
Time Controls	YES	YES	YES	YES	YES	YES
Observations	8,961	8,961	8,961	8,961	8,961	8,961
R-squared	0.318	0.318	0.318	0.317	0.318	0.318

Robust standard errors in parentheses, clustered at the firm and year level
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The dependent variable is the lagged quarterly capital expenditures divided by the level of capital stock multiplied by 100, so investment rate can be interpreted as a percentage. Statistical Policy Uncertainty is the estimated log of statistical volatility of the Policy Index. The log of Direct Policy Uncertainty measures policy uncertainty using newspaper article text analysis following Baker, Bloom, and Davis (2016). The log of Policy Index measures policy activity using newspaper article text analysis. Cashflow is the ratio of cash flow to assets for a firm in a quarter. Sales growth is the growth of revenue for a firm from last quarter. Real GDP growth comes from FRED. Consumer Sentiment Index is the University of Michigan's Consumer Sentiment survey which summarizes consumer perception of economic conditions. The Leading Index is the predicted six-month growth rate for the coincident index which measures economic conditions.

Table 5: Heterogenous Effects of Policy Uncertainty and Firm-level Investment

Dependent Variable: Firm Investment Rate	(1)	(2)	(3)	(4)	(5)	(6)
Statistical Policy Uncertainty (V)	0.115**	0.162***	0.181***			0.172***
	(0.046)	(0.059)	(0.053)			(0.061)
Statistical Policy Uncertainty (V) * Revenue	-0.000	-0.000*	-0.000*			-0.000
	(0.000)	(0.000)	(0.000)			(0.000)
Direct Policy Uncertainty (ln(PU))			-0.183***	-0.061	-0.172**	-0.174**
			(0.062)	(0.054)	(0.068)	(0.071)
Direct Policy Uncertainty (ln(PU)) * Revenue			0.000*	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)
Policy Index (ln(P))		-0.031			0.295***	0.081
		(0.093)			(0.112)	(0.121)
Policy Index (ln(P)) * Revenue		0.000			-0.000	0.000
		(0.000)			(0.000)	(0.000)
Firm FE	YES	YES	YES	YES	YES	YES
Time Controls	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES
Observations	8,961	8,961	8,961	8,961	8,961	8,961
R-squared	0.318	0.318	0.318	0.317	0.318	0.319

Robust standard errors in parentheses, clustered at the firm and year level.
*** p<0.01, ** p<0.05, * p<0.1
Controls include cashflow, sales growth, real GDP growth, consumer sentiment index, and leading index. The dependent variable is the lagged quarterly capital expenditures divided by the level of capital stock multiplied by 100, so investment rate can be interpreted as a percentage. Statistical Policy Uncertainty is the estimated log of statistical volatility of the Policy Index. The log of Direct Policy Uncertainty measures policy uncertainty using newspaper article text analysis following Baker, Bloom, and Davis (2016). The log of Policy Index measures policy activity using newspaper article text analysis. The statistical policy uncertainty index, direct policy uncertainty index, and policy index are interacted with the gross revenue for a firm in the quarter. This allows the effect of policy uncertainty to change depending on the size of the firm.

Table 6: Economic Policy Uncertainty and Firm-level Investment

Dependent Variable: Firm Investment Rate	(1)	(2)	(3)	(4)	(5)	(6)
Statistical Economic Policy Uncertainty (V)	0.085*	0.090**	0.100**			0.100**
	(0.045)	(0.045)	(0.047)			(0.047)
Direct Economic Policy Uncertainty (ln(PU))			-0.180*	-0.116	-0.084	-0.150
			(0.100)	(0.095)	(0.100)	(0.106)
Economic Policy Index (ln(P))		-0.290			-0.126	-0.115
		(0.222)			(0.237)	(0.237)
Firm FE	YES	YES	YES	YES	YES	YES
Time Controls	YES	YES	YES	YES	YES	YES
Observations	8,961	8,961	8,961	8,961	8,961	8,961
R-squared	0.317	0.317	0.318	0.318	0.318	0.318

Robust standard errors in parentheses, clustered at the firm and year level

*** p<0.01, ** p<0.05, * p<0.1

The dependent variable is the lagged quarterly capital expenditures divided by the level of capital stock multiplied by 100, so investment rate can be interpreted as a percentage. Statistical Economic Policy Uncertainty is the estimated log of statistical volatility of the Economic Policy Index. The log of Direct Economic Policy Uncertainty measures economic policy uncertainty using newspaper article text analysis replicating Baker, Bloom, and Davis (2016). The log of Economic Policy Index measures economic policy activity using newspaper article text analysis. Cashflow is the ratio of cash flow to assets for a firm in a quarter. Sales growth is the growth of revenue for a firm from last quarter. Real GDP growth comes from FRED. Consumer Sentiment Index is the University of Michigan's Consumer Sentiment survey which summarizes consumer perception of economic conditions. The Leading Index is the predicted six-month growth rate for the coincident index which measures economic conditions.

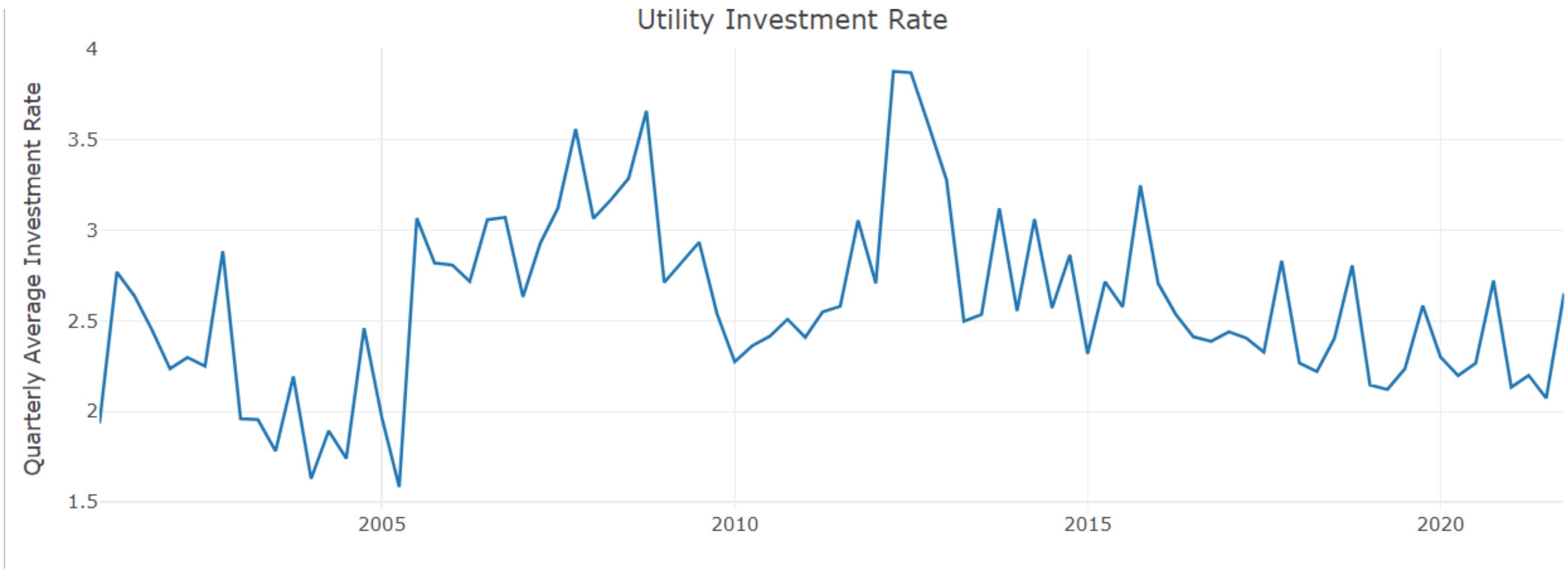
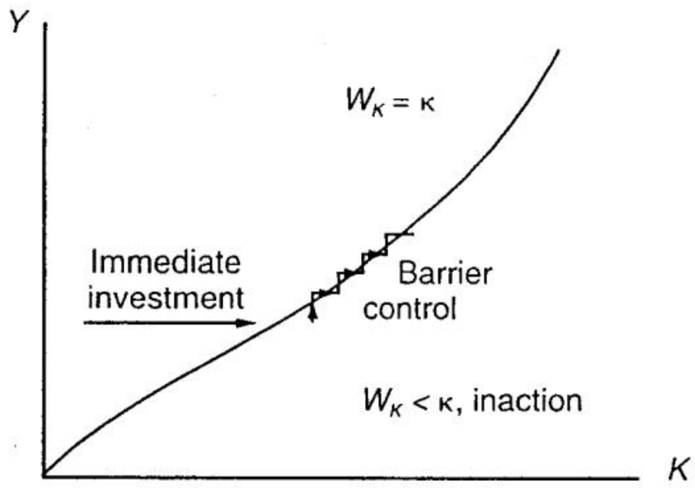
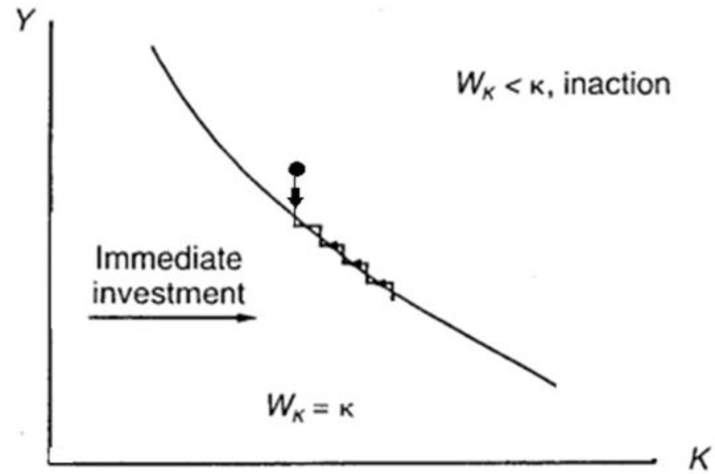


Figure 1. Quarterly Average Electric Utility Investment Rates from 2001 to 2022.



Investment Boundary Condition $\beta = 1$



Investment Boundary Condition $\beta = -1$

Figure 2. Dixit and Pindyck (1994) Investment Boundary Condition when β =1 (left) and Investment Boundary Condition when β=-1 (right).

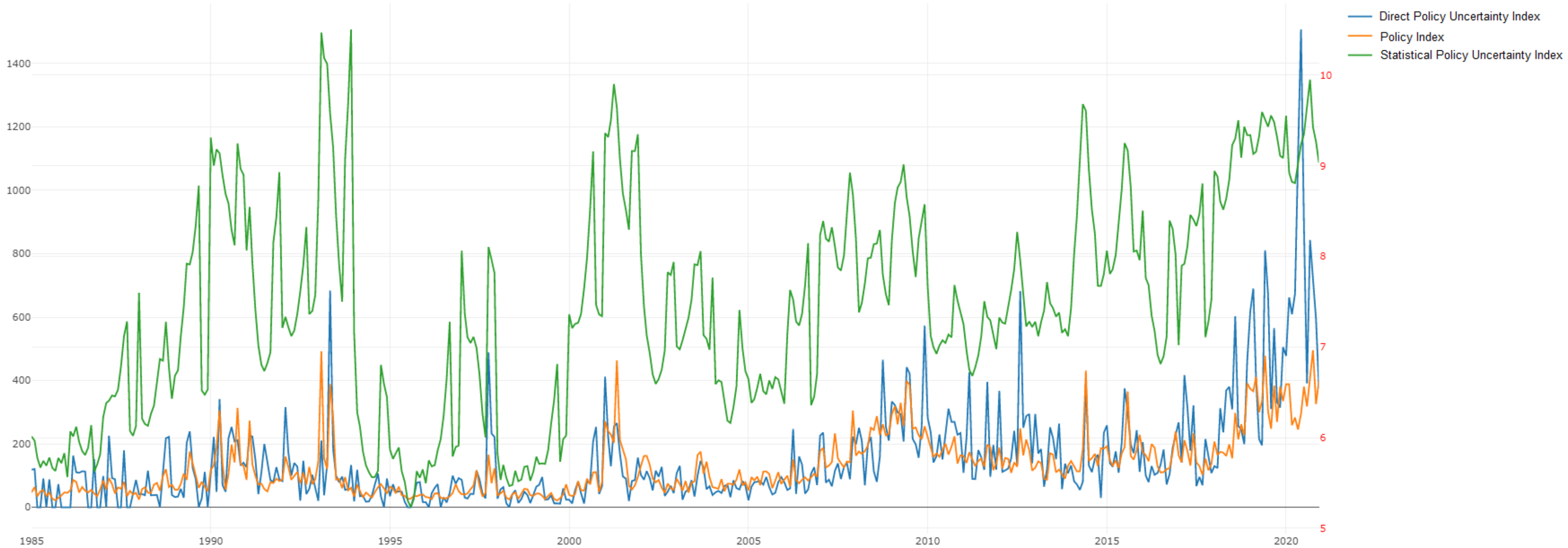


Figure 3. Electric Utility Policy (left scale), Direct Policy Uncertainty (left scale), and Statistical Policy Uncertainty (right scale) Indices 1985-2022.

THEORETICAL MODEL DERIVATION

In this appendix, I provide the mathematical steps to the theoretical model starting from rewriting the Geometric Brownian motion in terms of profit, $\boldsymbol{\pi}$.

Using Ito's Lemma, I rewrite (2), the Geometric Brownian motion, in terms of $\boldsymbol{\pi} = \boldsymbol{Y^{\beta} P H(K)}$.

$$d\pi = \beta Y^{\beta-1} H(K) Y \alpha dt + \frac{1}{2}\beta(\beta-1) Y^{\beta-2} H(K) \sigma^2 Y^2 dt + \beta Y^{\beta-1} H(K) \sigma Y dz$$

$$= \beta \pi \alpha dt + \frac{1}{2}\beta(\beta-1)\pi(K,Y)\sigma^2 dt + \beta\pi\sigma dz$$

Rewriting the Bellman equation in terms of $\boldsymbol{\pi(K,Y)}$

$$W(\pi) = \pi dt + e^{-\rho dt}\{E[W(\pi) + dW(\pi)]\}$$

Using Ito's Lemma and substituting in for $\boldsymbol{d\pi}$

$$dW(\pi) = W'(\pi) d\pi + \frac{1}{2} W''(\pi)(d\pi)^2$$

$$= W'(\pi)\left(\beta\pi\alpha dt + \frac{1}{2}\beta(\beta-1)\pi\sigma^2 dt + \beta\pi\sigma dz\right) + \frac{1}{2} W''(\pi)(\beta^2\pi^2\sigma^2 dt)$$

Substituting this into the Bellman equation,

$$W(\pi) = \pi dt + (1-\rho dt) E\left\{W(\pi) + W'(\pi)\left(\beta\pi\alpha dt + \frac{1}{2}\beta(\beta-1)\pi\sigma^2 dt + \beta\pi\sigma dz\right)\right.$$
$$\left. + + \frac{1}{2} W''(\pi)(\beta^2\pi^2\sigma^2 dt)\right\}$$

$$W(\pi) = \pi dt + W(\pi) + W'(\pi)\left(\beta\pi\alpha dt + \frac{1}{2}\beta(\beta-1)\pi\sigma^2 dt\right) + \frac{1}{2} W''(\pi)(\beta^2\pi^2\sigma^2 dt)$$
$$- \rho W(\pi) dt$$
$$- \rho(dt)^2\left\{W'(\pi)\left(\beta\pi\alpha + \frac{1}{2}\beta(\beta-1)\pi\sigma^2\right) + \frac{1}{2} W''(\pi)(\beta^2\pi^2\sigma^2)\right\}$$

$$W(\pi) = W(\pi) + dt\left\{\pi + W'(\pi)\left(\beta\pi\alpha + \frac{1}{2}\beta(\beta-1)\pi\sigma^2\right) + \frac{1}{2}W''(\pi)(\beta^2\pi^2\sigma^2) - \rho W(\pi)\right\}$$

This gives the differential equation characterizing the value of investing for the firm.

$$\mathbf{0 = \pi + W'(\pi)\left(\beta\pi\alpha + \frac{1}{2}\beta(\beta-1)\pi\sigma^2\right) + \frac{1}{2}W''(\pi)(\beta^2\pi^2\sigma^2) - \rho W(\pi)}$$

Solutions to the second-order differential equation are given by

$$W(\pi) = \mathrm{A}_1\pi^{\eta_1} + \mathrm{A}_2\pi^{\eta_2} + \frac{\pi}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)}$$

where η_1, η_2 are positive and negative roots of the fundamental quadratic, respectively.

The fundamental quadratic is

$$\boldsymbol{Q \equiv \frac{1}{2}(\beta^2\sigma)^2\eta(\eta-1) + \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)\eta - \rho = 0}$$

$$\boldsymbol{Q \equiv \frac{1}{2}(\beta^2\sigma)^2\eta^2 + \left(\beta\alpha - \frac{1}{2}\beta\sigma^2\right)\eta - \rho = 0}$$

Due to boundary conditions $\mathbf{A_2 = 0}$, so the solution simplifies further.

$$W(\pi) = \mathrm{A}_1\pi^{\eta_1} + \frac{\pi}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)}$$

$$W(K,Y) = \mathrm{A}_1\left(Y^\beta PH(K)\right)^{\eta_1} + \frac{Y^\beta PH(K)}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta-1)\sigma^2\right)}$$

Where

$$\boldsymbol{\eta_1 = \beta^2\sigma^2 - 2\beta\alpha\frac{\sqrt{(-\beta\sigma^2 + 2\beta\alpha)^2 + 8\beta^2\sigma^2\rho}}{2\beta^2\sigma^2}}$$

$$= \frac{\mathbf{1}}{\mathbf{2}} - \frac{\boldsymbol{\alpha}}{\boldsymbol{\beta\sigma^2}} + \frac{\mathbf{2}\boldsymbol{\beta}}{\mathbf{2}\boldsymbol{\beta^2\sigma^2}}\sqrt{\boldsymbol{\alpha^2 - \sigma^2\alpha} + \frac{\mathbf{1}}{\mathbf{4}}\boldsymbol{\sigma^4} + \mathbf{2}\boldsymbol{\sigma^2\rho}}$$

$$= \frac{\mathbf{1}}{\mathbf{2}} - \frac{\boldsymbol{\alpha}}{\boldsymbol{\beta\sigma^2}} + \frac{\mathbf{1}}{\boldsymbol{\beta\sigma^2}}\sqrt{\left(\boldsymbol{\alpha} - \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\sigma^2}\right)^2 + \mathbf{2}\boldsymbol{\sigma^2\rho}}$$

$$\eta_1 = \frac{1}{2} - \frac{\alpha}{\beta\sigma^2} + \sqrt{\left(\frac{\alpha}{\beta\sigma^2} - \frac{1}{2\beta}\right)^2 + \frac{2\rho}{\sigma^2}}$$

Returning to the boundary condition of inaction for the firm

$$W_K(K, Y) = \kappa$$

$$\mathrm{A}_1\eta_1\left(Y^\beta P\right)^{\eta_1} H(K)^{\eta_1 - 1} H'(K) + \frac{Y^\beta P H'(K)}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta - 1)\sigma^2\right)} = \kappa$$

$$\left[\kappa - \frac{Y^\beta P H'(K)}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta - 1)\sigma^2\right)}\right]\frac{1}{(Y^\beta P)^{\eta_1}} = \mathrm{A}_1\eta_1 H(K)^{\eta_1 - 1} H'(K)$$

The smooth-pasting condition for the solution is:

$$W_{KY}(K, Y) = 0$$

$$\mathbf{A_1}\boldsymbol{\eta_1}(\boldsymbol{\eta_1\beta})\boldsymbol{P^{\eta_1}Y^{\beta\eta_1 - 1}H(K)^{\eta_1 - 1}H'(K)} + \frac{\boldsymbol{\beta Y^{\beta - 1}PH'(K)}}{\boldsymbol{\rho} - \left(\boldsymbol{\beta\alpha} + \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta(\beta} - \mathbf{1})\boldsymbol{\sigma^2}\right)} = \mathbf{0}$$

$$-\frac{\beta}{\eta_1\beta P^{\eta_1}Y^{\beta\eta_1 - 1}}\frac{Y^{\beta - 1}PH'(K)}{\rho - \left(\beta\alpha + \frac{1}{2}\beta(\beta - 1)\sigma^2\right)} = \mathrm{A}_1\eta_1 H(K)^{\eta_1 - 1} H'(K)$$

Combining these two gives us the final boundary condition of inaction for the firm.

$$\left[\boldsymbol{\kappa}-\frac{\boldsymbol{Y^{\beta}PH'(K)}}{\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)}\right]\frac{\mathbf{1}}{(\boldsymbol{Y^{\beta}P})^{\boldsymbol{\eta_1}}}$$

$$= -\frac{\boldsymbol{\beta}}{\boldsymbol{\eta_1\beta P^{\eta_1}Y^{\beta\eta_1-1}}}\frac{\boldsymbol{Y^{\beta-1}PH'(K)}}{\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)}$$

$$\left[\boldsymbol{\kappa}-\frac{\boldsymbol{Y^{\beta}PH'(K)}}{\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)}\right] = -\frac{\mathbf{1}}{\boldsymbol{\eta_1}}\frac{\boldsymbol{Y^{\beta}PH'(K)}}{\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)}$$

$$\boldsymbol{\kappa}\left[\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)\right] = \boldsymbol{Y^{\beta}PH'(K)}-\frac{\mathbf{1}}{\boldsymbol{\eta_1}}\boldsymbol{Y^{\beta}PH'(K)}$$

$$\frac{\boldsymbol{\kappa}}{\boldsymbol{PH'(K)}}\left[\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)\right] = \boldsymbol{Y^{\beta}}-\frac{\mathbf{1}}{\boldsymbol{\eta_1}}\boldsymbol{Y^{\beta}}$$

$$\frac{\boldsymbol{\kappa}}{\boldsymbol{PH'(K)}}\left[\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)\right] = \boldsymbol{Y^{\beta}}\left(\frac{\boldsymbol{\eta_1}-\mathbf{1}}{\boldsymbol{\eta_1}}\right)$$

$$\left(\frac{\boldsymbol{\eta_1}}{\boldsymbol{\eta_1}-\mathbf{1}}\right)\frac{\boldsymbol{\kappa}}{\boldsymbol{PH'(K)}}\left[\boldsymbol{\rho}-\left(\boldsymbol{\beta\alpha}+\frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{\beta}(\boldsymbol{\beta}-\mathbf{1})\boldsymbol{\sigma}^{\mathbf{2}}\right)\right] = \boldsymbol{Y^{\beta}}$$

$$Y = \left\{\left(\frac{\eta_1}{\eta_1-1}\right)\frac{\kappa}{PH'(K)}\left[\rho-\left(\beta\alpha+\frac{1}{2}\beta(\beta-1)\sigma^2\right)\right]\right\}^{\frac{1}{\beta}}$$

Note that when $\boldsymbol{\beta = 1}$, I recover the boundary condition found in Dixit and Pindyck (1994):

$$\boldsymbol{Y = \left(\frac{\eta_1}{\eta_1 - 1}\right)\frac{\kappa}{PH'(K)}[\rho - \alpha]}$$

Now, let $\boldsymbol{\beta = -1}$.

$$\boldsymbol{Y = \left\{\left(\frac{\eta_1}{\eta_1 - 1}\right)\frac{\kappa}{PH'(K)}\left[\rho - \left(-\alpha + \frac{1}{2}(-1)(-2)\sigma^2\right)\right]\right\}^{-1}}$$

$$\boldsymbol{Y = \left\{\left(\frac{\eta_1}{\eta_1 - 1}\right)\frac{\kappa}{PH'(K)}[\rho + \alpha - \sigma^2]\right\}^{-1}}$$

$$\boldsymbol{Y = \left(\frac{\eta_1 - 1}{\eta_1}\right)\frac{PH'(K)}{\kappa[\rho + \alpha - \sigma^2]}}$$

Now, I turn to the derivation of the investment rate from the barrier control problem. First, consider the novel case where $\boldsymbol{\beta = -1}$. Equation (11) can be rewritten as

$$YK^{1-\theta} = \bar{M}$$

where $\boldsymbol{\bar{M} = \left(\frac{\eta_1-1}{\eta_1}\right)\frac{P\theta}{\kappa[\rho+\alpha-\sigma^2]}}$ is a constant given model parameters. When $\boldsymbol{YK^{1-\theta} \leq \bar{M}}$ then the firm increases investment, decreasing $\boldsymbol{YK^{1-\theta}}$ until $\boldsymbol{YK^{1-\theta} = \bar{M}}$. When $\boldsymbol{YK^{1-\theta} \geq \bar{M}}$ then the firm does not invest in new capital. When the level of capital does not change, then $\boldsymbol{YK^{1-\theta}}$ follows the same Geometric Brownian Motion as $\boldsymbol{Y}$. Let $\boldsymbol{M = YK^{1-\theta}}$, and $\boldsymbol{m = \ln\left(YK^{1-\theta}\right)}$. Then $\boldsymbol{m}$ follows an Arithmetic Brownian Motion so long as the firm does not invest in new capital.

$$m = \left(\alpha - \frac{\sigma^2}{2}\right)t + \sigma W_t$$

Since $\boldsymbol{m}$ is bounded below, then it has the following density function, $\boldsymbol{\Pi}(\boldsymbol{m})$, assuming $\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1} < \boldsymbol{0}$ or $\boldsymbol{\alpha} < \frac{\boldsymbol{\sigma^2}}{\boldsymbol{2}}$

$$\boldsymbol{\Pi}(\boldsymbol{m}) = -\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right) \mathbf{exp}\left(\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right)(\boldsymbol{m} - \boldsymbol{\bar{m}})\right)$$

for $\boldsymbol{\bar{m}} < \boldsymbol{m} < \infty$.

To derive the investment rate, consider the scenario where a firm will invest in new capital. A firm invests in new capital when $\boldsymbol{m}$ falls to hit the boundary condition. The probability that $\boldsymbol{m}$ hits the boundary condition is equal to the probability that $\boldsymbol{m}$ is sufficiently close to the boundary times the probability that $\boldsymbol{m}$ decreases causing it to hit the boundary condition. The probability that $\boldsymbol{m}$ is sufficiently close to the barrier times is $-\boldsymbol{dh}\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right)$ where $\boldsymbol{dh} = \boldsymbol{\sigma}\sqrt{\boldsymbol{dt}}$ is a small partition of $\boldsymbol{m}$. The probability that $\boldsymbol{m}$ decreases is $\frac{\boldsymbol{1}}{\boldsymbol{2}}\left[\boldsymbol{1} - \frac{-\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right)\sqrt{\boldsymbol{dt}}}{\boldsymbol{\sigma}}\right]$. So, the probability that a firm will invest in new capital is equal to $-\boldsymbol{dh}\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right)\frac{\boldsymbol{1}}{\boldsymbol{2}}\left[\boldsymbol{1} - \frac{-\left(\frac{\boldsymbol{2\alpha}}{\boldsymbol{\sigma^2}} - \boldsymbol{1}\right)\sqrt{\boldsymbol{dt}}}{\boldsymbol{\sigma}}\right]$.

Next, consider the size of the investment when a firm does invest in new capital. Taking the natural logs of the boundary condition

$$\ln(Y) + (1 - \theta)\ln(K) = \ln(\bar{M})$$

If $\boldsymbol{Y}$ decreases, then it must be the case that the firm invests to keep $\boldsymbol{m} = \boldsymbol{\bar{m}}$. In this case

$$dm = 0$$

$$\boldsymbol{lnY + (1-\theta)lnK = 0}$$

$$\boldsymbol{-dh + (1-\theta)dk = 0}$$

$$\boldsymbol{\frac{dK}{K} = dk = \frac{dh}{1-\theta}}$$

so the change in capital when $\boldsymbol{m}$ hits the lower barrier is $\boldsymbol{\frac{dh}{1-\theta}}$.

Finally, the investment rate is the product of the probability that $\boldsymbol{m}$ is sufficiently close to the barrier, the probability that $\boldsymbol{m}$ decreases and hits the barrier, and the magnitude of investment. Divide this product by $\boldsymbol{dt}$ to convert it into a rate. As we evaluate this investment rate, $\sqrt{\boldsymbol{dt}}$ terms drop out since in the limit they go to zero faster than $\boldsymbol{dt}$ terms.

$$\boldsymbol{\frac{\dot{K}}{K} = \left(-dh\left(\frac{2\alpha}{\sigma^2}-1\right)\right)\frac{1}{2}\left[1-\frac{-\left(\frac{2\alpha}{\sigma^2}-1\right)\sqrt{dt}}{\sigma}\right]\left(\frac{dh}{1-\theta}\right)\left(\frac{1}{dt}\right)}$$

$$\boldsymbol{= -\left(\frac{2\alpha}{\sigma^2}-1\right)\left(\frac{1}{2}\right)\left(\frac{dh^2}{1-\theta}\right)\left(\frac{1}{dt}\right)}$$

$$\boldsymbol{= -\left(\frac{2\alpha}{\sigma^2}-1\right)\left(\frac{1}{2}\right)\left(\frac{(\sigma^2 dt)}{1-\theta}\right)\left(\frac{1}{dt}\right)}$$

$$\boldsymbol{= -\left(\frac{2\alpha}{\sigma^2}-1\right)\left(\frac{1}{2}\right)\left(\frac{(\sigma^2)}{1-\theta}\right)}$$

$$\frac{\dot{K}}{K} = \left(-\alpha + \frac{\sigma^2}{2}\right)\left(\frac{1}{1-\theta}\right) > 0$$

CHAPTER II
REAL OPTIONS AND LOW-PROBABILITY HIGH-SEVERITY EVENTS: EXPERIMENTAL EVIDENCE

ABSTRACT

I experimentally test whether real option theory describes how individuals value information, or equivalently option value, under low-probability, high-severity outcomes. I show how behavioral deviations resulting from probability weighting and risk aversion could cause deviations from real option theory. However, theoretically these behavioral deviations from real option theory have largely ambiguous effects on willingness to pay for information. I turn to an experimental context to estimate how low probabilities, high spreads, and loss aversion affect individuals' willingness to pay for information. I find that participants behave consistently with directional predictions from real option theory from changes in probability and spread. However, in contexts with low-probability, high-severity outcomes, participants' behavior systematically deviates from real option theory point predictions. In contexts such as a low probability lifesaving medical procedure, individuals would wait too long or gather too much information than would be optimal according to real option theory. In the context of public policy, low-probabilty high-severity outcomes would cause voter preferences to deviate from the optimal timing of policy as described by real option theory. Policy makers might need to conduct excess research about potential outcomes compared to what real option theory would suggest.

2.1 INTRODUCTION

Economic agents often make decisions under uncertainty with low-probability, high-severity outcomes. These contexts include investing in risky assets, choosing climate change policy, or choosing among healthcare treatments. Real option theory describes how agents should behave when choices are irreversible and agents can delay their choice to gain more information. However, I might expect to observe behavioral deviations from optimal choices for decisions with low-probability high-severity outcomes. Individuals may exhibit behavior consistent with probability weighting with low-probability outcomes (e.g. Tversky & Kahneman, 1992; Gonzalez & Wu, 1999) or increased risk aversion with high-severity events (Pratt, 1964). Ex-ante, it is not clear how these observed phenomena will change how agents value the option to wait or equivalently the value of information. By understanding how individuals value information in a real option context, policy makers can identify areas where public opinion might deviate from optimal policy implementation.

In this paper, I experimentally test whether individuals act consistently with real option theory with low-probability, high-severity outcomes. For individuals who recognize option value, I theoretically show how probability weighting and high-severity outcomes might change their valuation of the option to wait or equivalently their willingness to pay for new information relative to real option theory. Probability weighting has differential effects on willingness to pay for information conditional on characteristics of the outcomes relative to a certain outside option. Risk aversion has an ambiguous effect on the willingness to pay for information, since there are two potential mechanisms that would affect willingness to pay. While these two behavioral phenomena give insight into how individuals might deviate from real option theory, ultimately there are few clear theoretical predictions. This motives experimentally testing how participants value information under low-probability high-severity outcomes. Further, I test low-probability high-severity outcomes in both gains and loss space, as loss aversion might interact uniquely with these behavioral deviations. I experimentally test whether individuals adhere to real option theory, their sensitivity to gains versus losses, their tendency toward probability weighting, and if their responsiveness to increases in the spread of outcomes in a real option context.

I design an experiment to test these theoretical predictions in a controlled laboratory setting. Similar to List and Haigh (2010), I utilize a simplified real option context where individuals choose between playing a lottery immediately, choosing a certain outside option, or paying a cost to learn new information about the lottery outcome. This setup abstracts from familiar continuous-time real option settings, which have been examined in Oprea et al. (2009). However, abstracting from a realistic dynamic setting allows for a simplified participant experience. The experimental setting also allows us to isolate the effect of changes in probabilities, outcome spreads, and gains versus losses. By independently changing the probability and spread of outcomes, I identify potential deviations from real option theory due to probability weighting and risk aversion separately.

This work contributes to the growing experimental literature finding evidence for real option theory. Prior work indiciates that individuals behave consistently with real option theory in both a simplified lottery setting (List and Haigh, 2010) and complex continuous-time settings (Oprea et al., 2009; Descamps et al., 2022). Some deviations from optimal behavior have been attributed to risk aversion (Miller and Shapira, 2004; Della Seta et al., 2014). Outside of real option contexts, low-probability outcomes have been studied theoretically and empirically (e.g. Barberis, 2013). However, real option theory has never been tested in settings with low-probability high-severity outcomes.

This paper also contributes to the literature on the willingness to pay for information or the reduction of uncertainty. The tests of real option theory are framed as paying for information which eliminates the uncertainty of a lottery. Empirical research shows that uncertainty over a good or policy decreases its value relative to a certain outcome (e.g. Cameron, 2005; Riddel & Shaw, 2006; Roberts et al., 2008). In some applications, there is mixed evidence that individuals value certainty independently from the primary good of interest (e.g. Akter et al., 2012; Rolfe & Windle, 2015; Torres, et al., 2017). The related literature on the Contingent Valuation Method has acknowledged the importance of carefully considering how uncertainty might affect willingness to pay estimates (e.g. Johnston et al., 2017). This paper sheds light on how individuals might value information under ideal circumstances of known probabilities without preferences or beliefs regarding a specific context. If individuals do not behave according to real option theory in a laboratory setting with low-probability high-severity events, then real option theory likely does not apply in more complicated settings such as climate change policy or valuing environmental goods.

The results of this paper give valuable insight into policy-making decisions. For example, Conrad (1997) argues that option value should be included in climate change policy decisions due to scientific uncertainty. I find that participants behaved according to directional predictions from real option theory for changes in probabilities and spread. This suggests that real option theory reasonably describes individual behavior, meaning most voters would support the optimal timing of policies with irreversible outcomes as described by real option theory such as climate change policies. Second, I found that participants deviate from point predictions from real option theory under low-probability high-severity outcomes consistent with probability weighting. Under different circumstances, participants overvalued and undervalued the option to wait relative to real option theory. In general, I find that participants undervalued information relative to real option theory when considering low-probability high-severity undesirable events. When considering low-probability high-severity desirable events, participants overvalued information relative to real option theory. This highlights scenarios where policy makers would need to deviate from voters' preferences to implement an optimal policy according to real option theory. Alternatively, policy makers might need to provide additional information on policy outcomes in these contexts to garner voter support.

2.2 THEORETICAL FRAMEWORK

I modify List and Haigh's (2010) simplified two-period real option theoretical framework, originally derived from the simple case presented in Dixit and Pindyck (1994). Suppose an economic agent ispresented with the opportunity to invest in a project with uncertain outcomes. I can simplify this to a lottery that gives a high payoff $H >$

OUT with probability p and a low payoff $L < OUT$ with probability $1 - p$, where OUT is the certain outside option instead of playing the lottery. In period 1, the economic agent has three options. They can play the lottery without knowing the realization of payoffs, they can choose the certain outside option OUT, or they can pay a cost, $C \geq 0$, to observe the realization of the lottery outcome before they decide to play the lottery or not. This can be thought of as a simplified version of real option theory where paying the cost is like “waiting” for all uncertainty to be resolved. In contrast to Dixit and Pindyck (1994) and List and Haigh (2010), the cost, C, is the cost of observing the realization of the lottery outcomes rather than the cost of the playing the lottery.

To analyze this scenario under real option theory, I make a few simplifying assumptions. Under real option theory, I assume the economic agent is a risk-neutral expected utility maximizer. I consider two scenarios where lotteries are considered over gains space and loss space. In this context, I define a lottery to be in gains space when $H > OUT > L > 0$. The corresponding definition for loss space is $0 > H > OUT > L$. While the original Dixit and Pindyck (1994) model does not include lotteries, I show how this setup is mathematically equivalent in the Appendix.

Consider the expected value of playing the lottery with the information available in period 1. This relates to the termination value in Dixit and Pindyck (1994), which is the value of playing the lottery if there is no option to wait. The termination value is then defined as $max(EV(O_1|I_1), OUT)$ where $EV(O_1|I_1)$ is the expected value of the lottery.

$$EV(O_1|I_1) = pH + (1 - p) \qquad (23)$$

Consider the decision in period 2 after they see the realization of the lottery. Since $L < 0$, then they will not play the lottery if the low outcome occurs. In the context of Dixit and Pindyck (1994), the continuation value is defined as $max(EV(O_2|I_1), OUT)$, where $EV(O_2|I_1)$ is the value of the decision in period 2 with information in period 1.

$$EV(O_2|I_1) = pH + (1-p)(OUT) - C = p(H - OUT) + OUT - C \qquad (24)$$

If the lottery resolves in the high outcome, they play the lottery. Otherwise, playing the lottery with the low outcome will result in a loss, so they forego the option to play the lottery. Note that they pay a cost of C regardless of the lottery outcome since they wait until period 2 to see the resolution of the uncertain payoffs.

Finally, the value of the option to play the lottery as defined by Dixit and Pindyck (1994) is calculated as

$$max(EV(O_1|I_1), EV(O_2|I_1), OUT) \qquad (25)$$

and option value is defined as

$$OV = max(EV(O_1|I_1), EV(O_2|I_1), OUT) - max(EV(O_1|I_1), OUT) \qquad (26)$$

Three relevant conditions classify individuals' behaviors. First, when $OV > 0$, then there is value in the information and they should pay the cost to see the outcome of the lottery before making the decision. Second, when $OV = 0$ and $EV(O_1|I_1) > OUT$, then they should play the lottery immediately. Third, when $OV = 0$ and $EV(O_1|I_1) < OUT$, then they should take the certain outside option. Table 7 summarizes the optimal choice under each condition using List and Haigh's (2010) notation.

In this setup, the cost, C, can also be interpreted as the individuals' willingness to pay for new information. As the analysis relies on estimating willingness to pay for information, it is worth considering the willingness to pay function from the real option framework. Simply put, the economic agents' willingness to pay should be exactly equal to C^*, which is the critical value where option value is equal to 0 in the theoretical framework. I can write WTP as

$$WTP = C^* = \begin{cases} (1-p)(OUT-L) & if\ pH + (1-p)L \geq OUT \\ p(H-OUT) & if\ pH + (1-p)L < OUT \end{cases} \tag{27}$$

As I can see, WTP is a function of both the probability of outcomes and the difference between the outside option and lottery outcomes. This means that as I change the probabilities and spread of outcomes, I would expect to see changes in WTP accordingly.

First, consider how changing the probability changes WTP. Formally, I take the partial of the willingness to pay function with respect to the probability, p.

$$\frac{\partial WTP}{\partial p} = \begin{cases} -(OUT-L) < 0 & if\ pH + (1-p)L \geq OUT \\ (H-OUT) > 0 & if\ pH + (1-p)L < OUT \end{cases} \tag{28}$$

In other words, when the expected value of the lottery is greater than the outside option, increasing the probability of the high outcome decreases willingness to pay. Note that increasing the probability of the high outcome also increases the expected value of the lottery. This means that when $pH + (1-p)L = OUT$ an increase in p increases the expected value of the lottery such that $pH + (1-p)L > OUT$. This causes a discrete change in WTP from $p(H-OUT)$ to $(1-p)(OUT-L)$. Since $pH + (1-p)L > OUT$, then $p(H-OUT) > (1-p)(OUT-L)$, meaning this discrete change decreases WTP. When the expected value of the lottery is less than the outside option, an increase in p increases WTP. While there are clear directional predications in changes of probabilities, they are conditional on the expected value of the lottery relative to the outside option.

Second, increasing the spread of outcomes increases WTP, assuming the distance from the outside option to both the high and low outcome increases. In other words, consider the comparative static assuming no change in the expected value of the lottery.

$$\frac{\partial WTP}{\partial(H-L)} = \begin{cases} (1-p) > 0 & if\ pH + (1-p)L \geq OUT \\ p > 0 & if\ pH + (1-p)L < OUT \end{cases} \tag{29}$$

Note that there are scenarios where only the high outcome or low outcome change and WTP would still increase. There are also scenarios where changing the spread changes the expected value of the lottery which could cause in increase or decrease in WTP. Holding the expected value of the lottery relative to the outside option constant, I would expect an increase in WTP.

There are potential behavioral deviations from real option theory assumptions that would change WTP beyond what I would expect from real option theory predictions. Since I am interested in low-probability high-severity outcomes, I consider two sources of behavioral deviations from real option theory. First, individuals could behave differently with low-probability outcomes, keeping the severity of outcomes constant. I consider the theoretical explanation of probability weighting (e.g. Tversky & Kahneman, 1992; Gonzalez & Wu, 1999). Individuals overestimate the likelihood of low-probability events and underestimate the likelihood of high-probability events. Second, in the presence of uncertainty individuals could be risk-averse.

2.2.1 PROBABILITY WEIGHTING

First, consider how probability weighting changes the willingness to pay function. Let the true probability of the high outcome be p, and let $p' < p$ if $p > 0.5$ and $p' > p$ if $p < 0.5$. Similarly, let $q = 1 - p$, and let $q' < q$ if $q > 0.5$ and $q' > q$ if $q < 0.5$. That is, the decision maker in the model overweights the probability of low probability events occurring and underweights the probability of high probability events occurring. Now I can write the WTP function as

$$WTP_{weight} = \begin{cases} (q')(OUT - L) \;\; if \;(p')H + (q')L > OUT \\ (p')(H - OUT) \;\; if \;(p')H + (q')L < OUT \end{cases} \qquad (30)$$

Consider when $p < 0.5$ and $q > 0.5$. Notice there are two ways that probability weighting could create deviations of willingness to pay from optimal. First, the economic agent could perceive that the expected value of the lottery changes relative to the outside option. For example, even if $(p)H + (q)L < OUT$, probability weighting might cause the agent to perceive that $(p')H + (q')L > OUT$. Without assuming the probabilities need to sum to 1 ($p' + q' = 1$) or estimating parameters of the probability weighting function, I cannot determine how the perceived expected value might change. Second, the WTP will directly change since the WTP function depends on both p' and q'. If the expected value of the lottery is greater than the outside option, then WTP will decrease relative to real option theory. However, if the expected value of the lottery is less than the outside option, then WTP will increase relative to real option theory. Assuming no changes in perception of the expected value of the lottery, this can be summarized according to the expected value of the lottery. If the expected value is greater than the outside option, I would expect a decrease in WTP. If the expected value is less than the outside option, I would expect an increase in WTP.

Now consider when $p > 0.5$ and $q < 0.5$. Similar to before, there are two ways which the economic agent might deviate from optimal behavior: perceiving the expected value of the lottery to change relative to the outside option, and directly changing their WTP. Similar to before I can summarize the effects according to the expected value of the lottery relative to the outside option. When the expected value is greater than the outside option, WTP will increase relative to real option theory. When the expected value is less than the outside option, WTP will decrease.

Table 8 summarizes the effect of probability weighting on willingness to pay conditional on the expected value of the lottery assuming no change in the perception of the expected value. When considering changes in the perception of the expected value, the effects are ambiguous. While this framework gives some expectations of potential directional effects relative to real option theory, it motivates the experimental tests to determine which behavioral effect might dominate.

2.2.2 RISK AVERSION

Now, consider how risk aversion under severe outcomes affects the decisions in a real option model. Without specifying a functional form for utility, let us assume the economic agent is risk-averse. This implies that $p * U(H) + (1 - p) * U(L) < U(p * H + (1 - p) * L)$, where $U(x)$ is the utility of outcome x. To see how risk aversion changes the optimal behavior consider the following. Assume that the cost they face is equal to the WTP in (27), $C = C^*$, assuming $EV(O_2|I_1) = EV(O_1|I_1) > OUT$.

By definition, real option theory states they are indifferent between playing the lottery now or paying the cost for information. Consider the utility of the three options:

$$U(OUT) \tag{31}$$

$$U(O_1|I_1) = p * U(H) + (1-p) * U(L) \tag{32}$$

$$U(O_2|I_1) = p * U(H - C^*) + (1-p) * U(OUT - C^*) \tag{33}$$

Under real option theory, the agents' preferences are $U(O_2|I_1) = U(O_1|I_1) > U(OUT)$. By construction, the expected value of paying for information or playing the lottery immediately is equal and greater than the outside option, or $EV(O_2|I_1) = EV(O_1|I_1) > OUT$. Under risk aversion, the agent would least prefer $(O_1|I_1)$ as it is strictly dominated by $(O_2|I_1)$ since the spread of outcomes is the largest at $H - L$. However, their preferences between $(O_2|I_1)$ and (OUT) depend on their level of risk aversion. The spread of $(O_2|I_1)$ is $H - OUT$ which is greater than the spread of (OUT), but $EV(O_2|I_1) > OUT$. If they prefer $(O_2|I_1)$ then their WTP would be larger than the real option theory would predict. However, if they prefer (OUT) then their WTP would be smaller. This means risk aversion in this context has an ambiguous effect on WTP.

Now assume that $EV(O_2|I_1) = OUT > EV(O_1|I_1)$. By definition, real option theory states they are indifferent between the outside option or paying for information. Consider the utility of the three options in (31), (32), and (33). Under real option theory, the agents' preferences are $U(O_2|I_1) = U(OUT) > U(O_1|I_1)$. By construction, the expected value of paying for information is equal to the outside option and larger than playing the lottery immediately, or $EV(O_2|I_1) = OUT > EV(O_1|I_1)$. Under risk aversion, the agent would most prefer (OUT) as the spread of outcomes is smallest and the expected value is greater than or equal to all other options. Since they have a clear preference for (OUT) then their WTP would be less than is predicted by real option theory.

To summarize, as I increase the spread of outcomes, I would expect a decrease in WTP relative to real option theory if the expected value of the lottery is less than the outside option. However, there is an ambiguous effect when the expected value is greater than the outside option.

As I am primarily interested in how low-probability high-severity outcomes might affect participants' behavior, I now examine the interaction between probability weighting and risk aversions. This can be summarized in Table 9 assuming that probability weighting does not change the perceived expected value of the lottery. Note that the effect of increasing spread when the expected value of the lottery is greater than the outside option is ambiguous from the previous results. This means the interaction effect when the expected value is greater than the outside option will also be ambiguous. When the expected value of the lottery is less than the outside option, risk aversion would decrease the WTP. However, when the probability of the high outcome is small probability weighting would cause an increase in WTP. It is unclear which effect would be dominant, so the interaction effect is ambiguous. Lastly, probability weighting and risk aversion would predict a decrease in WTP when the probability is large and the expected value is less than the outside option. This gives us the only unambiguous prediction of a decrease in WTP.

Finally, consider the behavioral effect of loss aversion as I shift the outcomes from gains to loss space. List and Haigh (2010) consider loss aversion as a potential explanation for participant behavior which appeared like real option theory. While I focus on low-probability high-severity outcomes, I briefly consider loss aversion to address this concern. Following Tversky and Kahneman (1992) consider the following value function,

$$v(x) = \begin{cases} (x)^{\alpha} & if\ x > 0 \\ -\lambda(-x)^{\beta} & if\ x \leq 0 \end{cases} \quad (34)$$

where x is the outcome of interest, α and β determine the curvature, and λ weights losses more relative to gains. Note that the value function is concave in gains space and convex in loss space. Without estimating parameters, this gives insight into a potential deviation from real option theory. The concavity in gains space gives the same results as risk-aversion considered previously. The preference for certain outcomes relative to uncertain outcomes with the same expected value, creates a decrease in WTP relative to real option theory if the expected value of the lottery is less than the outside option and an ambiguous effect otherwise.

The convexity in loss space gives the opposite effect, the agent now prefers uncertain outcomes relative to certain outcomes with the same expected value. Consider the utility of the economic agent's three choices: (31), (32), and (33). In the first scenario, assume the expected value of the lottery is less than the outside option, or $EV(O_2|I_1) = OUT > EV(O_1|I_1)$. By definition, real option theory states they are indifferent between the outside option or paying for information since the cost they face is exactly their WTP for information. Since the value function is convex, they prefer to pay for information, $(O_2|I_1)$. This would suggest that their WTP would be higher than real option theory predicts. Depending on the specific parameter estimates, it is possible that they would prefer playing the lottery immediately, $(O_1|I_1)$, since the spread of outcomes is larger. In other words, they might prefer a riskier lottery at the expense of a lower expected value. If they prefer to play the lottery immediately, this would decrease their WTP. This means there is an ambiguous effect of loss aversion on WTP when the expected value of the lottery is less than the outside option. In the second scenario assume that the expected value of the lottery is greater than the outside option, or $EV(O_2|I_1) = EV(O_1|I_1) > OUT$. Since the cost of information is equal to real option theory's predicted WTP, the expected value of playing the lottery immediately or paying for information is equal. Note that the expected value of the outside option is less than the lottery and the spread is smaller than the lottery, so under loss aversion the economic agent would not choose the outside option. The expected value of paying for information is equal to playing the lottery immediately, but the spread of outcomes when playing the lottery immediately is larger. Due to the convex value function in losses, the economic agent prefers to play the lottery immediately as they prefer the riskier option. This means their WTP would decrease relative to the predictions from real option theory.

To summarize, in gains space WTP would decrease relative to real option theory when the expected value of the lottery is less than the outside option, and in loss space WTP would decrease relative to real option theory when the expected value of the lottery is greater than the outside option. Under other conditions, the effect of loss aversion is ambiguous. Due to the ambiguous results, I cannot clearly identify situations where WTP should be different when directly comparing gains and losses. I do not consider scenarios where the lottery outcomes are in gains and loss space, which would change the predictions previously discussed.

This theoretical framework shows how probability weighting, high severity outcomes, and loss aversion might affect individuals' willingness to pay for new information relative to traditional real option theory. Real option theory gives point predictions for willingness to pay for information, and I hope to attribute any deviations from these point predictions to the behavioral deviations previously discussed. These different frameworks give different predictions when changing specific characteristics of the lottery. For example, as I've considered it here, probability weighting does not change conditional on outcomes occurring in gains or losses. This gives rise to potential interaction effects from these behavioral deviations. I do not consider every interaction since the predicted deviations from real option theory are largely ambiguous.

2.3 EXPERIMENTAL DESIGN

The experimental design reflects the experiment conducted by List and Haigh (2010) with minor changes. Participants choose between playing a lottery in period 1, playing a lottery in period 2 after paying a cost, C, or receiving a certain payout instead of playing the lottery. If the participant plays the lottery in period 1, they earn the high outcome of the lottery, H, with probability p and the low outcome of the lottery, L, probability $1 - p$. Participants have the option of not playing the lottery and receiving a certain payoff, which I refer to as the outside option or OUT. Outcomes are always constructed such that $L < OUT < H$. Participants have a third option, if they pay a cost, C, they may observe the outcome of the lottery before making their decision to play the lottery. If the low outcome occurs, the participant can choose the outside option which will always be preferable to the low outcome. In this way, the cost, C, can be thought of as the participants' willingness to pay for information about the lottery outcome or the willingness to pay to reduce uncertainty over their potential earnings.

The experimental design differs from List and Haigh (2010) in two ways. First, List and Haigh (2010) change the lottery payoffs between period 1 and period 2. I simplify the design by keeping the lottery payoffs constant but introducing a cost that must be paid to move to period 2. This introduces a second difference: participants may choose to receive a certain payout of the outside option. The Appendix shows how the design setup is theoretically equivalent to Dixit and Pindyck (1994).

I implement a full factorial experimental design for a total of 24 lottery parameterizations (2x3x2x2)[4]. The first lottery treatment variable varies the expected value of the lottery relative to the certain outside option from negative, $EV(O_1|I_1) - OUT < 0$, to positive, $EV(O_1|I_1) - OUT > 0$. This allows testing unambiguous effects of probability weighting and risk aversion identified in the theoretical framework. The second treatment variable varies the probabilities of high lottery outcomes from 0.5, 0.85, and 0.15. In the base case, each lottery outcome occurs with equal probability. I compare these results to lotteries where the negative outcome occurs with low probability ($p = 0.85$) and lotteries where the positive outcome occurs with low probability ($p = 0.15$).

[4] 4 treatment variables with 2, 3, 2, and 2 outcomes respectively.

Prior research shows evidence that individuals exhibit probability weighting for this range of probabilities (e.g. Gonzalez & Wu, 1999). The third treatment variable adjusts the spread of the lottery outcomes, where I wish to consider high-spread outcomes to simulate high-severity events. I simultaneously need to balance participants' expected earnings and incentives to pay the cost for information, which limits the extent to which I can vary the spread. I choose to vary the spread of lottery outcomes from $4 to $8, which I argue is significant when the highest lottery outcome is only $7 larger than the certain outside option. The last treatment variable allows us to examine the effect of loss aversion. By shifting the high outcome, low outcome, and certain outside option by the same amount, I retain the same predictions from real option theory. First, consider all positive values where the certain outside option is $10. The second group of lotteries has a certain outside option of -$10 and the lottery outcomes are both negative. Participants are guaranteed to lose money in this second group of lotteries. These groups give variation between loss and gains space without mathematically changing any other characteristics of the lotteries. Each participant faces the 24 decision tasks presented in Table 10.

For each parameterization, the cost of obtaining new information will vary. This allows us to estimate willingness to pay for new information to test for differences predicted by the theoretical framework. Column 5 shows the expected value of playing the lottery immediately, and column 6 shows the expected value of the lottery with the information, assuming no cost. Column 7 shows the value of information according to real option theory. From the theoretical framework, this is the critical value where individuals should pay the cost when $C < C^*$, but should not pay the cost when $C > C^*$. Cost values are drawn from a uniform distribution between \$0 and \$2 in \$0.25 increments. The maximum value for some lotteries is adjusted to ensure participants face reasonable costs. For example, consider when the high outcome is \$3.50 over the certain outside option, but the low outcome is \$0.50 less than the certain outside option. If participants face a cost of \$1, they face a strictly worse scenario if they pay the cost of information. If the high outcome occurs, they earn \$2.50, but if the low outcome occurs, they should choose the certain option and lose \$1. These outcomes occur with the same probability as the initial lottery but are objectively worse. When drawing random cost values, I remove any cost value that would create a strictly worse scenario. Further, I remove any cost values that are exactly equal to the critical value, C^*, since participants should be exactly indifferent between paying the cost or not according to real option theory. The distribution of cost values for each parameterization contains values above and below the critical value, so I can adequately test the theoretical predictions.

Each participant makes a total of 24 decisions during the experiment using a within-subject design. Rather than rely solely on variation across participants, I utilize variation within participants by having them make decisions for each lottery. Participants make a decision for each lottery from Table 10, but they face a random cost within the appropriate distribution for that lottery. This gives between-subject variation in decisions for a specific lottery since individuals face different costs. Although participants make decisions for each parameterization, I group the lotteries to reduce the cognitive burden. I group all parameterizations based on gains or loss space. I randomly assign each participant to view only gains or loss space parameterizations in the first half of the experiment before switching for the second half. Within the gains or loss space grouping, I further group lotteries by the probability of the high outcome occurring. The order in that participants see probabilities within the gains or loss space grouping and the order of lotteries within a probability group are both randomized. This means that individuals make decisions for 4 lotteries in a group where the probability of lottery outcomes and certain outside option do not change. For example, a participant might be randomly assigned to see loss space lotteries first. After this assignment, they might be randomly assigned to see lotteries where the probability of the high outcome is 0.85. They then make decisions for the 4 lotteries within the group of lotteries with a high outcome probability of 0.85 and loss space. I construct the experiment in this way so that participants do not need to quickly jump between positive and negative values as well as different probabilities.

2.3.1 HYPOTHESIS TESTS AND POWER ANALYSIS

I examine five testable hypotheses that come from the theoretical framework. I test most of these hypotheses by estimating the willingness to pay for information for the various lottery parameterizations. In a few instances, I complement the willingness to pay results with a multinomial logistic regression to examine how participants alter their choices between taking the outside option, playing the lottery immediately, and paying for information. I state the hypotheses as null hypotheses consistent with real option theory. Any deviations from the null represent an opportunity to examine potential behavioral deviations, as described in the theoretical framework.

Hypothesis 1: *Participants' WTP for information in gains space is equal to their WTP in loss space.*

Hypothesis 2: *Increasing the spread of the lottery increases WTP for information.*

Hypothesis 3: *Changing the expected value of the lottery relative to the outside option will not change WTP for information.*

Hypothesis 4: *Increasing the probability of the high outcome from p=0.5 to p=0.85 will decrease WTP.*

Hypothesis 5: *Increasing the probability of the high outcome from p=0.15 to p=0.5 will increase WTP.*

The first hypothesis states that there is no difference in WTP in gains space and WTP in loss space. Under real option theory there is an equivalent lottery in both gains and loss space. In other words, real option theory would predict the same WTP for 12 pairs of lotteries. I use a two-sided t-test based on regression coefficients to compare the estimated WTP for lotteries in gains and loss space. Recall the theoretical framework predicted ambiguous differences between gains and losses, so I simply test if there is a difference in WTP.

The second hypothesis states that increasing the spread of outcomes should increase participants' WTP for information. The theoretical framework shows that increasing the spread of outcomes will increase WTP according to real option theory, assuming the distance from the outside option increases for both the high and low outcomes. Note for the experimental lottery parameters this assumption holds. To test this hypothesis, I use a two-sided t-test based on regression coefficients to test whether the estimated WTP for lotteries with low spread not equal to the estimated WTP for lotteries with high spread.

The third hypothesis states that changing the expected value of the lottery from less than the outside option to greater than the outside option will not change the estimated WTP. Real option theory does not predict that this will be true for all lotteries. Rather the lotteries were chosen such that I would expect this to be true. List and Haigh (2010) use the expected value of the lottery to test real option theory. They argue that a naïve participant will play the lottery immediately if the expected value is greater than the outside option, but the naïve participant will pay for information when the expected value is less than the outside option. If participants follow real option theory, then the expected value of the lottery should not impact their decision as I have constructed the lotteries. I use a two-sided t-test based on regression coefficients to compare whether the estimated WTP for lotteries is equal when the expected value is greater than or less than the outside option.

The fourth hypothesis states that increasing the probability of the high outcome from $p = 0.5$ to $p = 0.85$ should decrease WTP. This prediction from real option theory does not hold in general, but rather it holds for the specific lottery parameters chosen. As such tests of this hypothesis examine if participants behave consistent with real option theory as the probability changes from equal probabilities to a high-probability of the high outcome. I use a two-sided t-test based on regression coefficients to test whether the estimated WTP is not equal lotteries where $p = 0.5$ than $p = 0.85$.

The fifth hypothesis states that increasing the probability of the high outcome from $p = 0.5$ to $p = 0.85$ should increase WTP. This hypothesis closely mirrors the previous hypothesis but with a different directional effect. This prediction from real option theory does not hold in general, but rather it holds for the specific lottery parameters chosen. As such tests of this hypothesis examine if participants behave consistent with real option theory as the probability changes from equal probabilities to a low-probability of the high outcome. I use a two-sided t-test based on regression coefficients to test whether the estimated WTP is not equal for lotteries where $p = 0.5$ than $p = 0.15$.

Now I undertake a power analysis to determine the sample size using a significance level of 0.05 and a statistical power level of 0.8. Since I state the hypotheses with no predicted differences, I perform the power analyses to be able to detect a deviation of $0.15 from the predictions. I use data from the pilot of 19 participants to estimate the relevant standard deviations and within-subject correlation. The hypothesis tests rely on comparing estimates of willingness to pay for subsets of lotteries. The least powered test corresponds to testing hypothesis 5 which compares the willingness to pay for information in equal probability lotteries to low probability of high outcome $(p = 0.15)$ lotteries. I perform a two means power test in STATA to detect a difference of $0.15. Each group of lotteries in the hypothesis only contains 4 separate lottery parameterizations. I estimate the standard deviation of each group of lotteries separately, using a random effects interval regression including dummy variables for each lottery. The random effects regression controls for correlations between individuals' choices in each of the lotteries. Since each lottery has a different predicted willingness to pay, I must control for each lottery otherwise I would overstate the actual variance in willingness to pay. To estimate the coefficient of within-subject correlation, I pool both groups together in a random effects interval regression. This allows me to estimate a single correlation coefficient accounting for choices across both groups. The results of this two means power analysis in STATA suggest a sample of 87 participants. While not an explicit hypothesis, the theoretical framework suggests differential effects for the hypotheses conditional on the expected value of the lottery relative to the outside option. As such I rerun the power analysis conditional on the expected value of the lottery. I follow the procedure previously outlined except this subset only has 2 lotteries rather than 4. The least powered test resulting from these additional power analyses suggests a sample of 158 participants to detect a difference of $0.15. I aim for a sample of 150 participants which would allow me to detect a minimum difference of $0.11 for the primary hypotheses, and a minimum difference of $0.15 for the additional analyses.

2.3.2 EXPERIMENTAL PROCEDURES

The experiment occurs in four distinct sections. First, I obtain risk aversion data on each participant through a multiple-price list mechanism developed by Holt and Laury (2002). Second, I obtain loss aversion data through a similar multiple-price list mechanism (Bibby & Ferguson, 2011; Gächter et al., 2022). Next, I explain the primary real option game which includes a monetized quiz to check understanding and two unpaid practice rounds. Finally, participants made 24 decisions during the main experimental task.

A typical experimental session begins with participants being randomly assigned one of the 24 experimental lab computers. Participants enter all decisions using individually assigned computers in the experimental lab through the z-Tree program (Fischbacher, 2007). I place the consent form and instructions at each computer for participants to read through at their leisure. At the start time, the moderator reiterates that all decisions will be anonymous, and the instructions only contain true information. Afterward, the moderator takes any questions regarding the consent form and asks for confirmation that all individuals agree to participate in the experiment. At that time, the moderator begins reading through the instructions for the risk aversion task, pausing for questions. After all participants finish the risk aversion task, the moderator reads the instructions for the loss aversion task. All participants make their decisions for the loss aversion task at that time. Finally, the moderator reads through the instructions for the main experiment. Participants go through 2 unpaid practice rounds, after which the moderator asks for any clarifying questions about the procedures of the experiment. Participants then answer 4 quiz questions regarding the main experiment for which they are compensated for correct answers. After a final pause for questions, participants begin the main experiment which consists of 24 decision periods. Participants are shown a breakdown of their earnings from each component of the experimental session and answer a short demographic questionnaire. Finally, participants are paid privately, and in cash, before they leave the experimental lab.

Since each participant makes decisions for lotteries in each treatment group, I need to carefully consider order effects. As previously mentioned, I break the 24 tasks into 6 groups of 4 lotteries. Participants see the 4 lotteries in a random order. The 6 groups can be further classified by the probability of the high outcome with 3 groups in loss space and 3 groups in gains space. The groups in loss and gains space are randomized for each participant. Finally, participants are randomly selected to make decisions in gains or loss space before switching to the other treatment. This random variation allows us to account for potential order effects. This is particularly important as similar studies have found evidence of learning over time when making decisions in a real option context (e.g. Oprea et al., 2009).

Participants are recruited through the University of Tennessee Experimental Economics Laboratory. Participants are primarily undergraduate students at the University of Tennessee across many different majors. Each participant will participate in 24 decision problems, and each decision problem takes less than 1 minute on average. Participants were informed that the experiment would take no longer than 70 minutes to allow time for instructions, risk elicitation, loss aversion elicitation, questions, and unexpected technical problems. The experiment took approximately 60 minutes for the majority of the 8 sessions.

I conducted the experiment in person on computers in the University of Tennessee Experimental Economics Laboratory. Even though the experiment does not include any interactions between players, I wished to ensure understanding and effort in the tasks due to the complicated nature of the experiment. The use of computer programs streamlines many aspects of the experiment, such as randomization and pacing participants so that individuals do not finish a treatment earlier than others. Participants could not continue to the next decision task until every other participant had completed their task. This means that participants were discouraged from taking a low-effort strategy, such as taking the certain outside option, to complete the experiment quickly.

Participants on average received $22 in cash for participation. Payouts ranged from $13.50 to $31, depending on their performance. I ran a total of 8 sessions including one pilot for a total of 154 participants. Since there were no issues during the pilot, I included all observations in the final data set. Individual payoffs include a monetized quiz to check understanding for which participants can earn up to $2, the Holt and Laury (2002) risk elicitation in which participants are expected to earn between $0 and $4, the loss aversion task from Bibby and Ferguson (2011) and Gächter et al. (2022) in which participants earn between -$3 and $3, and the experimental game itself in which participants earn $10 in expectation. I simulated earnings using naïve, optimal, risky, and risk-averse strategies to ensure a proper range of payouts. Parameters were chosen such that I expected participants to earn between $10 and $30 with an average of around $21. I randomly selected a subset of choices during the experiment to determine participants' earnings. One of the ten risk elicitation tasks and one of the six loss aversion tasks were independently chosen at random. All earnings from the experimental setting quiz questions were added to participants' earnings. To ensure a sufficient positive payout, I randomly selected two decisions from gains space parameterizations and one decision from loss space parameterizations. Finally, participants were given a $7 show-up fee to strike a balance between variation in earnings and tying payout directly to decisions.

Table 11 shows summary statistics for the students who participated in the experiment. The average student was 20 years old with a 3.5 GPA, having taken 1.3 economics courses. Approximately 83% of participants were either Freshman, Sophomores, or Juniors. Males made up a slight majority of participants at 52%. Participants seemed to understand the experiment, with an average of 3.4 correct quiz question answers out of a possible 4. On a Likert Scale from 1 to 5 indicating how much they understood the instructions of the experiment, responses averaged 4.6. This indicates most participants felt like they understood the experimental instructions.

2.4 ANALYSIS

To test the hypotheses, I must estimate willingness to pay for information for each decision task. Since willingness to pay is an unobserved latent variable, I use an interval regression where I code participants' decisions into upper and lower bounds on their true willingness to pay. If a participant chose to pay for information, then I know the cost they paid is a lower bound on their true willingness to pay. If a participant chose to not pay for information, then I know the cost they paid is an upper bound on their true willingness to pay. I impose a $0 lower bound on willingness to pay since obtaining information at a cost of $0 is strictly better. By obtaining information at a cost of $0, participants still have every previously available option but with additional information about the outcome of the lottery. I choose the most flexible specification since I do wish to constrain any lottery treatment variables to have the same effect across all decisions. In other words, I do not expect the spread to have the same effect across all decision tasks. This gives us the following specification

$$WTP_{ik}^{*} = \sum_{k=1}^{24} \beta_k * Lottery_k + \epsilon_{ik} \tag{35}$$

where WTP_{ik}^{*} is the willingness to pay for information for participant i in decision task k and $Lottery_k$ is an indicator variable for each of the 24 different decision tasks. I allow for heteroskedastic error variances for each different decision tasks, or $\ln(\sigma) = Lottery_k * \gamma_k$. I am primarily interested in the estimates of β_k as these are the estimated willingness to pay for information for lottery k. Table 12 reports the parameter estimates. Since real option theory gives point predictions for WTP, Table 12 also shows simple t-tests based on regression coefficients comparing estimated WTP to the point predictions from real option theory.

Examining the results from comparing estimated WTP to point predictions from real option theory reveals a few patterns. Every estimated WTP that is less than the point prediction occurs in lotteries where the expected value of the lottery is less than the outside option (decision tasks 2, 4, 6, 8, 18, 20). Additionally, four of these lotteries have a high probability of the high outcome (p=0.85). All three lotteries where the estimated WTP is greater than the predicted value occur in loss space with a low probability of the high outcome (p=0.15).

It is also worth examining the cost distributions for each decision task. Table 12 shows that the estimated WTP falls within the cost distribution for every decision task except decision task 11, where the estimated WTP is larger than the highest possible cost. I restricted the maximum cost for information for this task to $1 since playing the lottery immediately is strictly better than paying the cost in this scenario. When faced with a cost of \$1, the participants could choose the outside option (\$10), play the lottery immediately (0.15 probability of \$17 and 0.85 probability of \$9), or pay the cost (0.15 probability of \$16 and 0.85 probability of \$9). Note that playing the lottery immediately is strictly better in this scenario. However, 54.3% of participants still paid the cost for information when faced with a \$1 cost. This suggests caution should be taken when analyzing WTP for this decision task, as the true WTP is likely higher than I estimated. Second, this suggests that participants might not have fully understood the tradeoffs they were facing. It is possible that participants used heuristics to make decisions rather than careful evaluation of the lotteries. However, as seen in the post-experiment questionnaire and quiz questions, participants generally understood the experiment. Further, this anomaly does not show up in other lotteries, including a lottery where the tradeoffs are identical to decision task 11, except payoffs are in loss space.

I test the hypotheses by comparing the average estimated willingness to pay for sets of lotteries. I use a t-test based on regression coefficients to test the difference in the linear combinations of parameter estimates. For two-sided tests, the tests typically take the form of

$$\left[\frac{1}{n_1}\sum_{k\in K}\beta_k - \frac{1}{n_2}\sum_{j\in J}\beta_j\right] = 0 \tag{36}$$

where I am testing for differences between one group of n_1 lotteries, K, and another group of n_2 lotteries, J. I summarize the results of the hypothesis tests in Table 13.

To test hypothesis 1, I compare the average WTP for lotteries in gains space to loss space. I find that participants' willingness to pay for information is statistically significantly higher in loss space than in gains space (p<0.001). The theoretical framework did not have clear predictions on the effect of loss aversion. The experimental results suggest that participants pay more for information when considering losses, but this could come from a decrease in participants playing the lottery immediately or choosing the outside option. To examine this further, I estimate the following multinomial logit regression model

$$Choice_{ik} = \sum_{k=1}^{24} \beta_k * Lottery_k + \epsilon_{ik} \tag{37}$$

where $Choice_{ik}$ is the decision choice (play lottery immediately, take outside option, or pay for information) for participant i for lottery k and $Lottery_k$ is an indicator variable for each of the 24 different decision tasks. I cluster the errors at the participant level to account for potential correlation across decision tasks. Table 14 reports the parameter estimates.

I test for differences between participants' decisions under loss space and gains space. Using a t-test based on marginal effect estimates from the regression, I find that participants are more likely to take the outside option when in gains space compared to loss space ($p < 0.001$). I also find that participants are less likely to pay for information ($p < 0.001$) and less likely to play the lottery immediately ($p = 0.003$) This suggests that the difference in WTP is driven by changes in the probability of choosing the outside option. This would be consistent with individuals choosing the riskier option in losses relative to gains.

In hypothesis 2, I find that participants have a higher WTP with an increase in spread of outcomes. I reject the null hypothesis (p<0.001) that the WTP is equal for low and high spread lotteries, suggesting that participants behave consistently with real option theory. In addition to the directional predictions from real option theory, I examine the point predictions. While the hypothesis test suggests behavior consistent with real option theory, it is possible that the magnitude of the effect is not consistent. Additional behavioral deviations could cause the magnitude of WTP to be larger or smaller than the point predictions from real option theory. The theoretical framework explored how risk aversion could cause deviations from real option theory when the spread of outcomes increases. I test the difference between the average WTP for low spread lotteries and the average point predictions for those lotteries from real option theory. I find no statistical difference between the WTP and point predictions for low spread lotteries ($p = 0.970$). This suggests that participants behave consistent with real option theory even when considering the magnitudes. Similarly, I test the difference between the WTP for high spread lotteries and the point predictions, and I find no statistical difference ($p = 0.478$). These results suggest that participants behave consistently with real option theory with changes in the spread of outcomes.

In hypothesis 3, I examine the effect of changing the expected value of the lottery relative to the outside option on willingness to pay. I find that participants have a higher WTP for lotteries with an expected value greater than the outside option ($p < 0.001$). For my experimental lotteries, real option theory suggests that the expected value relative to the outside option should not change WTP. This suggests that participants perceive lotteries conditional on the expected value. For example, participants might categorize lotteries with an expected value less than the outside option as an undesirable lottery. Rather than consider the value of paying for information, they might choose the outside option. This would decrease the estimated WTP which is consistent with my results.

In hypothesis 4, I test whether increasing the probability of the high outcome from p=0.5 to p=0.85 decreases WTP. For the experimental lotteries, real option theory predicts a lower WTP for high probability of high outcome lotteries. I reject the null hypothesis ($p < 0.001$) that the WTP is equal, suggesting that participants respond to changes in probability according to real option theory. However, the magnitude of the effect could be inconsistent with the point predictions from real option theory. To test this, I compare the estimated WTP for lotteries with p=0.85 to the point predictions from real option theory. I find that participants have a lower WTP than is predicted by real option theory. However, as seen in Table 8, the effect of probability weighting is conditional on the expected value of the lottery relative to the outside option. I retest this separately conditional on the expected value of the lottery. I would expect the willingness to pay to increase relative to real option theory when the expected value of the lottery is larger than the outside option, but I do not find a statistically significant difference ($p = 0.492$). I would expect the willingness to pay to decrease relative to real option theory when the expected value of the lottery is less than the outside option, and I do find a statistically significant decrease in WTP ($p < 0.001$). I conclude that participants behavior is consistent with probability weighting for high probability high outcome lotteries.

In hypothesis 5, I test whether increasing the probability of the high outcome from p=0.15 to p=0. 5 increases WTP. For the experimental lotteries, real option theory predicts a higher WTP. I reject the null hypothesis ($p < 0.001$) that WTP is equal for p=0.15 and p=0. 5, suggesting that participants respond to changes in probability according to real option theory. Similar to before, the magnitude of the effect could be inconsistent with the point predictions from real option theory. To test this, I compare the estimated WTP for lotteries with p=0.15 to the point predictions from real option theory. I find that participants have a higher WTP than is predicted by real option theory ($p < 0.001$). The theoretical framework gives further insight into the predicted effect conditional on the expected value of the lottery, as seen in Table 8

Table 8. I would expect the opposite effect as in hypothesis 4. When the expected value of the lottery is greater than the outside option, I find a marginal increase in willingness to pay relative to real option theory ($p = 0.061$). I would expect the willingness to pay to decrease under these circumstances, but the effect is only marginally statistically significant. When the expected value of the lottery is less than the outside option, I find a statistically significant increase in willingness to pay relative to real option theory ($p < 0.001$). I would expect willingness to pay to increase under these circumstances, and the statistical evidence is much more convincing. I conclude that participants exhibit behavior consistent with probability weighting when faced with low probability of high outcome lotteries.

Finally, I consider the special case of low probability and high severity events. Real option theory does not give clear directional predictions, so I focus on deviations from the predicted magnitude of WTP. To test this, I compare estimated WTP for lotteries with low-probabilities and high spread of outcomes to the predictions from real option theory. For low-probability high-severity undesirable events (p=0.85), I find evidence that participants' willingness to pay decreases relative to real option theory for lotteries with a high probability of the high outcome and large spread ($p = 0.004$). Unlike previously, the predicted interaction effects between probability weighting and risk aversion are largely ambiguous, as seen in Table 9. The only predicted effect is a decrease in willingness to pay when the expected value of the lottery is less than the outside option. For an expected value greater than the outside option, I find no significant effect ($p = 0.360$). However, for an expected value less than the outside option, I find a significant decrease in WTP relative to real option theory ($p < 0.001$) which would be consistent with interaction of probability weighting and risk aversion from the theoretical framework. I conclude that participants behave consistent with probability weighting and risk aversion when faced with low probability high severity undesirable events.

For low-probability high-severity desirable events (p=0.15), I find evidence that participants' willingness to pay increases relative to real option theory for lotteries with a low probability of the high outcome and large spread ($p < 0.001$). The theoretical framework does not give any insight into the expected behavior. However, it is useful to understand that under low-probability high-severity outcomes, magnitude predictions from real option theory do not accurately describe participants' behavior. Simultaneously, participants behaved consistently with directional predictions from real option theory.

2.5 CONCLUSION

When economic agents make decisions in low-probability high-severity contexts, such as choosing among climate change policies, real option theory provides insight into the value of information or the timing of implementing irreversible decisions. In this paper, I experimentally tested whether individuals behave according to real option theory specifically under low-probability high-severity conditions. First, I found that real option theory accurately describes participant behavior when changing the probabilities and increasing the spread of the outcomes. However, changing outcomes from gains to loss space and changing the expected value of the lottery relative to the outside option both significantly change WTP when real option theory predicts no change. Second, I compare real option theory point predictions to estimated WTP to test whether the magnitude of predictions accurately describe participants' behavior. I find evidence consistent with probability weighting as described in the theoretical framework when participants face low-probability high-spread outcomes. When the expected value of the lottery is less than the outside option, WTP is lower than real option theory predicts for p=0.85 and higher than real option theory predicts for p=0.15. Both results are consistent with the predicted deviations from real option theory that comes from probability weighting in the theoretical framework. These results suggest that caution should be used when using real option theory to describe individual behavior. While the results generally support the directional predictions of real option theory for low-probability high-severity events, participants' behavior exhibit deviations from point predictions. When policymakers are considering low-probability high-severity outcomes, voters' preferences may differ from real option theory predictions. For example, real option theory describes the optimal timing of implementing climate change policy, but my results show that voters may not support such policy.

These results do not come without limitations. The experiment and analysis avoided any context which might influence participant behavior. This means the results apply to a wide range of applications, but caution should be taken when making inferences about any policy as other contextual preferences are likely to change the results. Further, the severity of the lottery outcomes that participants faced was arguably smaller than most contexts individuals might face due to financial constraints. For example, environmental policies have much higher variability in outcomes than the difference of $8 in the experiment. I argue that the effects seen in the results would be further amplified with a greater spread and lower probability.

I conclude that individuals behave according to directional predictions from real option theory with changes in probability and spread, making real option theory an appropriate starting place to model individual behavior. However, when considering point predictions, behavior systematically deviates from real option theory, suggesting individuals exhibit probability-weighting. When considering environmental policy, I would expect voters to value the option to wait and support regulation that reflects real option theory. However, when considering low-probability high-severity outcomes, I conclude that individuals exhibit probability-weighting causing their preferences to diverge from real option theory. In such cases, policymakers face a tradeoff between acting in line with constituents' preferences and implementing the optimal timing of policy according to real option theory.

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APPENDIX

Table 7: Optimal Choice for Lottery Conditions

Conditions	OV	Optimal Choice
$EV(O_2\|I_1) > EV(O_1\|I_1) > OUT$	$EV(O_2\|I_1) - EV(O_1\|I_1) > 0$	Pay Cost for Information
$EV(O_2\|I_1) > OUT > EV(O_1\|I_1)$	$EV(O_2\|I_1) - OUT > 0$	Pay Cost for Information
$EV(O_1\|I_1) > EV(O_2\|I_1) > OUT$	0	Play Lottery Immediately
$OUT > EV(O_1\|I_1) > EV(O_2\|I_1)$	0	Take Outside Option

Table 8: Effect of Probability Weighting on WTP

Probability of high outcome p	Expected value of lottery $(p)H + (1-p)L$	Probability Weighting Effect on WTP relative to real option theory predictions
Small	$> OUT$	Decrease
Small	$< OUT$	Increase
Large	$> OUT$	Increase
Large	$< OUT$	Decrease

Table 9: Interaction Effect of Probability Weighting and High Spread on WTP

Probability of high outcome p	Spread of outcomes	Expected value of lottery $(p)H + (1-p)L$	Interaction Effect on WTP relative to real option theory predictions
Small	High	$> OUT$	Ambiguous
Small	High	$< OUT$	Ambiguous
Large	High	$> OUT$	Ambiguous
Large	High	$< OUT$	Decrease

Table 10: Lottery Parameterizations

(1) Task	(2) Certain Outside Option	(3) Probability of High Outcome (p)	(4) Spread	(5) High Outcome (H)	(6) Low Outcome (L)	(7) $EV(O_1 \| I_1)$	(8) $EV(O_2 \| I_1)$	(9) C^*	(10) Cost Distribution
1	10	0.5	4	12.5	8.5	10.5	11.25	0.75	U(0,1.5)
2	10	0.5	4	11.5	7.5	9.5	10.75	0.75	U(0,1.5)
3	10	0.5	8	15	7	11	12.5	1.5	U(0,3)
4	10	0.5	8	13	5	9	11.5	1.5	U(0,3)
5	10	0.85	4	11	7	10.4	10.85	0.45	U(0,1)
6	10	0.85	4	10.5	6.5	9.9	10.425	0.425	U(0,0.75)
7	10	0.85	8	12	4	10.8	11.7	0.9	U(0,2)
8	10	0.85	8	11	3	9.8	10.85	0.85	U(0,1)
9	10	0.15	4	13.5	9.5	10.1	10.525	0.425	U(0,0.75)
10	10	0.15	4	13	9	9.6	10.45	0.45	U(0,1)
11	10	0.15	8	17	9	10.2	11.05	0.85	U(0,1)
12	10	0.15	8	16	8	9.2	10.9	0.9	U(0,2)
13	-10	0.5	4	-7.5	-11.5	-9.5	-8.75	0.75	U(0,1.5)
14	-10	0.5	4	-8.5	-12.5	-10.5	-9.25	0.75	U(0,1.5)
15	-10	0.5	8	-5	-13	-9	-7.5	1.5	U(0,3)
16	-10	0.5	8	-7	-15	-11	-8.5	1.5	U(0,3)
17	-10	0.85	4	-9	-13	-9.6	-9.15	0.45	U(0,1)
18	-10	0.85	4	-9.5	-13.5	-10.1	-9.575	0.425	U(0,0.75)
19	-10	0.85	8	-8	-16	-9.2	-8.3	0.9	U(0,2)
20	-10	0.85	8	-9	-17	-10.2	-9.15	0.85	U(0,1)
21	-10	0.15	4	-6.5	-10.5	-9.9	-9.475	0.425	U(0,0.75)
22	-10	0.15	4	-7	-11	-10.4	-9.55	0.45	U(0,1)
23	-10	0.15	8	-3	-11	-9.8	-8.95	0.85	U(0,1)
24	-10	0.15	8	-4	-12	-10.8	-9.1	0.9	U(0,2)

The cost of information is randomly drawn from a distribution in increments of $0.25 with values both above and below C^*.

Table 11: Summary Statistics

Variable	Definition	Mean	Std. Dev.
Number of Quiz Questions Correct	Number of the 4 quiz questions answered correctly. Quiz questions were used to assess understanding of the experiment.	3.5	0.74
Understood Instructions	Self-reported understanding of instructions on a Likert Scale from 1 to 5.	4.6	0.9
Compensated Fairly	Self-reported agreement that participants were compensated fairly for their time on a Likert Scale from 1 to 5.	4.3	0.99
Age	Age of participant	20	1.3
GPA	Grade Point Average for participant coded as the midpoint of range	3.5	0.39
Economic Courses	Number of economic courses participant had taken prior to experiment	1.3	2
Female	Participant identified as female	0.47	0.5
Male	Participant identified as male	0.52	0.5
Freshman	Student classification for participant was Freshman	0.23	0.42
Sophomore	Student classification for participant was Sophomore	0.29	0.45
Junior	Student classification for participant was Junior	0.31	0.46
Senior	Student classification for participant was Senior	0.16	0.37
Masters	Student classification for participant was Masters Student	0.0065	0.081
Doctoral	Student classification for participant was Doctoral Student	0.0065	0.081
Full Time Student	Participant was a full-time student	0.99	0.081
Part Time Student	Participant was a part-time student	0.0065	0.081
Data for each variable is available for all 154 participants.			

Table 12: Willingness to Pay Regression Results

	WTP for Information	Real Option Theory Prediction	Difference Between Estimated and Predicted
Decision Task 1	0.709***	0.75	-0.041
	(0.077)		
Decision Task 2	0.424***	0.75	-0.326***
	(0.077)		
Decision Task 3	1.558***	1.5	0.058
	(0.174)		
Decision Task 4	0.984***	1.5	-0.516***
	(0.090)		
Decision Task 5	0.429***	0.45	-0.021
	(0.048)		
Decision Task 6	0.245***	0.425	-0.180***
	(0.033)		
Decision Task 7	0.864***	0.9	-0.036
	(0.086)		
Decision Task 8	0.437***	0.85	-0.413***
	(0.046)		
Decision Task 9	0.387***	0.425	-0.038
	(0.046)		
Decision Task 10	0.571***	0.45	0.121
	(0.083)		
Decision Task 11	1.136***	0.85	0.286
	(0.202)		
Decision Task 12	1.013***	0.9	0.113
	(0.140)		
Decision Task 13	0.846***	0.75	0.096
	(0.084)		
Decision Task 14	0.834***	0.75	0.084
	(0.072)		
Decision Task 15	1.789***	1.5	0.289
	(0.199)		
Decision Task 16	1.544***	1.5	0.044
	(0.127)		
Decision Task 17	0.449***	0.45	-0.001
	(0.049)		
Decision Task 18	0.322***	0.425	-0.103***
	(0.036)		
Decision Task 19	1.067***	0.9	0.167
	(0.114)		

Table 12: Continued

Decision Task 20	0.670***	0.85	-0.180***
	(0.061)		
Decision Task 21	0.641***	0.425	0.216***
	(0.082)		
Decision Task 22	0.653***	0.45	0.203**
	(0.094)		
Decision Task 23	0.837***	0.85	-0.013
	(0.090)		
Decision Task 24	1.424***	0.9	0.524***
	(0.133)		
Observations	3,696		

Error variance varies by decision task. Statistical significance of differences between estimated and point predictions come from t-test. Decision task numbers correspond to the labels in
.
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Hypothesis Test Results

Hypothesis	Testable Hypothesis	Difference in WTP (P-value from T-test)	Conclusion
H1: Participants' WTP for information in gains space is equal to their WTP in loss space.	H1: $\frac{1}{12}\sum_{k\in K}\beta_k - \frac{1}{12}\sum_{j\in J}\beta_j = 0$ Where K is the set of lotteries in gains space and J is the set of lotteries in loss space.	-2.312***	I reject the null hypothesis that the WTP is equal. I find that participants have a higher WTP in loss space.
H2: Increasing the spread of the lottery increases WTP for information	H2: $\left[\frac{1}{12}\sum_{k\in K}\beta_k - \frac{1}{12}\sum_{j\in J}\beta_j\right] = 0$ Where K is the set of lotteries with high spread and J is the set of lotteries with low spread.	6.814***	I reject the null hypothesis. Participants' WTP increases as the spread increases.
H3: Changing the expected value of the lottery relative to the outside option will not change WTP for information.	H3: $\left[\frac{1}{12}\sum_{k\in K}\beta_k - \frac{1}{12}\sum_{j\in J}\beta_j\right] = 0$ Where K is the set of lotteries with expected value greater than the outside option and J is the set of lotteries with expected value less than the outside option.	1.590***	I reject the null hypothesis. Participants' WTP is higher for lotteries with expected value greater than the outside option.
H4: Increasing the probability of the high outcome from $p = 0.5$ to $p = 0.85$ will decrease WTP.	H4: $\left[\frac{1}{8}\sum_{k\in K}\beta_k - \frac{1}{8}\sum_{j\in J}\beta_j\right] = 0$ Where K is the set of lotteries with p=0.85 and J is the set of lotteries with equal probabilities	-4.205***	I reject the null hypothesis. Increasing the probability from p=0.5 to p=0.85 decreases WTP.
H5: Increasing the probability of the high outcome from $p = 0.5$ to $p = 0.15$ will increase WTP.	H5: $\left[\frac{1}{8}\sum_{k\in K}\beta_k - \frac{1}{8}\sum_{j\in J}\beta_j\right] = 0$ Where K is the set of lotteries where p=0.15 and J is the set of lotteries with equal probabilities	2.026***	I reject the null hypothesis. Increasing the probability from p=0.15 to p=0. 5 increases WTP.
*** p<0.01, ** p<0.05, * p<0.1			

Table 14: Choice Regression Results

	(1) Pay for Information	(2) Play Lottery Immediately	(3) Outside Option
Decision Task 1	-	-	-
Decision Task 2	-0.156***	-0.182***	0.338***
	(0.0546)	(0.0396)	(0.0523)
Decision Task 3	0.182***	-0.0195	-0.162***
	(0.0500)	(0.0456)	(0.0396)
Decision Task 4	0.0584	-0.169***	0.110**
	(0.0523)	(0.0410)	(0.0501)
Decision Task 5	-0.0390	-0.0584	0.0974*
	(0.0536)	(0.0404)	(0.0511)
Decision Task 6	-0.0714	-0.149***	0.221***
	(0.0569)	(0.0430)	(0.0531)
Decision Task 7	-0.0195	0.0455	-0.0260
	(0.0556)	(0.0499)	(0.0478)
Decision Task 8	0.00649	-0.143***	0.136***
	(0.0500)	(0.0396)	(0.0505)
Decision Task 9	0.0390	-0.000	-0.0390
	(0.0589)	(0.0513)	(0.0460)
Decision Task 10	0.0584	-0.0649	0.00649
	(0.0531)	(0.0467)	(0.0456)
Decision Task 11	0.227***	-0.0779	-0.149***
	(0.0549)	(0.0475)	(0.0410)
Decision Task 12	0.0390	-0.104***	0.0649
	(0.0512)	(0.0382)	(0.0502)
Decision Task 13	0.0649	0.0519	-0.117***
	(0.0519)	(0.0468)	(0.0432)
Decision Task 14	0.0325	-0.0909**	0.0584
	(0.0564)	(0.0436)	(0.0523)
Decision Task 15	0.247***	-0.0325	-0.214***
	(0.0516)	(0.0436)	(0.0412)
Decision Task 16	0.247***	-0.175***	-0.0714
	(0.0516)	(0.0370)	(0.0471)
Decision Task 17	-0.0260	0.117***	-0.0909**
	(0.0504)	(0.0441)	(0.0436)
Decision Task 18	0.0260	-0.0519	0.0260
	(0.0537)	(0.0449)	(0.0504)
Decision Task 19	0.0390	0.0390	-0.0779*
	(0.0567)	(0.0504)	(0.0456)

Table 14: Continued

Decision Task 20	0.123**	-0.104**	-0.0195
	(0.0563)	(0.0462)	(0.0483)
Decision Task 21	0.175***	0.0325	-0.208***
	(0.0546)	(0.0474)	(0.0387)
Decision Task 22	0.0844	-0.0649	-0.0195
	(0.0537)	(0.0467)	(0.0456)
Decision Task 23	0.201***	-0.0260	-0.175***
	(0.0540)	(0.0422)	(0.0424)
Decision Task 24	0.162***	-0.130***	-0.0325
	(0.0533)	(0.0429)	(0.0455)
Observations	3,696	3,696	3,696

Standard errors clustered at the individual level.
Decision task numbers correspond to the labels in Table 10.
Reported values are the marginal effects compared to the base scenario under decision task 1.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX: THEORETICAL EQUIVALENCE

It may be unclear how the theoretical setup is equivalent to Dixit and Pindyck's (1994) real option theory exposition. In this section, I walk through Dixit and Pindyck's (1994) simple model to show how it is mathematically equivalent to the theoretical model.

Consider investing in a factory which produces one unit of output which can be sold at a price, $\boldsymbol{P}$. At period 0, the price of the output is known with certainty, $\boldsymbol{P_0}$. In period 1, the price could increase to $\boldsymbol{P_1 = 1.5P_0}$ with probability $\boldsymbol{q = 0.5}$, or decrease to $\boldsymbol{P_1 = 0.5P_0}$ with probability $\boldsymbol{1 - q = 0.5}$. For all periods after period 1, the price will not change; that is $\boldsymbol{P_1 = P_2 = P_3 = \cdots}$. The cost of investing in this factory is $\boldsymbol{I}$, and the investment is irreversible in that $\boldsymbol{I}$ is entirely a sunk cost. Let $\boldsymbol{r}$ be the discount rate.

The decision problem in period 0 is to invest or wait until period 1. If they invest in period 0, then they earn a profit of

$$\boldsymbol{V_0 = P_0 + \sum_{t=1}^{t=\infty} \frac{EV[P_1]}{(1+r)^t} - I}$$

where the expected value of $\boldsymbol{P_1}$ is $\boldsymbol{0.5(0.5P_0) + 0.5(1.5P_0) = P_0}$. Thus, the profit is

$$\boldsymbol{V_0 = P_0 + \sum_{t=1}^{t=\infty} \frac{P_0}{(1+r)^t} - I}$$

$$\boldsymbol{V_0 = P_0 + \frac{P_0}{r} - I}$$

If they wait until period 1, then they know $\boldsymbol{P_1}$ with certainty. As in Dixit and Pindyck (1994), assume that if the price falls, then the discounted stream of future profits does not justify the cost of investment, or $\boldsymbol{\frac{0.5P_0}{r} < \frac{I}{1+r}}$. This means that if the price falls, they will not invest in the factory. When they wait until period 1, then they forgo the profits in period 0 but the cost of investment is lower due to discounting. These two components make up the primary source of opportunity cost in the model. The manager must decide whether to invest immediately or forgo potential additional profits to wait. The expected profits of waiting until period 1 is

$$\boldsymbol{F_o = \frac{1}{2}\left(\sum_{t=1}^{t=\infty} \frac{1.5P_0}{(1+r)^t} - \frac{I}{1+r}\right) = \frac{1}{2}\left(\frac{1.5P_0}{r} - \frac{I}{1+r}\right)}$$

Note that the probability of the price rising is $\boldsymbol{q = 0.5}$, and the cost of investment is only incurred if the price rises.

Dixit and Pindyck (1994) define the option value as $\boldsymbol{F_0 - V_0}$.

$$\boldsymbol{F_0 - V_0 = \frac{1}{2}\left(\frac{1.5P_0}{r} - \frac{I}{1+r}\right) - \left(P_0 + \frac{P_0}{r} - I\right)}$$

$$\boldsymbol{F_0 - V_0 = \frac{Ir + \frac{1}{2}I}{1+r} - \frac{rP_0 + 0.25P_0}{r}}$$

The key piece of this simplified model is that there is an opportunity cost to wait until period 1. This comes from the fact that the factory starts earning revenue, $\boldsymbol{P_0}$, immediately in period 0, but it’s mitigated by the fact that the investment cost is discounted if they wait until period 1.

Now let us consider how the simple model is equivalent to Dixit and Pindyck (1994).

First, let $\boldsymbol{H = \frac{1.5P_0}{r} - 2I + 2P_0}$ be the high outcome of the lottery, and $\boldsymbol{L = \frac{0.5P_0}{r} - 2I +}$

$\mathbf{2}\boldsymbol{P}_{\mathbf{0}}$ be the low outcome of the lottery. Then the expected profit from investing immediately in Dixit and Pindyck (1994) becomes

$$\boldsymbol{V}_{\mathbf{0}} = \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{H} + \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{L}$$

The expected payoff of investing in the factory immediately is the expected value of the lottery. If they wait until period 1, then the expected payoff is

$$\boldsymbol{F}_{\boldsymbol{o}} = \frac{\mathbf{1}}{\mathbf{2}}\left(\boldsymbol{H} + \frac{\boldsymbol{I} + \mathbf{2}\boldsymbol{r}\boldsymbol{I}}{(\mathbf{1} + \boldsymbol{r})} - 2\boldsymbol{P}_{\mathbf{0}}\right) = \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{H} + \frac{\boldsymbol{I} + \mathbf{2}\boldsymbol{r}\boldsymbol{I}}{\mathbf{2}(\mathbf{1} + \boldsymbol{r})} - \boldsymbol{P}_{\mathbf{0}}$$

Let $\boldsymbol{C}$=$\boldsymbol{P}_{\mathbf{0}} - \frac{\boldsymbol{I}+\mathbf{2}\boldsymbol{r}\boldsymbol{I}}{\mathbf{2}(\mathbf{1}+\boldsymbol{r})}$ be the cost of waiting until period 1 to invest. Then

$$\boldsymbol{F}_{\boldsymbol{o}} = \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{H} - \boldsymbol{C}$$

Assume the option value is non-negative. This implies that the low outcome of the lottery is sufficiently negative. This assumption is not critical, but simply reflects the primary lottery parameterizations and simplifies the mathematical exposition. The option value can be written

$$\boldsymbol{F}_{\mathbf{0}} - \boldsymbol{V}_{\mathbf{0}} = -\boldsymbol{C} - \frac{\mathbf{1}}{\mathbf{2}}\boldsymbol{L}$$

From this I can see that this is equivalent to a simple lottery with outcomes $\boldsymbol{H}, \boldsymbol{L}$ and some cost to observe the realization of the lottery outcomes, $\boldsymbol{C}$. Mathematically, the two models are equivalent, but there are some experimental benefits to using the model. Most importantly, the setup is simpler for participants to understand. There is a single lottery that they are considering whose outcomes are not changing across periods. They are faced with a choice to take the lottery immediately, not take the lottery and keep their current earnings, or pay some cost, $\boldsymbol{C}$, to see the realization of the lottery and then make their decision. This adds one more decision compared to List and Haigh (2010). However, I avoid changing lottery values in the two periods of the same game, simplifying the mental calculations individuals must perform. I also gain additional information from this extra choice which allows us to test additional hypotheses. This setup also draws a close analogy to willingness to pay studies, as this cost can be thought of as a bound on the individuals' willingness to pay for the option to wait. For these reasons, I prefer my model setup compared to Dixit and Pindyck (1994) and List and Haigh (2010).

APPENDIX: EXPERIMENTAL INSTRUCTIONS

Introduction

Thank you for participating in this study.

The study has four parts: Experiment 1, Experiment 2, Experiment 3 and a short questionnaire. We will proceed through the written materials together. Please do not enter any decisions on the computer until instructed to do so. Please follow along with your copy as I read the instructions aloud. Do not hesitate to stop me at any time to ask a question.

There are two important protocols in experimental economics that we would like you to be aware of. First, we are forbidden from providing you with misleading or false information. The instructions contain only true information. There are no hidden tasks, and the experiment works exactly as stated in the instructions.

Second, your decisions are confidential. You have been randomly assigned an ID number. You will never be asked to reveal your identity to anyone. All decisions you make will be associated with this ID number and not your name. When we analyze the data and present results your name in no way will be affiliated with this study.

We have provided everyone with a pencil, calculator, and paper. Use these items, if you wish, as you make your decisions. Also, feel free to write on the instructions.

In this study you will be asked to make a series of market-like decisions. There are no right and wrong decisions. However, your earnings from this study are based on the decisions you make. This means that different people will earn different amounts, and some decisions will lead to higher earnings than others. You will be paid privately, and in cash, after the study is completed.

The decisions we ask you to make may be unfamiliar to you. This is normal. In writing the instructions for this experiment, we have done our very best to clearly describe to you all relevant information for you to make your decision. It is important for the integrity of this research that you understand the instructions and we encourage you to ask questions as we go through the instructions.

Instructions for Experiment 1

Please refer to your computer screen while we read the instructions.

We would like you to make a decision for each of 10 scenarios. Each scenario involves a choice between playing a lottery that pays either $4 or $0 according to specified chances (Option A) or receiving $2 for sure (Option B). All money amounts are denominated in US Dollars ($).

You will notice that the only differences across scenarios are the chances of receiving the high or low payout for the lottery. At the end of today's study, ONE of the 10 scenarios will be selected at random, and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Instructions for Experiment 2

Now we would like you to make a decision for each of the following 6 scenarios. Each scenario involves a choice between playing a lottery or not.

In each scenario, if you choose to play the lottery (Option A), there is a 50% chance you will win $3 and a 50% chance you will lose a specified amount. If you do not play the lottery (Option B), you earn $0.

You will notice that the only difference across scenarios is the amount at stake to lose by playing the lottery.

At the end of today's session, ONE of the 6 scenarios will be selected at random and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected. Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be used to determine your earnings.

Note that, in contrast to the previous task, if you choose to play the lottery there is a 50% chance of losing money. If this happens, the amount of the loss will be subtracted from your overall earnings in the session.

Instructions for Experiment 3

This experiment involves a sequence of 24 scenarios. Half of the scenarios involve losing money and the other half involve earning money. After you complete the experiment, you will be paid based off TWO randomly selected scenarios involving earning money and ONE randomly selected scenario involving losing money. You will not know beforehand which scenarios will be selected, and so it is best to make decisions for all scenarios carefully.

Each scenario is independent, in the sense that the decisions you make in one scenario will not affect the payoff or earnings of any other scenario. All money amounts are denominated in US Dollars ($).

In each scenario, you will have the option to play a lottery. The lottery will result in either a high or low payout according to specified chances.

You can pay a cost to learn whether you will receive the high or the low payout if you play the lottery. If you do not pay the cost, you will not know the payoff of the lottery until after you decide whether to play the lottery. If you pay the cost, you will learn the payout from the lottery before you make the choice of whether to play the lottery.

The alternative to playing the lottery is to receive a certain amount of money.

Given the possibilities described above, we summarize your options as follows.

- **Choose the alternative payout immediately**: If you choose this option, you will receive the alternative payout and proceed to the next scenario.
- **Play the lottery immediately**: If you choose this option you will lock in your choice to play the lottery. You will then receive either the low or high payout based on the stated chances.
- **Pay to see the payoff of the lottery, and then decide whether to play the lottery or take the alternative payout**: If you choose this option, you will pay the specified cost and be shown the payoff of the lottery. Only after seeing this payoff will you be asked to choose between playing the lottery or taking the alternative payout.

The possible lottery payout amounts, the chances of receiving either payout, the cost of obtaining information, and the alternative payout amount will all be known at the start of each scenario. These figures vary from one scenario to the next, so please pay close attention before making any decision.

It is possible for you to lose money. In all scenarios, one or more payouts are negative. If your choice(s) result in a negative payout for a given scenario, and this scenario is selected by the computer to be paid out, this amount will in fact be subtracted from your overall earnings for this study. The study is designed so that if you make careful choices you will earn a positive and significant amount of money from your participation.

Example:

Let’s work through an example scenario. From the image below, you should notice that the high lottery payout is $15, and the low payout is -$5. There is a 15% chance of receiving the high payout, and an 85% chance of the low payout. You can pay $1 to see the payoff of the lottery before you make your choice. You have an alternative option of receiving $0 for sure.

In this scenario you may choose to gain $0 for sure or play the following lottery:

This lottery pays:
$15.00 with a 15% chance
-$5.00 with a 85% chance.

You have the option to pay $1.00 to see the payoff of the lottery before you make your choice.

Your decision:
- Gain $0 for sure
- Play the lottery immediately
- Pay $1.00 to see the payoff of the lottery

Let's consider your three choices and your earnings if the lottery payoff is $15 or -$5:

- **Choose the alternative payout immediately**: You will receive $0 and proceed to the next scenario.
- **Play the lottery immediately**: You will lock in your choice to play the lottery. You will then receive either the low or high payout based on the stated chances.
  - If the lottery payoff is $15, then you will earn $15.
  - If the lottery payoff is -$5, then you will lose $5.
- **Pay to see the payoff of the lottery, and then decide whether to play the lottery or take the alternative payout**: If you choose this option, you will pay $1 and be shown the payoff of the lottery. After seeing the payoff of the lottery, you will be asked to make a decision to play the lottery or take the alternative payout.
  - If the lottery payoff is $15, then you can play the lottery and earn $14 after paying the cost to see the payoff ($15-$1).
  - If the lottery payoff is -$5, then you can choose the alternative option and lose $1 after paying the cost to see the payoff ($0-$1).

CHAPTER III
POWER PLANT RESPONSE TO TRANSBOUNDARY AIR POLLUTION REGULATION

ABSTRACT

I investigate whether power plant managers respond to the Clean Air Interstate Rule and Cross State Air Pollution Rule by switching fuel type, retiring polluting boilers, or installing new pollution control technology. These recent transboundary air pollution regulations have effectively reduced emissions in regulated states (Andaloussi & Isaken, 2022). I test if these reductions came from switching fuel type, boiler retirements, or new pollution control technologies. The results suggest that recent transboundary air pollution regulations effectively achieved emissions reductions by changing the composition of pollution control technology without causing boiler retirements. I find that regulated boilers are no less likely to retire compared to unregulated boilers. I find that plant managers change fuel type in response to SO_2 regulation. I examine the different types of pollution control technologies installed separately for SO_2 and NO_x emissions. I find that plant managers are more likely to install dry type technologies in response to SO_2 regulation and selective noncatalytic reduction technology in response to NO_x regulation. These two categories of technologies can be classified as relatively cheap and less effective than their counterparts.

3.1 INTRODUCTION

In this paper, I examine whether power plant managers[5] respond to the Clean Air Interstate Rule (CAIR) and Cross State Air Pollution Rule (CSAPR) by switching fuel type, retiring polluting boilers, and installing new pollution control technology. Before regulation, policymakers typically do not know the cost of compliance. By examining how plant managers respond ex post, I contribute to understanding the marginal cost of abatement in recent years. Using pollution control technology data from the Energy Information Administration, I analyze which types of technologies plant managers are more likely to install. I also explore heterogenous responses by fuel type.

The estimation strategy relies on the assumption that the timing of transboundary air pollution regulation occurs exogenously from the perspective of the power plant manager. Policy makers endogenously target specific geographic areas with high concentrations of pollution spillover. Despite plant managers expecting to be regulated, the timing of regulation is effectively exogenous due to legal and policy uncertainty. This allows me to interpret regulations as an exogenous shock in the cost of emissions. I favor using a reduced form estimation strategy because plant managers have developed expectations about future regulations conditional on their location. I am unable to

[5] In this paper, I use boilers as the unit of analysis, but I refer to the plant manager as the decision maker. Energy generation in a power plant occurs through a complex system of boilers and generators. Many boilers might be connected to a single generator, and power plants might utilize many generators and boilers. For this reason, I avoid using power plant as the decision making entity, as is common, to prevent confusion in the relationship between multiple boilers and a single power plant.

separate beliefs about future regulations and the direct effect of regulation making a reduced form approach most appropriate. Using these assumptions, I compare regulated plant managers' decisions to unregulated plant managers to capture the effect of regulation.

I focus on CAIR and CSAPR, the EPA's most recent transboundary air pollution regulations. Power plants' emissions have been regulated under a series of laws since the 1970s, making it difficult to attribute any response to a particular regulation. Since the beginning of the Clean Air Act, federal regulation has evolved to address transboundary spillovers with the Acid Rain Program and the NO_x Budget Trading Program. CAIR and CSAPR created new permit markets for SO_2 and NO_x emissions, effectively replacing previous regulatory permit markets. Additional legal uncertainties over both CAIR and CSAPR introduced complex dynamics affecting plant managers' expectations of future regulation. For these reasons, the primary analysis groups both CAIR and CSAPR regulations together, treating them as a suite of transboundary air pollution regulations.

The results show that plant managers do not retire boilers in response to regulation on average. This result is robust to examining retirements by fuel type. The raw data shows a retirement rate of 16.6% and 19.3% respectively for SO_2 and NO_x regulation, respectively. However, regression results do not suggest a statistically significant difference compared to boilers not regulated under CAIR and CSAPR.

I find that managers respond to SO_2 regulation by switching fuel type, but no evidence of fuel switching for NO_x regulation. Most switching that occurs happens within the fuel group, meaning that plant managers switch from one type of coal to another or one type of natural gas fuel to another. This suggests that managers are not changing the primary source of fuel input, for example from coal to natural gas which might require expensive capital investments. Instead, they switch from different types of the same fuel group, for example from bituminous coal to refined coal.

My results also speak to the types of technologies installed. I examine the different types of pollution control technologies installed separately for SO_2 and NO_x emissions. I find evidence that plant managers are more likely to install dry type technologies in response to SO_2 regulation and selective noncatalytic reduction technology in response to NO_x regulation. These two categories of technologies can be classified as relatively cheap and less effective than their counterparts. Plant managers complied with CAIR and CSAPR through low-cost pollution control technology. Without observing power plant costs, this suggests that CAIR and CSAPR successfully improved the composition of pollution control technology without pushing plant managers toward high-cost responses.

These results contribute to a larger conversation about the efficacy of air pollution regulations. Prior research has shown air pollution regulations in the United States have successfully improved air quality (e.g. Currie & Walker, 2019; Aldy, et al., 2022). Little research has focused specifically on recent transboundary air pollution regulations. Dorsey (2019) found that uncertainty over the Clean Air Interstate Rule (CAIR) caused plant managers to delay additional investments. Andaloussi and Isaken (2022) documented decreases in emissions in response to CAIR. This paper addresses how plant managers responded to achieve these reductions in emissions. In this way, I also contribute to the literature on pollution control technology selection. Fowlie (2010) found that deregulated plants chose relatively cheap pollution control technologies, relying on market restructuring for identification. Raff and Walter (2020) find that managers choose to install NO_x abatement technologies to comply with air quality standards but choose cleaner fuel inputs to comply with SO_2 regulations. Previous research focuses on earlier regulations such as the Acid Rain Program, NO_x Budget Trading Program, and the Clean Air Act's air quality standards. Carlson, et al. (2000) model marginal abatement cost functions to estimate the cost savings from plant compliance strategies under the Acid Rain Program. Chan, et al. (2018) found that 11% of generators installed scrubbers, 28% switched to low-sulfur coal, and the rest mixed fuel types in response to the Acid Rain Program. EPA (2011) and DeMocker (2011) considered the costs of the Clean Air Act. They estimate the capital cost of compliance in 2010, and they find 17.5% of costs come from wet and dry technology, 12.8% of costs come from selective catalytic reduction, and 2.5% of costs come from selective noncatalytic reduction. This suggests that emissions reductions come from wet and dry technology installations and selective catalytic reduction technology. DeMocker (2011) rely on an integrated energy generation model which aggregates energy generation such that they do not model specific generator compliance strategies. CAIR and CSAPR could elicit different responses due to the history of regulation and changes in expectations of future regulation. My results build on this literature, describing the response to progressive air pollution regulations and estimating responses for individual boilers.

My results highlight two important contributions to air pollution regulation policy. On average, regulated plant managers were not more likely to retire boilers than unregulated counterparts. This suggests there were not unintended consequences from regulation such as many generators shutting down causing ripple effects in the electric grid. Second, plant managers were most likely to install relatively cheap pollution control technologies compared to other alternative technologies. If permit markets are functioning effectively, we would expect power plants to respond most cost-effectively. Thus, boilers choosing inexpensive pollution control technology represents the most cost-effective approach to regulatory compliance. I conclude that these recent transboundary air pollution regulations achieved reductions in pollution by changing the composition of pollution control technology and fuel switching for SO_2 emissions.

3.2 BACKGROUND

The Clean Air Interstate Rule (CAIR) and Cross State Air Pollution Rule (CSAPR) represent federal regulation shifting from improving air quality to addressing the transboundary nature of air pollution. Meaningful federal regulation of air pollution began with the Clean Air Act (CAA) amendments in 1970. The CAA effectively improved air quality, but the transboundary nature of air pollution remained unaddressed.[6] The EPA charged states with meeting standards for their counties, but states were powerless to address emissions coming from other upwind states. The Clean

[6] For an overview, see Aldy, et al. (2022) or Currie and Walker (2019).

Air Act contains a “good neighbor” provision that requires states to eliminate upwind emissions that significantly contribute to the non-attainment of standards in downwind states. Without financial incentives, states did a poor job adhering to the “good neighbor” provision prompting the EPA to propose cap-and-trade regulations on emissions with the Acid Rain Program (ARP) and the NO_x Budget Trading Program (NBP). The Clean Air Interstate Rule (CAIR) replaced the NBP in 2009, regulating a total of 27 states and implementing an annual NO_x cap in addition to seasonal caps. In 2010, CAIR expanded further to include a cap on SO_2 emissions. Replacing CAIR in 2015, the Cross-State Air Pollution Rule (CSAPR) regulates annual NO_x, annual SO_2, and seasonal NO_x emission caps.

Both CAIR and CSAPR have faced legal difficulties since their conception, creating uncertainty and complicating the identification of treatment effects for individual regulation. In 2008, the D.C. Circuit vacated CAIR partially in response to a complaint that permit trading across states did not achieve the intended outcome of the “good neighbor” provision of the CAA. The court allowed CAIR to remain in place until the EPA could construct a rule in line with the court’s decision. In 2011, the EPA announced its response to the court’s ruling, CSAPR, which caps state-level emissions while still allowing for limited trading across states. Immediately, the regulation was taken to court, with the Supreme Court ultimately ruling in favor of CSAPR in 2014. The implementation of CSAPR occurred on January 1, 2015. In the fall of 2015, another lawsuit emerged regarding compliance with the 2008 NAAQS. In September 2016, the EPA released the CSAPR Update which would be implemented in May 2017 reducing the summertime NOx emission cap. The EPA announced that they were closing out the CSAPR Update, ending the transboundary regulation entirely as states were deemed to be compliant with the “good neighbor” provision. This decision was taken to court in December 2018 and vacated in September 2019 by the D.C. Court of Appeals. In March 2021, stricter emissions caps were implemented under the Revised CSAPR Update. A summary of major regulatory events can be found in Figure 4.

In addition to legal uncertainties, the EPA’s implementation process introduces further complications to understanding the effect of a specific policy. Before the official implementation of CAIR, the EPA began monitoring emissions during a training year. Affected plant managers did not have to hold permits during this year, but Andaloussi and Isaken (2022) found evidence that managers began decreasing their emissions. CAIR officially established the annual and seasonal NO_x permit markets in 2009, but I use 2008 as the first year of regulation corresponding to the training year. I use 2009 as the first year of SO_2 regulation under CAIR despite the official implementation occurring in 2010.

Both CAIR and CSAPR created a cap-and-trade market mechanism. After the EPA determines which states significantly contribute to air quality issues downwind, they set a state-level emissions budget for annual and summertime NO_x and annual SO_2 allocating permits based on energy generator characteristics. After the initial annual allocation, permits can be traded between designated managers. Under CAIR, permits could be traded between any states under the same market. CSAPR restricted this further, only allowing trades to occur within the same state. At the end of the year, if a designated manager does not hold sufficient permits for their emissions, they are subject to fines or penalties as applicable under the Clean Air Act.[7] Under CSAPR, states are further held responsible for ensuring the sum of permits within their borders does not exceed their state budget.

Since both CAIR and CSAPR replaced the previous market-based cap-and-trade policy, there are additional dynamics worth considering. Affected units could transfer banked allowances from the previous permit market. Unused allowances from the current permit market could be saved for a future year, eventually expiring. This means that once a regulation has been implemented, effected generating units could continue using permits from prior years without changing their behavior. Alternatively, power plant managers could reduce emissions to bank permits in anticipation of new regulations.[8] This introduces a complication where plant managers could behave strategically by using banked allowances at the cost of stricter future allowances. Further, since multiple cap-and-trade policies are being implemented, a particular market for permits might not be binding. For example, in 2020 annual NO_x permits sold for $2.00 per ton of emissions. In contrast, the 2020 seasonal NO_x permits sold for as much as $175 per ton of emissions. This suggests that the annual NO_x permits might not be binding for 2020, but the EPA has shown a history of adjusting permit allocations to achieve the appropriate reductions

[7] In addition to individual fines and penalties, the CAA allows for withholding federal infrastructure spending to states or local governments not in compliance.
[8] See Fraas and Richardson (2010) for a discussion of the EPA's response to permit rollovers in cap-and-trade market transitions.

necessary to address transboundary air pollution. These complications highlight how messy transboundary air pollution regulations have been in the United States.

I offer a brief comparison between treatment under CAIR and CSAPR at a high level. Both CAIR and CSAPR target emissions through three permit markets: annual NO_x, annual SO_2, and seasonal NO_x. In this paper, I group annual and seasonal NO_x regulations together when identifying treated states. I am primarily interested in plant managers' response in abatement technology choice, so I would not expect the type of treatment to have a meaningful impact on abatement technology choice. As an example in CAIR, Texas is only regulated through the annual NO_x market, and Arkansas is only regulated in the seasonal NO_x market. However, plant managers in both states need to change their emissions through some means, including adopting new abatement technology or retiring a boiler. Figure 5 shows how states were regulated for NO_x emissions under CAIR and CSAPR. A total of 23 states were regulated under both CAIR and CSAPR, 4 states were regulated under CAIR but not CSAPR, and 4 states were regulated under CSAPR but not CAIR. Figure 6 shows the corresponding map for SO_2 emissions. A total of 19 states were regulated under both CAIR and CSAPR, 5 states were regulated under CAIR but not CSAPR, and 3 states were regulated under CSAPR but not CAIR. These slight differences give variation across types of emission regulation as well as the timing of treatment.

Regulated states are determined by an EPA model of air pollution dispersion. The primary goal of both CAIR and CSAPR is to reduce transboundary air pollution, so the EPA relies on state level results to determine if a particular state significantly contributes to the non-attainment status of the Clean Air Act in a neighboring state. The EPA does not use plant specific results to determine permit allocations due to concerns over model accuracy at the plant level. However, the EPA defends model results aggregated to the state level as a valid way to identify which states have significant levels of transboundary air pollution. Variation in regulated states comes from this dispersion model, but as Figure 5 and Figure 6 show, regulated states are primarily located in the Eastern United States where the density of power plants is higher and states are generally smaller.

From this background discussion, I conclude three points that inform the estimation strategy. First, transboundary air pollution policies regulate states according to an endogenous process but with exogenous timing from the perspective of plant managers. Second, power plants form expectations about future policies according to previous regulations. With the passage of a new regulation, power plants change their behavior due to the direct effects of regulation and changes in expectations. This suggests a reduced form estimation strategy to be most appropriate to jointly estimate the direct effect of regulation and changes in expectations of future regulation. Finally, the lag structure between policy implementation and plant managers' decisions is unclear due to regulatory uncertainty, anticipation effects, and interactions between current and previous permit markets. As such, I prefer to consider these regulations as a suite of transboundary regulations.

3.3 ESTIMATION STRATEGY

The estimation strategy relies on the assumption that the timing of transboundary air pollution regulations is an exogenous shock to the cost of emissions for plant managers. These regulations target specific geographic locations with large spillovers, meaning the regulations themselves are endogenous. From the perspective of the plant manager when these regulations are implemented occurs exogenously. Plant managers have observed regulatory changes over the years and have developed beliefs about future regulation, but they cannot fully anticipate when the EPA will implement the next set of regulations. I argue this supports the assumption that regulation behaves as an exogenous cost shock. However, this also means any observed changes in plant manager behavior capture the effect of changing expectations about future regulation in addition to the regulation itself. Since I cannot observe changes in beliefs about future regulation, the reduced form estimation strategy appropriately captures both the indirect effect on beliefs and the direct effect of regulation. Using these assumptions, I compare treated plant managers' decisions to untreated plant managers' to capture the effect of regulation.

The choice of estimation strategy is constrained by data availability for pollution control technology. I obtain data from the U.S. Energy Information Administration (EIA) for abatement technology, boiler retirement, and boiler characteristics from 2009 to 2022. Abatement technology at the boiler level is unavailable prior to 2009, creating an identification challenge as CAIR began in 2009 as well. This data availability constraint does not violate the necessary assumptions since I consider these regulations as exogenous shocks to the cost of emissions.

CAIR and CSAPR impact treated plant managers through two channels. First, the creation of a new emission permit market directly affects plant managers in treated states. Second, due to the highly connected nature of the electric grid, the regulations cause a shock to the electricity grid in both treated and untreated states. In response to the regulation, a treated plant manager might choose to shut down a generating unit. This decision impacts other treated and untreated plant managers in the grid as they must collectively meet the electricity demand. Even untreated plant managers might experience a policy shock. By comparing the decisions of treated plant managers to untreated ones, I control for this secondary channel of changes in electricity generation. This means any estimations should be interpreted as the effect of regulation on regulated plant managers, controlling for any changes in electricity supply and demand.

While plant managers might respond to regulation in a variety of ways, I focus on two extensive margin responses: retirement and new abatement technology installation. These responses represent costly changes on the extensive margin that plant managers are unlikely to revert after regulation ends. While plant managers might respond in other unobserved ways, these other responses represent short-term compliance strategies characterized by low fixed costs and reversibility.[9] By focusing on decisions on the extensive margin, I capture more meaningful long-term responses to transboundary air pollution regulation.

The implementation of CAIR and CSAPR varies across the states and types of emissions that were regulated, enabling the estimation strategy. CAIR and CSAPR only directly affected 27 states primarily in the East, clearly defining the treated and control

[9] Other responses on the intensive margin could include lobbying against the regulation, switching fuel types, or decreasing generation output.

groups. Within each group, pollution control technology varies across boilers, giving another source of variation to identify effects specific to control technologies. Further, CAIR and CSAPR both affected the same 23 states, but each uniquely regulated 4 states. Figure 5 and Figure 6 show maps of state regulation. This gives a small amount of variation across the set of states regulated allowing us to identify the effect of regulation under CAIR but not CSAPR and the effect of regulation under CSAPR but not CAIR. Lastly, both these policies regulated NO_x and SO_2 separately. This means some states affected by CAIR or CSAPR were only regulated for NO_x or SO_2. This variation allows us to independently capture the effect of NO_x and SO_2 regulation. The identification strategy utilizes these four different sources of variation.

I analyze three dimensions of the regulatory effects: emission type, control technology type, and individual policy. Both CAIR and CSAPR target NO_x and SO_2 emissions, but not all states are regulated for both types of emissions. This creates some heterogeneity in regulation effects allowing me to identify the effect of NO_x and SO_2 regulation separately. Further, EIA abatement technology data identifies the type of emissions a specific control technology targets. This allows me to observe if a change in control technology is responding to NO_x or SO_2 regulation. This assumes that a control technology does not simultaneously reduce both NO_x and SO_2 emissions, which does not commonly occur (Asghar, et al., 2021). Second, I expect the effect of regulation to depend on the type of technology already installed. For example, plant managers using highly effective and costly abatement technology should not install new technology at the same rate as managers not using any technology. Highly effective pollution control technology can achieve 90% emissions reduction (Sorrels, et al., 2019a; Sorrels, et al., 2021), and even less effective technologies can achieve 25-70% reductions (Sorrels, et al., 2019b). Plant managers using highly effective pollution control technology likely met the required reductions, or they would retire the boiler due to the prohibitive cost of compliance. The third source of heterogeneity in regulation comes from differences in CAIR and CSAPR treated states. As previously outlined, some states are regulated for NO_x or SO_2 under CAIR but not under CSAPR and vice versa. The primary results group the effect of both regulations together since the EPA has established a history of incremental regulations targeting emissions. It is unclear what lag structures might exist between regulatory implementation and installation of new abatement technologies due to expectations of future regulations and investment lags. I attempt to capture CAIR and CSAPR specific effects using the small amount of variation in regulation between CAIR and CSAPR states.

First, I estimate the effect of regulation on what compliance strategy plant managers choose separately for NO_x and SO_2 using the following multinomial logit specification:

$$STRATEGY_{it} = \beta_1 * TREAT_{it} + \Gamma X_{it} + \epsilon_{it} \qquad (38)$$

where $STRATEGY_{it}$ is a categorical variable for compliance strategy for the following: fuel switching, type of technology installation, and boiler retirement for boiler i in year t, $TREAT_{it}$ is either an indicator function for NO_x or SO_2 treatment for boiler i in year t, and X_{it} is a vector of controls for boiler i in year t which vary across specifications. The coefficient of interest is β_1 which captures the aggregate effect of regulation on each type of technology adoption for both CAIR and CSAPR. From this specification, I can learn how regulation influences the types of technologies that power plants choose to install. Due to convergence issues, I am unable to include all controls that I would like. To show the robustness of these results, I estimate separate regressions for each compliance strategy separately.

I estimate the aggregate effect of regulation on the outcomes of interest separately for NO_x and SO_2. I choose to use a probit model specification with cluster robust standard errors at the boiler and year level using Gu and Yoo's (2019) STATA package. I estimate the following model specification:

$$Y_{it} = \beta_1 * TREAT_{it} + \Gamma X_{it} + \gamma_t + \epsilon_{it} \tag{39}$$

where Y_{it} is either an indicator for boiler retirement or new technology installation for boiler i in year t, $TREAT_{it}$ is either an indicator function for NO_x or SO_2 treatment for boiler i in year t, X_{it} is a vector of controls for boiler i in year t which vary across specifications, and γ_t is a set of year fixed effects. I use cluster robust standard errors, clustering at the boiler and year level. The coefficient of interest is β_1 which captures the aggregate effect of regulation across all technologies for both CAIR and CSAPR.

Next, I estimate fuel specific effects of regulation on the outcomes of interest separately for NO_x and SO_2 using a probit model specification. To allow for full flexibility, I separately estimate (39) for each of the following fuel groups: coal, petroleum, and natural gas. This gives further evidence for which types of boilers choose different strategies.

Lastly, I examine the effect of CAIR and CSAPR separately by estimating (39) but changing the definition of $TREAT_{it}$. I replace $TREAT_{it}$ with a vector of treatment variables: treated under CAIR but not CSAPR, treated under CSAPR but not CAIR, and treated under both CAIR and CSAPR. This allows me to separate potential responses for these three groups of treated boilers.

3.4 DATA AND DESCRIPTIVE STATISTICS

I combine boiler level data for power plants from the US Energy Information Administration (2023) and synthesized boiler level data from the Public Utility Data Liberation project (Catalyst Cooperative, et al., 2023). Between 2009 and 2022 I obtain data for 4,731 boilers for 1,745 unique plants. Each boiler has an average of 10.58 years of observations, meaning I have a total of 50,039 observations. The dataset consists of annual boiler characteristics including retirement, control technology, and other controls. Table 15, Table 16, and Table 17 describe the variables used in the analysis. Through CAIR or CSAPR, 73% and 80% of boilers are ever regulated for SO_2 and NO_x, respectively. From 2009 to 2022 I observe 24.7% of boilers retiring.[10] While this might appear like a large percentage of boilers, the relationship between boilers to generators is not a clear one-to-one. Many generators have multiple boilers, and I can identify instances where a boiler retires without the generator or power plant shutting down.

[10] CAIR and CSAPR collectively regulated all but 21 and 17 of the contiguous states for SO_2 and NO_x respectively. Although the percentage regulated might seem high, most unregulated states are relatively sparsely populated western states.

During this time, only 4.2% of boilers installed a new SO_2 technology, and 5.3% of boilers installed a new NO_x technology. Other important control variables available in the analysis include fuel type, boiler firing type, waste heat input, boiler efficiency rates, and turndown ratio among others. To address concerns about responses to other concurrent regulations, I include an indicator for county-level Clean Air Act compliance status. Further, I include indicators for North American Electric Reliability Corporation (NERC) regions as a control for potential regulations in neighboring states. The electric grid is highly interconnected meaning that including this control captures market responses to other regulations occurring within the region.

I use this dataset for the analysis since it contains detailed information about the pollution control technology used at the boiler level. This information has only been collected by the EIA since 2009 but provides a unique opportunity to observe how plant managers make decisions on the extensive margin in response to regulation. The data breaks down control technologies into 23 unique categories, described in Table 18. I aggregate these into 6 categories: wet type technology, dry type technology, selective noncatalytic reduction technology, selective catalytic reduction technology, particulate control technology, and other uncategorized technology. I choose this categorization for three reasons. First, the primary control technologies used to address SO_2 emissions are wet and dry type technologies. For NO_x emissions, selective noncatalytic and catalytic reduction technologies are the primary two categories to reduce emissions. This gives us 2 categories of technology of interest for each type of emission being regulated. Second, I can easily categorize the types of technology in terms of efficiency and cost. Wet type technology and selective catalytic reduction technology are both relatively more costly but highly effective in reducing their respective emission types. Dry type technology and selective noncatalytic reduction technology are relatively cheaper, easier to retrofit onto existing boilers, and less effective in reducing emissions. Third, EIA classifies existing control technologies as SO_2 or NO_x technology. As I examine changes in technology installation for each of these categories, it becomes clear that particulate control technology and other unclassified technologies are rarely seen in the data. I include them as controls since they might proxy for power plants' perceptions of future regulation or other unobservable characteristics. This rich emission control technology data provides the basis for the analysis.

While this unique dataset allows us to observe emission control technology, boiler characteristics are not available for all 4,721 boilers each year. To address these missing data, I utilize the dummy variable method where I create a dummy variable indicating when data is available for a variable and then replace the missing values with the mean value. While this method has its criticisms, I only have complete data for 6,262 boiler-years. Using this method, I can include an additional 43,777 observations in the analysis.

The location of each boiler in the dataset can be seen in Figure 7 and Figure 8. Red boilers are never regulated under CAIR or CSAPR. Purple boilers are regulated under both CAIR and CSAPR, meaning they are always regulated in the dataset. Blue boilers are only regulated under CAIR meaning they are regulated in 2009 and then become unregulated in 2015. Green boilers are only regulated under CSAPR meaning they became regulated in 2015. These images highlight the variation in regulation across states. Table 15 shows that 73% and 80% of boilers are ever regulated for SO_2 and NO_x, respectively, through CAIR or CSAPR. However, when separating treatment into both CAIR and CSAPR, CAIR but not CSAPR, and CSAPR but not CAIR, we see slightly more variation in treatment.

Table 19 shows the matrix of fuel switching with the previous fuel type indicated on the left-hand side of the matrix and the new fuel type indicated on the top of the matrix. Most fuel switching occurs within a fuel type rather than switching to a new fuel type. It is also worth noting that there might be more than one fuel type for a specific boiler, meaning that these changes might also indicate adding a new fuel type rather than fully replacing an old fuel type. This gives further insight into later results which examine if plant managers respond to regulation by switching fuel type.

Finally, I compare treated and control boilers for both SO_2 and NO_x in Table 20 and Table 21 respectively. There are distinct differences between the two groups including fuel type, Clean Air Act non-attainment status, and installed pollution control technology. This motivates looking at a smaller treatment and control group in the robustness checks of the results. I consider only the states on either side of the regulatory line rather than all regulated and unregulated states due to systematic differences.

3.5 RESULTS

The results focus on comparing compliance strategies for regulated boilers relative to unregulated boilers under CAIR or CSAPR. First, it is worth comparing raw data for treated boilers to previous compliance strategies under the Acid Rain Program and the Clean Air Act to show how strategies have changed. Chan, et al. (2018) report that 11%

of treated generators installed new pollution control technology in response to the ARP. In contrast, I find that 18.6% of regulated boilers installed new SO_2 technology, and 19.3% installed new NO_x technology. In contrast, Chan, et al. (2018) found 28% of generators switched to a lower sulfur content fuel type. However, I find that only 9% of boilers switched fuel type in response to SO_2 regulation and 9.8% in response to NO_x regulation. This shows a higher percentage of installing newer technology and a lower percentage of switching fuels. This gives us our first insight into the differences in compliance costs from recent air pollution regulations in CAIR and CSAPR compared to older regulations such as ARP.

I organize the results by the type of regulation. I define the treatment variable to be the effect of the suite of regulatory policies, constraining the effect of CAIR and CSAPR to be indistinguishable from one another. Within both SO_2 and NO_x regulations, I structure the analysis as follows. In the primary specification, I estimate the effect of regulation on compliance strategies using the multinomial logit specification. I examine the robustness of these results by individually estimating the effect of regulation on each strategy: fuel switching, boiler retirement, and installing new pollution control technology. I explore heterogenous effects by fuel type by re-estimating each of the previous regressions separately for the following fuel groups: coal, petroleum, and natural gas.

Note that I observe whether a technology has been labeled as SO_2 or NO_x, meaning that I can pinpoint a plant manager's response to SO_2 or NO_x regulation. This assumes that pollution control technology does not significantly affect both SO_2 and NO_x

emissions without being labeled for both. While pollution control processes exist to address both SO_2 and NO_x emissions, they are not common (Asghar, 2021). There are slight differences in the analysis across the two emission type sections. First, I am primarily interested in wet and dry type technologies when it comes to SO_2 regulation and selective noncatalytic reduction and selective catalytic reduction technologies when it comes to NO_x regulation. This is reflected in the types of technology installation choices included in the multinomial regression. Second, if a pollution control equipment is coded by the EIA as only a NO_x control, then it would not appear as a new control installation for the SO_2 regulation specifications.

The last section changes the definition of the treatment variable to estimate the independent effects of CAIR and CSAPR, CAIR but not CSAPR, and CSAPR but not CAIR regulations. I go through the same analyses as previously reported to understand potential interaction effects between the two regulatory policies.

3.5.1 SO_2 REGULATION

First, I examine every compliance strategy simultaneously: fuel switching, installing wet technology, installing dry technology, installing other technology, and retiring the boiler. Table 22 through Table 26 shows the results of the multinomial logit specification. Each table shows the results of adding in additional controls, highlighting the importance of fuel type and current technology installed in the effect of regulation. I find evidence that plant managers choose to install dry technology ($p<0.01$) or switch fuel types ($p<0.01$) in response to regulation. There is marginal evidence that boilers retire in response to SO_2 regulation ($p<0.1$). To achieve convergence, some controls are dropped from the multinomial logit specification. I examine the robustness of these results by estimating probit models for each of the specific compliance strategies separately.

Next, I examine if plant managers choose to switch fuel types in response to regulation. Table 27Table 28 shows the results for fuel switching while adding in additional controls. I find that plant managers are 1.3 percentage points more likely to switch fuels in treated states compared to untreated states after controlling for all boiler characteristics. Compared to a baseline of 13% of boilers switching fuel sources in a year, this corresponds to a 10% increase. Note that this result remains stable across each specification.

I examine plant managers' likelihood of retiring boilers in response to regulation. I visually compare the rate of boiler retirement between the treated and control groups in Figure 9**.** Two clear increases occurred in 2015 and 2019 in the treated states relative to the control states. This could coincide with the implementation of CSAPR in 2015 and the 2019 announcement that the CSAPR Update would not end. However, as previously mentioned the uncertainty around policy implementation and timing of power plant responses makes it difficult to attribute these two spikes to a singular event.

I estimate a probit model to statistically determine if plant managers' respond by retiring boilers after I control for other boiler characteristics. Table 28 reports the parameter estimates from the regression where column 1 contains no additional controls and column 4 includes all available controls. I find no statistical difference between boiler retirement rates for regulated and unregulated boilers once I control for all available boiler characteristics. This signals that the observable boiler characteristics contain important information and omitting them likely introduces bias into the parameter estimates. By sequentially adding in controls, we gain insight into the importance of different sets of control variables. Across the analyses, boiler fuel type proves to be an important characteristic. To gain insight into the types of boilers that retire, I explore heterogeneity by fuel type.

I estimate the same probit model of boiler retirement separately for each of the following fuel groups: coal, petroleum, and natural gas. This allows complete flexibility for the effect of regulation and other controls conditional on fuel type. Table 29 reports the parameter estimates of the probit model. To ensure convergence, some controls were dropped for all specifications to allow for direct comparison. I find no evidence that boilers retire even when considering boiler by fuel type. This gives further confidence to the previous results that showed no effect of regulation on boiler retirement. This suggests that the cost of compliance with regulation is less than the cost of retirement for all types of boilers.

Next, I consider plant managers' propensity to install new control technology in response to SO_2 regulation. Table 30 reports the parameter estimates from a probit model with a dependent binary variable for any new technology installation. I find that treated plant managers are 0.1 percentage points more likely to install new control technology even after controlling for observable boiler characteristics ($p<0.05$). On average, I observe 4.2% of managers installing new SO_2 technology on boilers. The effect of regulation represents a 2.4% increase relative to the average rate of technology adoption.

Table 31 reports parameters from the same probit model of technology installation separately for each of the following fuel groups: coal, petroleum, and natural gas. This allows complete flexibility for the effect of regulation and other controls conditional on fuel type. Some controls were dropped for all specifications to allow for direct comparison. After these controls were dropped, I find no evidence that plant managers installed new technology in general from the baseline specification. This highlights the importance of some of the controls, putting more importance on the probit regressions for each of the compliance strategies. I find no evidence that fuel type matters when plant managers install new pollution control technology. This result should be taken with caution, as the controls that were dropped for convergence likely have important effects.

Results show plant managers respond to regulation by installing new pollution control technology and switching fuel types. When breaking out the type of pollution control technology, I find that managers choose to install the dry type technology which is relatively cheap and less effective than wet type technology.

3.5.2 NO_x REGULATION

I perform the same analyses as the previous section for NO_x. First, I present results from a multinomial logit model that considers all compliance strategies: fuel switching, selective noncatalytic reduction technology, selective catalytic reduction technology, other technology, and boiler retirement. Table 32 through Table 36 shows the results of the multinomial logit specification. Each table shows the results of adding in additional controls, highlighting the importance of fuel type and current technology installed in the effect of regulation. I find evidence that plant managers choose to install selective noncatalytic reduction technology ($p<0.01$) in response to regulation. Similar to SO_2 regulation, to achieve convergence some controls are dropped from the multinomial logit specification. I examine the robustness of these results by estimating probit models for each of the specific compliance strategies separately.

First, I find no evidence of fuel switching in response to NO_x regulation once I control for all boiler characteristics. Table 37 reports parameter estimates for the probit model regression. This evidence provides more confidence in my prior results that plant managers do not change fuel type in response to NO_x regulation, unlike SO_2 regulation.

Next, consider boiler retirement in response to NO_x regulation. Visually, I observe similar spikes in boiler retirement in 2015 and 2019 in Figure 10. Table 38 shows parameter estimates from the probit model. After controlling for all observable boiler characteristics, I find no difference between boiler retirement in treated and control states.

I estimate the same probit model separately for each fuel type group and report parameter estimates in Table 39. Consistently across all fuel types, I find no evidence of boiler retirement. This provides further evidence that plant managers do not choose to retire boilers in response to regulation. In other words, the cost of compliance is lower than the cost of retiring a boiler.

Table 40 reports parameter estimates for new pollution control technology installations in response to NO_x regulation. I find no significant effect after controlling for all observable characteristics. Table 41 reports parameter estimates for each type of fuel group. Across all fuel groups, I find the same result that plant managers do not install new pollution control technology in general.

These results show evidence that plant managers do not retire boilers or switch fuel types in response to NO_x regulation. In general, managers also do not install new pollution control technology. However, I do find some evidence that managers choose to install selective noncatalytic reduction technology, which is relatively cheap and less effective compared to selective catalytic reduction technology.

3.5.3 CAIR AND CSAPR

In this last section, I rerun the main analyses but change the treatment variable definitions. I define CAIR treatment to be regulation under CAIR but not under CSAPR. Similarly, I define CSAPR treatment to be regulation under CSAPR but not CAIR. Finally, I define CAIR and CSAPR treatment to be regulation under both policies. This means that the identification of the CAIR and CSAPR treatment variable relies solely on spatial variation since any boiler regulated under both would be regulated for all available observations. The other two treatment variables have variation over time and space, as they only include boilers which move from treated to untreated status during the timeframe of observations.

First, I examine fuel switching in Table 42. For SO_2 regulations, I find no evidence of boiler retirement for any regulation or combination. However, for NO_x regulation, I find an increase in fuel switching of 2.8 percentage points in response to CAIR but not CSAPR and 1.3 percentage points in response to CSAPR and CAIR. The baseline rate of fuel switching is 13%, meaning this corresponds to a 21.5% and 10%

increase respectively. This suggests a stronger response to CAIR but not CSAPR regulation. This stands in contrast to my primary specification, which found consistent null effects of NO_x regulation on fuel switching. The identification of these treatment variables relies on relatively small variation, so I conclude that in general managers do not change fuel type in response to NO_x regulation but there is likely some heterogeneity. In other words, there are likely subsets of regulated managers who choose to switch fuel type in response to CAIR but not CSAPR regulation in particular, but on aggregate, there is no evidence.

I consider boiler retirement rates in Table 43. Consistent with the previous results, I find no evidence of boiler retirement.

I consider new pollution control technology installations in Table 44. I find no statistical difference between regulated and unregulated boilers. This is in contrast to prior evidence that managers installed new technology in response to SO_2 regulation. This highlights the challenges of identifying the effects of specific interactions of regulations. Small amounts of variation in combination with managers' complex expectations of future regulation reduce confidence in these results and highlight the contribution of my primary specifications.

The results in this section show many null effects when identifying the response to CAIR, CSAPR, and both CAIR and CSAPR separately. Naturally, we might wish to know whether these results are precisely estimated or simply underpowered. I use a t-test to determine whether any of the 16 null effects of interest could have been as large as 5% with a statistical significance of 0.05. I argue that an increase of 5 percentage points is significant in this context. Out of the 16 null effects, I can reject the null hypothesis that the effect was 5 percentage points or greater for all estimates. This provides evidence that these are precisely estimated null effects and are not meaningfully different from 0.

3.5.4 ROBUSTNESS

I examine one final robustness check to address potential systematic differences between treatment and control states. I restrict the sample to only states on either side of the regulatory line. In particular, for SO_2 I include North Dakota, South Dakota, Wyoming, Colorado, New Mexico, Minnesota, Wisconsin, Iowa, Texas, Oklahoma, Nebraska, Kansas, Missouri, Arkansas, Louisianna, Tennessee, Mississippi, and Alabama. For NO_x I include North Dakota, South Dakota, Wyoming, Colorado, New Mexico, Minnesota, Wisconsin, Iowa, Texas, Oklahoma, Nebraska, Kansas, Missouri, Arkansas, and Louisianna. I rerun three probit models for fuel switching, new technology installation, and retirement with all available controls.

Table 45 and Table 46 report the estimated effects of regulation on the restricted sample for SO_2 and NO_x respectively. For SO_2 regulation, I find a statistically significant increase in fuel switching for treated states, consistent with prior results. I find no effect for new pollution control technology in contrast to my primary results. I find a significant increase in boiler retirement in treated states ($p<0.01$). Retirement increases by 0.3 percentage points which translates into an increase of 1.2% compared to the baseline. For NO_x regulation, I find no effect on fuel switching, consistent with prior results. Similarly, I find no effect on new pollution control technology installation. However, I find a marginal increase in boiler retirements in treated states ($p<0.1$). Retirement increases by 0.3 percentage points which translates into an increase of 1.2% compared to the baseline. The economic significance of the retirement results is marginal. This approach might provide a cleaner identification of the effect of CAIR and CSAPR by restricting the sample to states with a more similar regulatory landscape and electric grid. However, the generalizability of the results might not hold. In other words, the composition of energy generation and responses to regulation might differ in the Midwest compared to Eastern and Western states.

3.6 CONCLUSION

As policy makers consider further air pollution regulation, it is critical to understand how power plant managers might respond. I contribute to this discussion by analyzing plant managers' responses to transboundary air pollution regulations. Policymakers typically do not know how managers will respond to regulation, so analyzing responses ex post provides insight into the cost of compliance. I find evidence that managers respond to SO_2 regulation by switching fuel types. The data suggests this fuel switching mostly occurs within the same fuel group, for example from bituminous coal to refined coal. I find that plant managers tend to not retire boilers. When I examine which types of technologies were installed, I find that plant managers chose relatively cheap control technologies. I conclude that plant managers chose to comply with regulations by switching fuel types and installing relatively cheap control technology.

Future work can build on my analysis and the growing data availability of pollution control technology. Because the analysis leverages new data on pollution control technology from the EIA, I am unable to obtain data for treated boilers before regulation. With the growing availability of this data, future regulatory changes would allow for cleaner identification of treatment effects. Further, these transboundary air pollution regulations try to reduce the amount of spillover pollution. While I have not addressed this in this paper, future work could examine how plant managers within a treated region respond differently depending on their level of pollution spillover to neighboring states. Future work could also examine the intensive margin of plant manager responses including decreased energy generation or political lobbying.

This work speaks to a larger conversation regarding air pollution regulation. Critics of air pollution regulation often worry about unintended consequences such as increased electricity prices resulting from retirements. I found no evidence that plant managers retired boilers in response to these regulations on average. Further, plant managers typically installed relatively cheap pollution control technologies. This suggests that the cost of compliance was not high enough to push boilers to retire or managers to install relatively more expensive pollution control technologies. The results show that recent transboundary air pollution regulations successfully improved the composition of pollution control technology without causing boiler retirements.

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APPENDIX

Table 15: Descriptive Statistics for Binary Boiler Attributes

Variable	(1) Description	(2) Count	(3) Proportion of Total
Boilers	Number of boilers	4731	-
Boiler Retirement	Boiler retired during 2009-2022	1169	0.247
New SO_2 Control Technology	Boiler ever installs new control technology for SO_2 emissions	200	0.042
New NO_x Control Technology	Boiler ever installs new control technology for NO_x emissions	250	0.053
SO_2 Treatment	Boiler is ever treated under CAIR or CSAPR for SO_2 emissions	3462	0.732
SO_2 CAIR Treatment	Boiler is ever treated under CAIR but not CSAPR for SO_2 emissions	965	0.204
SO_2 CSAPR Treatment	Boiler is ever treated under CSAPR but not CAIR for SO_2 emissions	147	0.031
SO_2 CAIR and CSAPR Treatment	Boiler is treated under CAIR and CSAPR for SO_2 emissions	2350	0.497
NO_x Treatment	Boiler is ever treated under CAIR or CSAPR for NO_x emissions	3767	0.796
NO_x CAIR Treatment	Boiler is ever treated under CAIR but not CSAPR for NO_x emissions	412	0.087
NO_x CSAPR Treatment	Boiler is ever treated under CSAPR but not CAIR for NO_x emissions	231	0.049
NO_x CAIR and CSAPR Treatment	Boiler is treated under CAIR and CSAPR for NO_x emissions	3124	0.497
Wet Type Technology	Boiler has ever used wet type technology	492	0.104

Table 15: Continued

Dry Type Technology	Boiler has ever used dry type technology	506	0.107
Particulate Control Technology	Boiler has ever used particulate control technology	11	0.002
Selective Noncatalytic Reduction Technology	Boiler has ever used selective noncatalytic reduction technology	466	0.099
Selective Catalytic Reduction Technology	Boiler has ever used selective catalytic reduction technology	1230	0.26
Other Technology	Boiler has ever used other technology	22	0.005
Boiler Firing Type -CB	Boiler ever used Cell Burner	7	0.001
Boiler Firing Type -CY	Boiler ever used Cyclone Firing	86	0.018
Boiler Firing Type -DB	Boiler ever used is Duct Burner	771	0.163
Boiler Firing Type -FB	Boiler ever used Fluidized Bed Firing (Circulating Fluidized Bed, Bubbling Fluidized Bed)	73	0.015
Boiler Firing Type -SS	Boiler ever used Stoker (Spreader, Vibrating Gate, Slinger)	72	0.015
Boiler Firing Type -TF	Boiler ever used Tangential Firing / Concentric Firing / Corner Firing	639	0.135
Boiler Firing Type -VF	Boiler ever used Vertical Firing / Arch Firing	50	0.011
Boiler Firing Type -WF	Boiler ever used Wall Fired (Opposed Wall, Rear Wall, Front Wall, Side Wall)	941	0.199
Boiler Firing Type -OT	Boiler ever used firing type classified as other	144	0.03

Table 16: Descriptive Statistics for Binary Boiler Attributes continued

Variable	(1) Description	(2) Count	(3) Proportion of Total
No Fly Ash Reinjection	Boiler explicitly does not have fly ash reinjection	2413	0.51
Fly Ash Reinjection	Boiler does have fly ash reinjection	166	0.035
No Heat Recovery Steam Generator	Boiler explicitly does not have a heat recovery steam generator	2332	0.493
Heat Recovery Steam Generator	Boiler does have a heat recovery steam generator	1315	0.278
Standards -D	Boiler ever subject to Standards of Performance for fossil-fuel fired steam boilers for which construction began after August 17, 1971.	321	0.068
Standards -Da	Boiler ever subject to Standards of Performance for fossil-fuel fired steam boilers for which construction began after September 18, 1978	511	0.108
Standards -Db	Boiler ever subject to Standards of Performance for fossil-fuel fired steam boilers for which construction began after June 19, 1984.	814	0.172
Standards -Dc	Boiler ever subject to Standards of Performance for small industrial-commercial-institutional steam generating units	61	0.013
Fuel Type -AB	Boiler ever used Agricultural By-Products	3	0.001
Fuel Type -BIT	Boiler ever used Bituminous Coal	861	0.182
Fuel Type -BLQ	Boiler ever used Black Liquor	59	0.013
Fuel Type -DFO	Boiler ever used Distillate Fuel Oil	506	0.107

Table 16: Continued

Fuel Type -LIG	Boiler ever used Lignite Coal	38	0.008
Fuel Type -MSW	Boiler ever used Municipal Solid Waste	10	0.002
Fuel Type -NG	Boiler ever used Natural Gas	1807	0.382
Fuel Type -OBS	Boiler ever used Other Biomass Solid	11	0.002
Fuel Type -OG	Boiler ever used Other Gas	97	0.021
Fuel Type -OTH	Boiler ever used Other Fuel	31	0.007
Fuel Type -PC	Boiler ever used Petroleum Coke	59	0.013
Fuel Type -RC	Boiler ever used Refined Coal	119	0.025
Fuel Type -RFO	Boiler ever used Residual Fuel Oil	299	0.063
Fuel Type -SGC	Boiler ever used Coal-Derived Synthesis Gas	3	0.001
Fuel Type -SLW	Boiler ever used Sludge Waste	17	0.004
Fuel Type -SUB	Boiler ever used Subbituminous Coal	530	0.112
Fuel Type -WC	Boiler ever used Waste/Other Coal	17	0.004
Fuel Type -WDL	Boiler ever used Wood Waste Liquids	2	0
Fuel Type -WDS	Boiler ever used Wood/Wood Waste Solids	91	0.019
NERC- ASCC	North American Electric Reliability Corporation – Alaska Systems Coordinating Council Region	33	0.007
NERC- FRCC	North American Electric Reliability Corporation – Florida Reliability Coordinating Council Region	14	0.003
NERC- HICC	North American Electric Reliability Corporation – Hawaii Coordinating Council Region	45	0.001

Table 16: Continued

NERC- MRO	North American Electric Reliability Corporation – Midwest Reliability Organization Region	535	0.113
NERC- NPCC	North American Electric Reliability Corporation – Northeast Power Coordinating Council Region	436	0.092
NERC- RFC	North American Electric Reliability Corporation – ReliabilityFirst Corporation Region	1050	0.222
NERC- SERC	North American Electric Reliability Corporation – SERC Reliability Corporation Region	1547	0.327
NERC- SPP	North American Electric Reliability Corporation – Southwest Power Pool Region	8	0.002
NERC- TRE	North American Electric Reliability Corporation – Texas Reliability Entity Region	354	0.075
NERC- WECC	North American Electric Reliability Corporation – Western Electricity Coordinating Council Region	705	0.149
CAA Non-attainment Status	Boiler ever in Clean Air Act non-attainment status county	1325	0.280

Table 17: Descriptive Statistics for Continuous Boiler Attributes

Variable	Description		Mean	Standard Deviation	Min	Max	N/n/T-bar
Fuel Switching	Boiler switches fuel type	overall	0.130	0.336	0	1	50039
		between	.	0.222	0	1	4731
		within	.	0.319	-0.703	1.059	10.577
Age in 2009	Boiler age in 2009, time invariant	overall	26.637	18.858	0	83	46410
		between	.	20.075	0	83	4240
		within	.	0	26.637	26.637	10.946
Efficiency 100% Load	Boiler efficiency when burning at 100 percent load (nearest 0.1 percent)	overall	0.848	0.105	0.264	1	27699
		between	.	0.099	0.264	0.996	2631
		within	.	0.019	0.446	1.121	10.528
Efficiency 50% Load	Boiler efficiency when burning at 50 percent load (nearest 0.1 percent)	overall	0.838	0.117	0.25	1	26834
		between	.	0.116	0.252	0.996	2577
		within	.	0.02	0.369	1.148	10.413
Air Flow 100% Load	Total air flow including excess air at 100 percent load, reported at standard temperature and pressure	overall	700133.4	745061.3	24	10000000	27717
		between	.	755426	24	8961832	2638
		within	.	95698.04	-2154338	8673515	10.507

Table 17: Continued

Max Steam Flow	Maximum continuous steam flow at 100% load (thousand pounds per hour)	overall	1585.017	1660.851	60	13000	28257
		between	.	1563.235	60	13000	2666
		within	.	63.606	-985.683	2441.917	10.599
Turndown Ratio	Ratio of maximum heat output to minimum heat output	overall	15.387	128.172	0.1	2034	18558
		between	.	185.365	0.1	2034	2314
		within	.	46.906	-991.263	1832.217	8.02
Waste Heat Input	Design waste-heat input rate at max continuous steam flow (million Btu per hour)	overall	6347.339	109670.8	0.2	2578684	9502
		between	.	143215.9	0.2	2578684	842
		within	.	1845.272	-19887.1	67560.94	11.285

Notes: since data are available for the panel, and vary over time, I report the overall, between, and within variation for boilers. N refers to the total number of observations, n refers to the number of boilers for which there are observations, and T-bar refers to the average number of observations.

Table 18: Pollution Control Equipment Description and Aggregation

EIA Equipment Type Code	Equipment Type Description	Aggregation
JB	Jet bubbling reactor (wet) scrubber	Wet Type Technology
MA	Mechanically aided type (wet) scrubber	Wet Type Technology
PA	Packed type (wet) scrubber	Wet Type Technology
SP	Spray type (wet) scrubber	Wet Type Technology
TR	Tray type (wet) scrubber	Wet Type Technology
VE	Venturi type (wet) scrubber	Wet Type Technology
BS	Baghouse (fabric filter), shake and deflate	Particulate Control Technology
BP	Baghouse (fabric filter), pulse	Particulate Control Technology
BR	Baghouse (fabric filter), reverse air	Particulate Control Technology
EC	Electrostatic precipitator, cold side, with flue gas conditioning	Particulate Control Technology
EH	Electrostatic precipitator, hot side, with flue gas conditioning	Particulate Control Technology
EK	Electrostatic precipitator, cold side, without flue gas conditioning	Particulate Control Technology
EW	Electrostatic precipitator, hot side, without flue gas conditioning	Particulate Control Technology
MC	Multiple cyclone	Particulate Control Technology
SC	Single cyclone	Particulate Control Technology
ACI	Activated carbon injection system	Particulate Control Technology
CD	Circulating dry scrubber	Dry Type Technology
SD	Spray dryer type / dry FGD / semi-dry FGD	Dry Type Technology
DSI	Dry sorbent (powder) injection type (DSI)	Dry Type Technology
LIJ	Lime injection	Dry Type Technology
SN	Selective noncatalytic reduction	Selective Noncatalytic Reduction Technology
SR	Selective catalytic reduction	Selective Catalytic Reduction Technology
OT	Other equipment	Other Technology

Notes: the first two columns give the EIA reported code and description for each technology present in the data. The last column gives the aggregated group used in the analysis. For example, when I refer to wet type technology this includes 6 different types of wet scrubber technologies.

Table 19: Fuel Switching Matrix

		To Fuel Type			
		Coal	Petroleum	Natural Gas	Total
From Fuel Type	Coal	12,450	629	428	13,507
	Petroleum	551	843	740	2,134
	Natural Gas	332	726	1,005	2,063
	Total	13,333	2,198	2,173	

Table 20: Comparison of Treated and Control – SO_2

	(1) SO2 Treated	(2) SO2 Control	(3) Difference
Total Observations	3,462	2,248	
Wet Type Technology (mean)	0.113	0.075	0.038***
Dry Type Technology (mean)	0.107	0.095	0.012
Particulate Control Technology (mean)	0.002	0.002	0
Selective Noncatalytic Reduction Technology (mean)	0.101	0.089	0.012
Selective Catalytic Reduction Technology (mean)	0.242	0.284	-0.042***
Other Technology (mean)	0.003	0.006	-0.004**
Fly Ash Reinjection	0.037	0.026	0.011
Heat Recovery Steam Generator	0.153	0.350	-0.197***
Fuel Type -AB	0.001	0.001	0*
Fuel Type -BIT	0.226	0.055	0.171***
Fuel Type -BLQ	0.014	0.009	0.005
Fuel Type -DFO	0.116	0.079	0.037***
Fuel Type -LIG	0.007	0.017	-0.01
Fuel Type -MSW	0.001	0.003	-0.002*
Fuel Type -NG	0.370	0.445	-0.075
Fuel Type -OBS	0.002	0.002	0*
Fuel Type -OG	0.025	0.031	-0.006***
Fuel Type -OTH	0.007	0.009	-0.002
Fuel Type -PC	0.017	0.008	0.009***
Fuel Type -RC	0.023	0.017	0.006
Fuel Type -RFO	0.056	0.059	-0.003*
Fuel Type -SGC	0.001	0	0*
Fuel Type -SLW	0.004	0.001	0.003
Fuel Type -SUB	0.120	0.090	0.03***
Fuel Type -WC	0.004	0.001	0.003
Fuel Type -WDL	0	0.001	-0.001
Fuel Type -WDS	0.021	0.014	0.007***
CAA Non-attainment Status	0.204	0.334	-0.13***

Note: Difference is Treated minus Control with statistical significance from t-test with unequal variances.

Table 21: Comparison of Treated and Control – NO_x

	(1) NO_x Treated	(2) NO_x Control	(3) Difference
Total Observations	3,767	1,539	
Wet Type Technology (mean)	0.105	0.087	0.018
Dry Type Technology (mean)	0.111	0.123	-0.012*
Particulate Control Technology (mean)	0.002	0.002	0
Selective Noncatalytic Reduction Technology (mean)	0.103	0.107	-0.004**
Selective Catalytic Reduction Technology (mean)	0.243	0.288	-0.045***
Other Technology (mean)	0.003	0.009	-0.006**
Fly Ash Reinjection	0.036	0.029	0.008
Heat Recovery Steam Generator	0.231	0.288	-0.057***
Fuel Type -AB	0.001	0.002	-0.001*
Fuel Type -BIT	0.213	0.068	0.145***
Fuel Type -BLQ	0.014	0.007	0.007**
Fuel Type -DFO	0.113	0.073	0.04***
Fuel Type -LIG	0.006	0.009	-0.003**
Fuel Type -MSW	0.002	0.004	-0.002
Fuel Type -NG	0.381	0.373	0.008
Fuel Type -OBS	0.002	0.003	0
Fuel Type -OG	0.024	0.008	0.016***
Fuel Type -OTH	0.006	0.007	-0.001
Fuel Type -PC	0.016	0.005	0.011***
Fuel Type -RC	0.024	0.018	0.007
Fuel Type -RFO	0.061	0.066	-0.006
Fuel Type -SGC	0.001	0.001	0*
Fuel Type -SLW	0.004	0.002	0.002
Fuel Type -SUB	0.117	0.099	0.018***
Fuel Type -WC	0.004	0.002	0.002
Fuel Type -WDL	0	0.001	-0.001
Fuel Type -WDS	0.022	0.013	0.009***
CAA Non-attainment Status	0.231	0.332	-0.101***

Note: Difference is Treated minus Control with statistical significance from t-test with unequal variances.

Table 22: Fuel Switching from SO2 Regulation - Multinomial Logit

Dependent Var: Switch Fuel Type	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO2 Treatment	0.553***	0.428***	0.459***	0.418***
	(0.062)	(0.086)	(0.086)	(0.094)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with switching fuel type reported in this table. SO2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO2 emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 23: New Wet SO_2 Abatement Technology - Multinomial Logit

Dependent Var: New Wet Technology Installation	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO2 Treatment	0.824***	0.063	0.041	-0.102
	(0.288)	(0.462)	(0.485)	(0.535)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with new wet type technology installation reported in this table. SO2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO2 emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 24: New Dry SO_2 Abatement Technology - Multinomial Logit

	(1)	(2)	(3)	(4)
Dependent Var: New Dry Technology Installation	No Controls	Controls - No Technology or Fuel Type	Controls - No Fuel Type	All Controls
SO2 Treatment	1.105***	1.257***	1.390***	1.342***
	(0.291)	(0.412)	(0.418)	(0.454)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with new dry type technology installation reported in this table. SO2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO2 emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 25: New Other SO_2 Abatement Technology - Multinomial Logit

	(1)	(2)	(3)	(4)
Dependent Var: New Other Technology Installation	No Controls	Controls - No Technology or Fuel Type	Controls - No Fuel Type	All Controls
SO2 Treatment	-1.366	15.334	18.140	5.258
	(1.118)	(1,234.926)	(1,816.254)	(29,250.556)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with other technology type installation reported in this table. SO2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO2 emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 26: Boiler Retirement by SO_2 Treatment - Multinomial Logit

Dependent Var: Boiler Retirement	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO2 Treatment	0.566***	0.278***	0.328***	0.177*
	(0.072)	(0.100)	(0.100)	(0.104)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with boiler retirement reported in this table. SO2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO2 emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 27: Fuel Switching by SO_2 Treatment

Dependent Var: Switched Fuel Type	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO_2 Treatment	0.013**	0.016***	0.016***	0.013***
	(0.006)	(0.004)	(0.004)	(0.004)
Observations	46,474	46,474	46,474	46,474
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is fuel switching at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 28: Boiler Retirement by SO_2 Treatment

Dependent Var: Boiler Retirement	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO_2 Treatment	0.009***	0.002*	0.003**	0.002
	(0.003)	(0.001)	(0.001)	(0.001)
Observations	49,578	49,578	49,578	49,578
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is fuel switching at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 29: Boiler Retirement by SO2 Treatment – Fuel Specific Effects

Dependent Var: Boiler Retirement	(1) Baseline	(2) Coal	(3) Petroleum	(4) Natural Gas
SO2 Treatment	0.003	0.003	-0.006	0.001
	(0.002)	(0.007)	(0.011)	(0.002)
Observations	49,885	11,587	5,135	17,989
Year FE	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES
All Controls	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level. Efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, and waste heat input control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is fuel switching at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 30: New SO_2 Abatement Technology

Dependent Var: New Technology Installation (any type)	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
SO2 Treatment	0.004***	0.002*	0.001**	0.001**
	(0.002)	(0.001)	(0.001)	(0.000)
Observations	20,561	20,561	20,561	20,561
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is an indicator for any technology installation at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 31: New SO_2 Abatement Technology – Fuel Specific Effects

	(1)	(2)	(3)	(4)
Dependent Var: New Technology Installation (any type)	Baseline	Coal	Petroleum	Natural Gas
SO2 Treatment	0.000	0.004	-0.000	0.016
	(0.000)	(0.003)	(0.000)	(0.011)
Observations	25,027	7,645	638	632
Year FE	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES
All Controls	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level.
Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, fly ash reinjection, heat recovery steam generator, and waste heat input control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is an indicator for any technology installation at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 32: Fuel Switching by NO_x Treatment - Multinomial Logit

Dependent Var: Switching Fuel Type	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	0.312***	0.086	0.054	-0.044
	(0.079)	(0.126)	(0.126)	(0.085)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, NERC regions, CAA attainment status, and waste heat input control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with fuel switching reported in this table. NOx treatment is an indicator variable for treatment under either CAIR or CSAPR for NOx emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 33: New Selective Noncatalytic Reduction NO_x Abatement Technology - Multinomial Logit

Dependent Var: New SNR Technology Installation	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	0.348	0.740	0.853*	0.859***
	(0.289)	(0.466)	(0.497)	(0.322)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, NERC regions, CAA attainment status, and waste heat input control variables were dropped for convergence.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with new technology installation for selective noncatalytic reduction technology reported in this table. NOx treatment is an indicator variable for treatment under either CAIR or CSAPR for NOx emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 34: Selective Catalytic Reduction NO_x Abatement Technology - Multinomial Logit

Dependent Var: New SCR Technology Installation	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	0.225	0.343	0.324	0.466
	(0.276)	(0.516)	(0.519)	(0.309)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, NERC regions, CAA attainment status, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with new technology installation for selective catalytic reduction technology reported in this table. NOx treatment is an indicator variable for treatment under either CAIR or CSAPR for NOx emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 35: Other NO_x Abatement Technology - Multinomial Logit

Dependent Var: Other Technology Installation	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	-2.717**	-3.011**	-3.204**	-42.401
	(1.081)	(1.285)	(1.408)	(2,947.272)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, NERC regions, CAA attainment status, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with new technology installation for other technology reported in this table. NOx treatment is an indicator variable for treatment under either CAIR or CSAPR for NOx emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 36: Boiler Retirement by NO_x Treatment - Multinomial Logit

Dependent Var: Boiler Retirement	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	0.327***	-0.038	-0.030	-0.021
	(0.067)	(0.106)	(0.106)	(0.077)
Observations	44,957	44,957	44,957	44,957
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Age, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, firing type indicators, fly ash reinjection, heat recovery steam generator, NERC regions, CAA attainment status, and waste heat input control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for compliance strategies at the annual level for 2009-2022, with boiler retirement reported in this table. NOx treatment is an indicator variable for treatment under either CAIR or CSAPR for NOx emissions. Wet type technology is the indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is the indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is the indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is the indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 37: Fuel Switching by NO_x Treatment

Dependent Var: Switched Fuel Type	(1) No Controls	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NO_x Treatment	0.005	0.006	0.005	0.004
	(0.005)	(0.005)	(0.005)	(0.004)
Observations	46,474	46,474	46,474	46,474
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is fuel switching at the annual level for 2009-2022. NO_x treatment is an indicator variable for treatment under either CAIR or CSAPR for NO_x emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 38: Boiler Retirement by NO_x Treatment

	(1)	(2)	(3)	(4)
Dependent Var: Boiler Retirement	No Controls	Controls - No Technology or Fuel Type	Controls - No Fuel Type	All Controls
NOx Treatment	0.006***	0.001	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	49,578	49,578	49,578	49,578
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler, year level. ***p<0.01, **p<0.05, *p<0.1

Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. NO_x treatment is an indicator variable for treatment under either CAIR or CSAPR for NO_x emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 39: Boiler Retirement by NO_x Treatment – Fuel Specific Effects

Dependent Var: Boiler Retirement	(1) Baseline	(2) Coal	(3) Petroleum	(4) Natural Gas
NO_x Treatment	0.000	-0.003	0.003	-0.001
	(0.001)	(0.005)	(0.004)	(0.002)
Observations	49,885	11,587	5,135	17,989
Year FE	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES
All Controls	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level. Efficiency 100% load, efficiency 50% load, NERC regions, and CAA attainment status control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. NO_x treatment is an indicator variable for treatment under either CAIR or CSAPR for NO_x emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 40: New NO_x Abatement Technology

Dependent Var: New Technology Installation (any type)	(1) Controls - No Technology or Fuel Type	(2) Controls - No Technology or Fuel Type	(3) Controls - No Fuel Type	(4) All Controls
NOx Treatment	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Observations	34,238	34,238	34,238	34,238
R-squared	0.002	0.007	0.010	0.012
Year FE	YES	YES	YES	YES
Base Controls	NO	YES	YES	YES
Technology Controls	NO	NO	YES	YES
Fuel Controls	NO	NO	NO	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is an indicator for new technology installation for any technology type at the annual level for 2009-2022. NO_x treatment is an indicator variable for treatment under either CAIR or CSAPR for NO_x emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 41: New NO_x Abatement Technology – Fuel Specific Effects

	(1)	(2)	(3)	(4)
Dependent Var: New Technology Installation (any type)	Baseline	Coal	Petroleum	Natural Gas
NO_x Treatment	0.000	0.001	-0.001	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
Observations	35,258	9,092	3,094	9,229
Year FE	YES	YES	YES	YES
Technology Controls	YES	YES	YES	YES
All Controls	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level.
Efficiency 100% load, efficiency 50% load, NERC regions, and CAA attainment status control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is an indicator for new technology installation for any technology type at the annual level for 2009-2022. NO_x treatment is an indicator variable for treatment under either CAIR or CSAPR for NO_x emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, turndown ratio, waste heat input, NERC region, CAA attainment status. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 42: Fuel Switching by Regulation - CAIR and CSAPR

	(1)	(2)
Dependent Var: Switch Fuel Types	SO_2 Treatment	NO_x Treatment
CAIR Treatment	0.008	0.028***
	(0.009)	(0.010)
CSAPR Treatment	0.001	0.002
	(0.011)	(0.009)
CAIR and CSAPR Treatment	-0.001	0.013***
	(0.004)	(0.004)
Observations	46,474	46,474
Year FE	YES	YES
All Controls	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. CAIR treatment is an indicator variable for treatment under CAIR but not CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. CSAPR treatment is an indicator variable for treatment under CSAPR but not CAIR for SO2 emissions in column 1 and NOx emissions in column 2. CAIR and CSAPR treatment is an indicator variable for treatment under both CAIR and CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. All controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, age of boiler, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, turndown ratio, waste heat input, technology indicators, fuel type indicators, CAA attainment status, and NERC regions.

Table 43: Boiler Retirement by Regulation - CAIR and CSAPR

	(1)	(2)
Dependent Var: Boiler Retirement	SO_2 Treatment	NO_x Treatment
CAIR Treatment	0.007	0.003
	(0.005)	(0.003)
CSAPR Treatment	0.002	-0.001
	(0.003)	(0.001)
CAIR and CSAPR Treatment	0.000	-0.000
	(0.001)	(0.001)
Observations	49,578	49,578
Year FE	YES	YES
All Controls	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. CAIR treatment is an indicator variable for treatment under CAIR but not CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. CSAPR treatment is an indicator variable for treatment under CSAPR but not CAIR for SO2 emissions in column 1 and NOx emissions in column 2. CAIR and CSAPR treatment is an indicator variable for treatment under both CAIR and CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. All controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, age of boiler, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, turndown ratio, waste heat input, technology indicators, fuel type indicators, CAA attainment status, and NERC regions.

Table 44: New Abatement Technology - CAIR and CSAPR

	(1)	(2)
Dependent Var: New Technology Installation (any type)	SO_2 Treatment	NO_x Treatment
CAIR Treatment	0.000	0.003
	(0.001)	(0.003)
CSAPR Treatment	0.003	0.001
	(0.002)	(0.002)
CAIR and CSAPR Treatment	-0.000	0.000
	(0.001)	(0.000)
Observations	20,561	34,238
Year FE	YES	YES
All Controls	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level. *** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is an indicator for new technology installation for any technology type at the annual level for 2009-2022. CAIR treatment is an indicator variable for treatment under CAIR but not CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. CSAPR treatment is an indicator variable for treatment under CSAPR but not CAIR for SO2 emissions in column 1 and NOx emissions in column 2. CAIR and CSAPR treatment is an indicator variable for treatment under both CAIR and CSAPR for SO2 emissions in column 1 and NOx emissions in column 2. Wet type technology (lag) is the lagged indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology (lag) is the lagged indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Year fixed effects (Year FE) are included in each regression. All controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, age of boiler, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, turndown ratio, waste heat input, technology indicators, fuel type indicators, CAA attainment status, and NERC regions.

Table 45: Compliance Strategy by SO_2 Treatment – Restricted Sample

Dependent Var:	(1) Fuel Switching	(2) Install New Technology (any)	(3) Retirement
SO_2 Treatment	0.019**	0.000	0.003***
	(0.008)	(0.000)	(0.001)
Observations	17,333	9,235	18,236
Year FE	YES	YES	YES
All Controls	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level. Efficiency 100% load and efficiency 50% load control variables were dropped for convergence.

*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, age of boiler, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, turndown ratio, waste heat input, CAA attainment status, and NERC regions. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

Table 46: Compliance Strategy by NO_x Treatment – Restricted Sample

	(1)	(2)	(3)
	Fuel	Install New	
Dependent Var:	Switching	Technology (any)	Retirement
NO_x Treatment	0.007	0.000	0.003*
	(0.008)	(0.000)	(0.001)
Observations	14,204	11,121	14,970
Year FE	YES	YES	YES
All Controls	YES	YES	YES

Robust standard errors in parentheses, clustered at boiler and year level. Efficiency 100% load and efficiency 50% load control variables were dropped for convergence.
*** p<0.01, ** p<0.05, * p<0.1
Notes: The dependent variable is boiler retirement at the annual level for 2009-2022. SO_2 treatment is an indicator variable for treatment under either CAIR or CSAPR for SO_2 emissions. Wet type technology is an indicator for jet bubbling reactor wet scrubber, mechanically aided type wet scrubber, packed type wet scrubber, spray type wet scrubber, tray type wet scrubber, and venturi type wet scrubber. Dry type technology is an indicator for circulating dry scrubber, spray dryer type/ dry FGD/ semi-dry FGD, dry sorbent powder injection type, or lime injection. Particulate technology is an indicator for baghouse filters, electrostatic precipitators, multiple and single cyclone technologies, and activated carbon injection system. Other technology is an indicator for all other technology types as indicated by the plant manager. Year fixed effects (Year FE) are included in each regression. Base controls include indicators for boiler firing type, fly ash reinjection, heat recovery steam generator, indicators for standards of performance, age of boiler, efficiency 100% load, efficiency 50% load, air flow 100% load, max steam flow, turndown ratio, waste heat input, CAA attainment status, and NERC regions. Technology controls refers to wet, dry, particulate, selective noncatalytic reduction, selective catalytic reduction, and other technology indicators previously described. Fuel controls include indicators for each fuel type listed by the EIA.

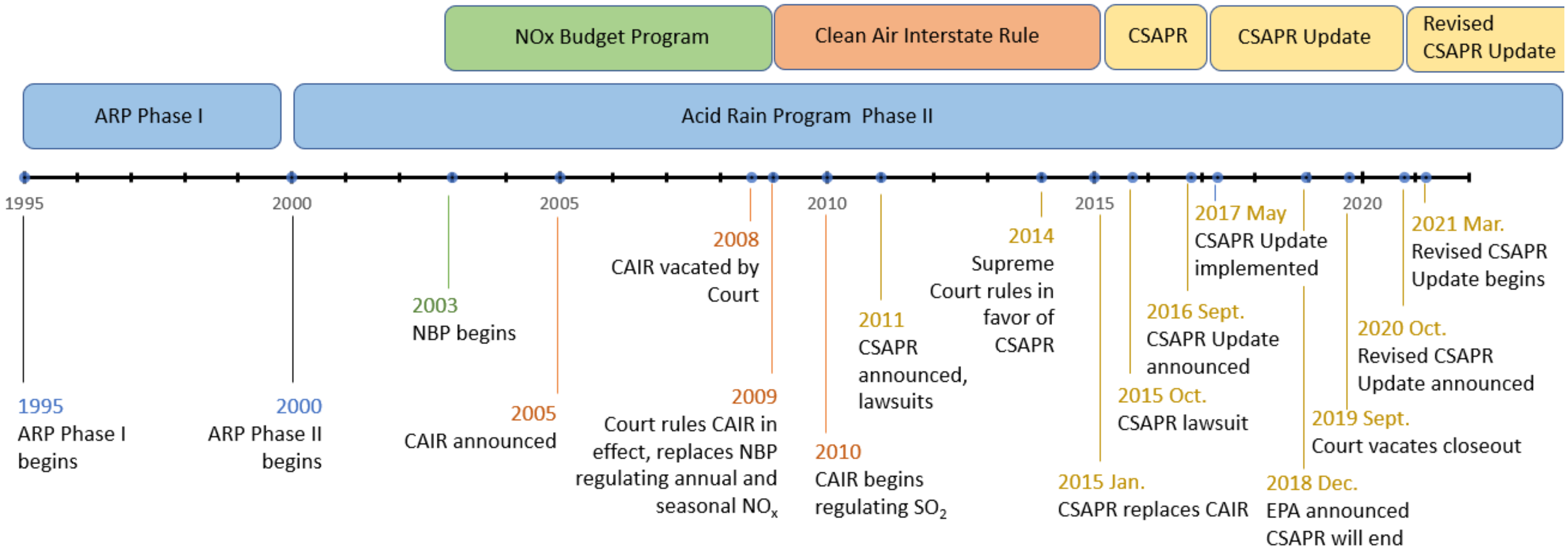

Figure 4. Timeline of Transboundary Air Pollution Regulation

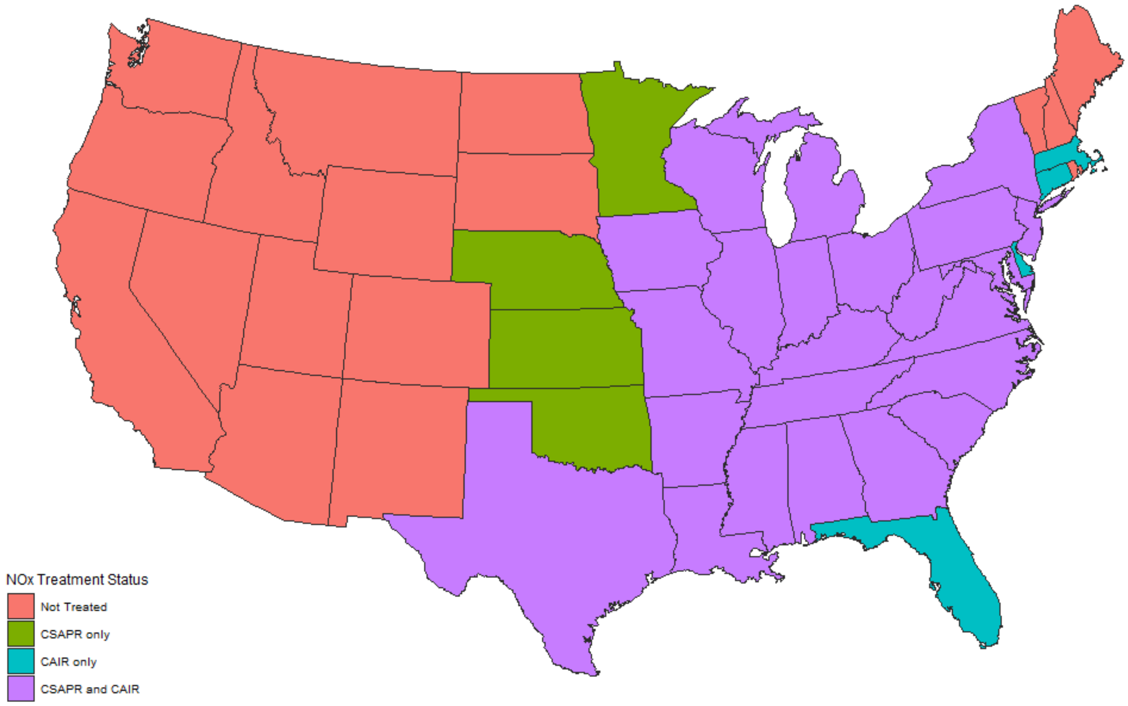

Figure 5. State NO_x Treatment Status Under CAIR and CSAPR

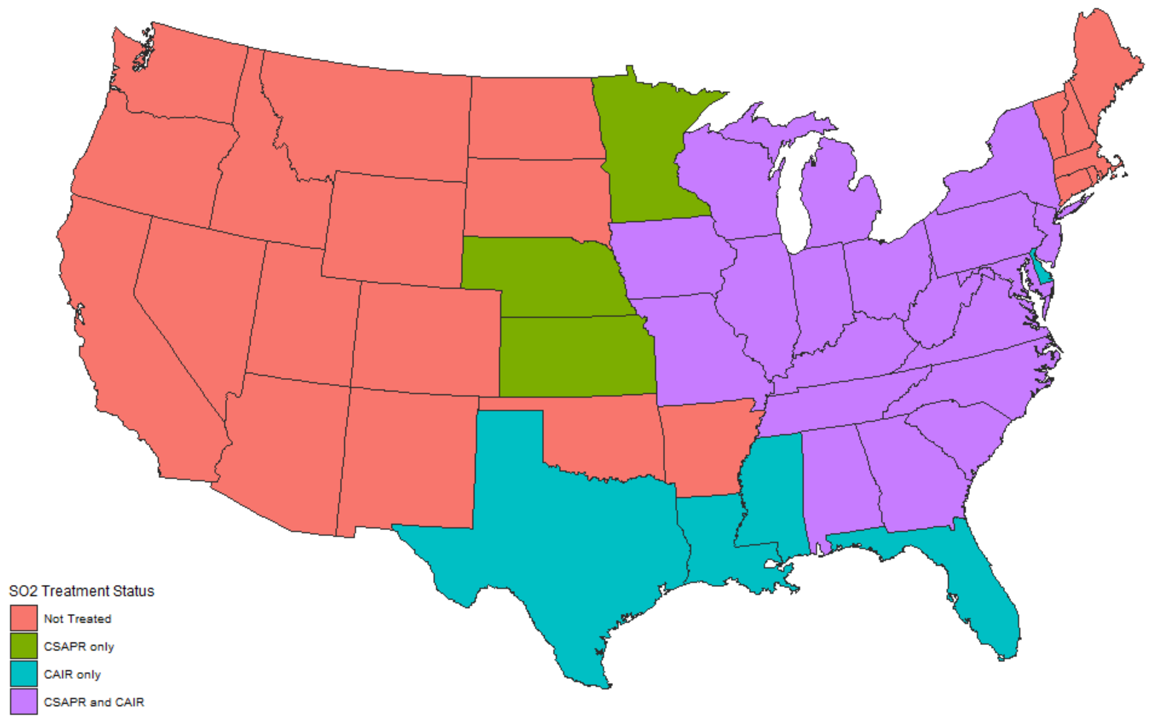

Figure 6. State SO_2 Treatment Status Under CAIR and CSAPR

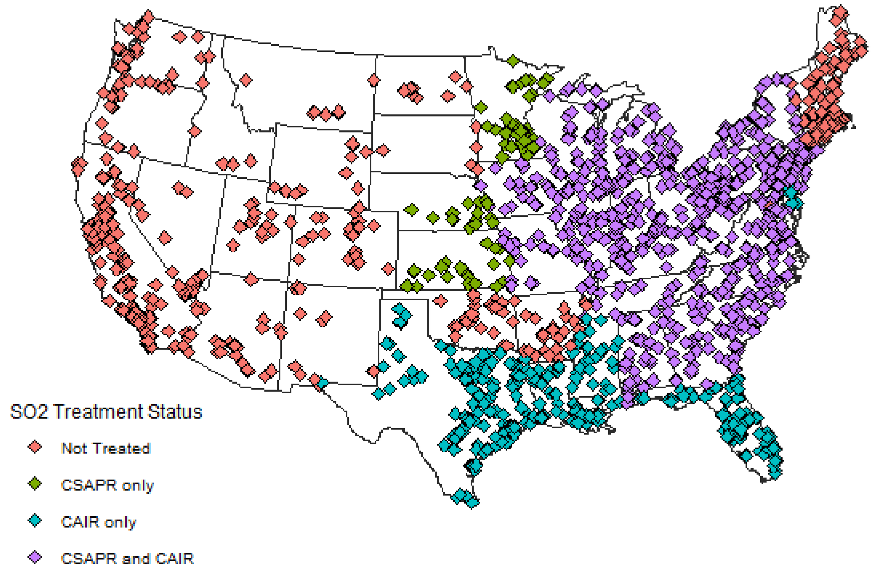

Figure 7. Boiler Level SO_2 Treatment Status Under CAIR and CSAPR

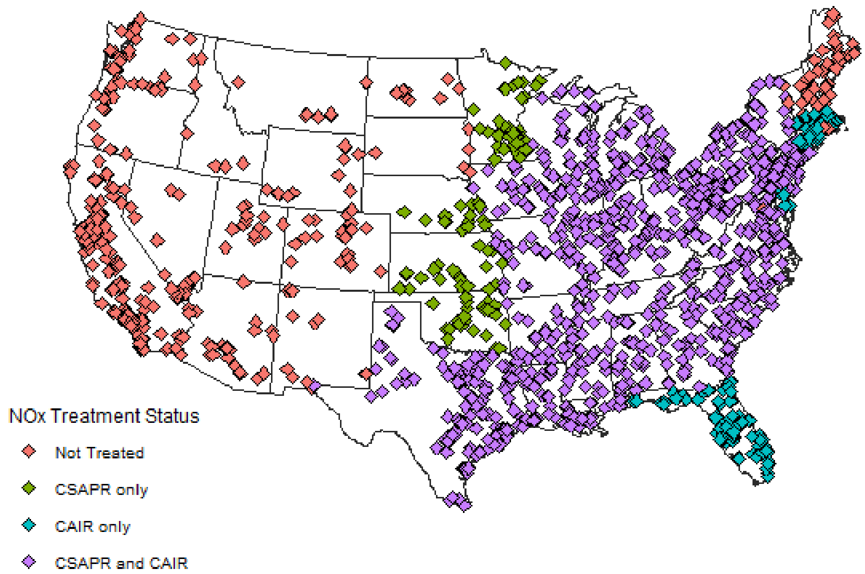

Figure 8. Boiler Level NO_x Treatment Status Under CAIR and CSAPR

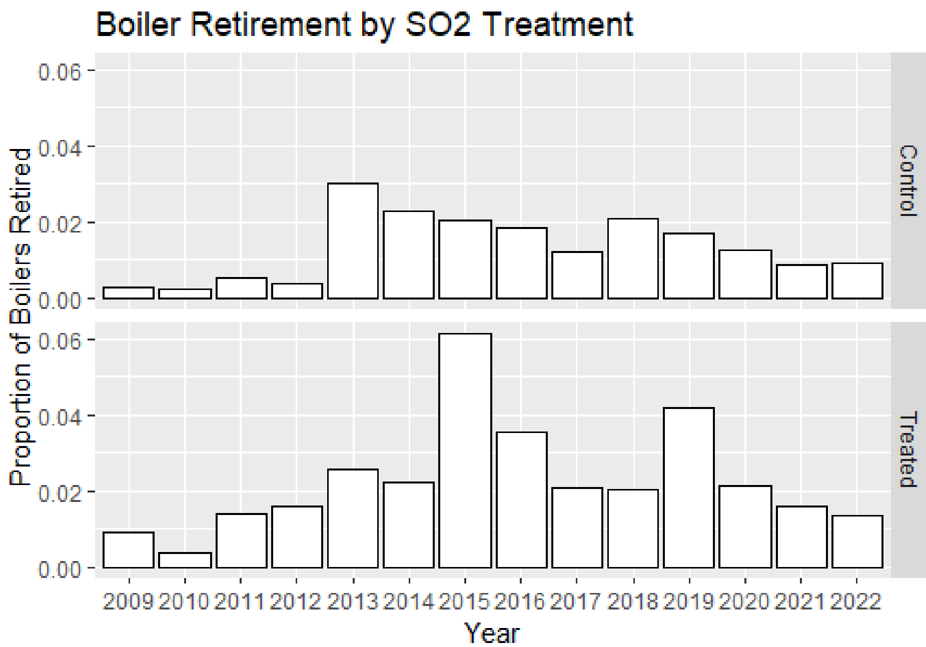

Figure 9. Boiler Retirement by SO_2 Regulation

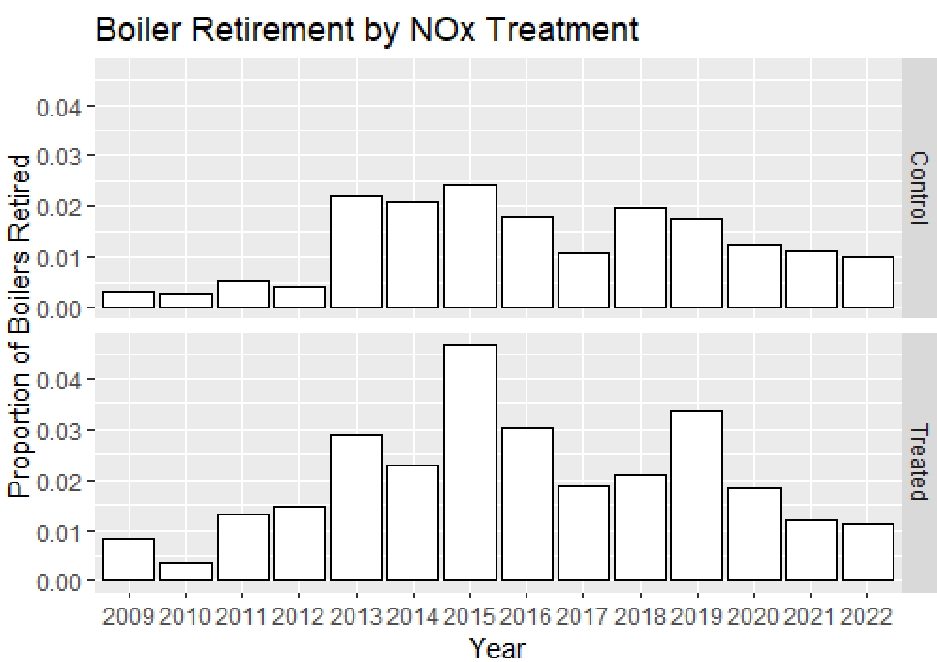

Figure 10. Boiler Retirement by NO_x Regulation

VITA

Ryan Swartzentruber earned a Bachelor of Science degree from Eastern Mennonite University in 2016 majoring in Mathematics and Economics. He earned a Masters of Science in Natural Resource Economics at Colorado State University in 2019. He spent the following year working for the United States Forest Service as a research assistant and coordinator for the Denver Urban Field Station. In 2020 he moved to Knoxville to begin his doctoral degree in Economics.