The Political Economy of Environmental Technology Developments in the United States

by

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Abstract

This dissertation consists of three chapters which investigates specific aspects of the political economy of environmental technology developments in the United States. It begins with a theoretical perspective of constrained political decision-making on environmental regulations, followed by an empirical analysis of anticipatory investment decisions, and a policy evaluation related to environmental technology.

The first chapter explores how a political party with a pro-environmental agenda can encourage a polluting firm to invest in clean technology, especially when there are voters who care about the environment. I find that there is a feasible range of effective regulations that can be used to make adopting clean technology a profitable choice. When the firm adopts clean technology, it benefits the environmentally conscious voters, who in turn, vote for the pro-environmental party. The second chapter studies how environmental policy divergence at the US state level affects the development of environmental technology. I find that pro-environmental policies and the anticipation of the same encourage innovation, beyond the natural trend in environmental innovation in those states' – owing to environmental preferences of the electorate, and the state's dependency on fossil fuels. In the third chapter, I explore the role of the Green Technology Pilot Program, inducted by the US federal government in 2009, in boosting the growth of environmental technology. I measure the effect of the program on the quantity and quality of the patents in the environmental technology domain, to find that there has been a positive impact on the quantity of patents in the given field. Yet the effect on quality, measured by citations, remains ambiguous.

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CHAPTER 1: Environmental Policy Commitments with Uninformed Green Consumers and a Dirty Firm

Dibyajyoti Sinha[1]

1.1 Introduction

Some voters are more affected by a particular policy than others. For example, voters who are pro-environment, maybe more affected by the environmental laws, over and above other pressing issues like inflation and government debt. The political economy literature emphasizes "*single-issue voters*" to be able to influence agendas and commitments of political parties on secondary policy issues (like gun laws, abortion laws and environmental laws).[2] The secondary policy issues may not guarantee an electoral victory, but it could play a significant role in electoral outcomes. In the given context, this paper offers an analysis of how a pro-environmental party seeks to retain its "*single-issue voters*" via commitments on environmental regulations. The latter interaction presents an interesting position for a polluting firm where the regulations affect the firm's environmental performance.

The analyses begin with a scenario where there is a pro-environmental party in office, who seeks to retain the allegiance of its environmentally conscious voters. Voters seek some form of tangible environmental benefits to remain in support of the party. To this end, the pro-environmental party commits to some form of environmental regulations. These regulations affect the environmental performance of a polluting monopolist. The emissions from the inherent dirty

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[2] In the context of secondary policy issues, a political party's strategy to move away from the median voter is to capture the "single-issue voters", - those who are specific policy motivated (Callander, 2008); McAusland, (2003), List and Sturm, (2006), Folke, (2014), Pacca et al., (2021), etc.

production technology of the monopolist, creates disutility for the consumers. Given the preference of the environmentally conscious consumers, they are willing to pay higher for the output from a cleaner production technique. This is known to the firm and it could invest in the development of clean technology which could abate the environmental damage by cutting down on the emissions. However, given the high marginal cost of the clean production technology, the polluting monopolist does not have an incentive to invest. The marginal cost of the clean production technique is significantly high, which makes the clean technology adoption unprofitable without any form of regulatory support. The pro-environmental party makes commitments on environmental policy to motivate the polluting monopolist to invest in clean technology. When the environmental policy support committed by the pro-environmental party is sufficiently high, the polluting monopolist invests in clean technology. Successful adoption of clean technology would attract the targeted consumers depending upon their level of environmental consciousness. The product from clean technology increases the consumer surplus of the environmentally conscious consumers, which serves as the tangible environmental benefit for those voting consumers to retain their partisan allegiance.

The objective of the pro-environmental party boils down to finding the effective level of environmental policy support which could motivate the polluting monopolist to adopt clean technology. However, the model involves market imperfections in the form of uncertainty and incomplete information regarding the investment outcome. The success of the investment is determined by nature, and only the firm can observe its actual type of environmental performance.[3] All other agents observe the firm investing in the development of clean technology but remain

[3] With a probability of μ, the firm develops the clean-type production technique and with a probability of $(1-\mu)$, it remains dirty.

unaware of the investment outcome. This structure is developed from an established industrial organization literature – where firms with private information attempt to signal their quality through prices ((Bagwell & Riordan, 1991); (Daughety & Reinganum, 1995); (Mahenc, 2008); (Sengupta, 2012)). A key feature of these models is the private information in terms of the vertical attribute, of a firm's product, or of the production process in general. As the agents other than the firm, do not observe the firms' type, signaling becomes important. The models in this domain assume that there is no credible direct disclosure mechanism and that pricing is the only channel of signaling private information. As the consumers cannot differentiate the type of production process used in the making of the product, they buy based on the 'price signal' from the producer. Due to this process of deviation from the price which would have been charged under no market imperfections, the voting consumers observe a change in their surplus. This change in the voter's tangible benefits alters the effectiveness of the environmental policy support and thus, commitment on the policy requires a closer introspection. This extension in the literature leads us to observe the model beyond the firm's reaction to environmental regulations and focus on the feasibility; and to the best of my knowledge, this paper is the first attempt in examining the effects of environmental partisanship on a polluting firm's investment behavior.

The market imperfections in the model arise due to the lack of monitoring technology or other forms of disclosure mechanisms. As in Sengupta (2015), this paper considers that monitoring is difficult but once the environmental damage becomes observable, the firms are liable to pay a penalty.[4] Intuitively, it does not matter if the liability is a punishment in the form of taxes or a

[4] In 2015, the Environmental Protection Agency (EPA) found that many Volkswagen cars being sold in America had a "defeat device" in diesel engines that could detect when they were being tested and alter the performance accordingly to improve results. This case led to numerous lawsuits and a huge financial and managerial burden. For more detailed discussion and application in this context, see Mahenc & Volle (2021).

forgone benefit in the form of a subsidy. The liability is valid under the application of both tools. Although the government and consumers cannot observe the environmental damage caused by the firm, the firm itself might have more information on the damage and be able to have an estimate of the liability when the damage becomes observable. Further, if firms can anticipate the environmental liability, firms are likely to adopt cleaner technology sooner under strategic compliance.[5] Due to the unavailability of monitoring technology, the clean type risks being mimicked by the dirty type and losing out on the committed environmental policy support. This makes the clean type distort its price (from the price under full information) to signal the true nature of its production process. The marginal cost of each type of firm's production is common knowledge, making signaling possible as the information on the marginal cost of both types set an ex-ante belief, for the consumers and the political party, on the production technique of the firm.

I analyze the effect of the pro-environmental party marginally increasing their commitment on environmental policy support to the clean type. When the pro-environmental party commits to low levels of environmental policy support, the clean type charges a higher price than its full information price to credibly signal the true environmental impact of its production process. The results show that an increase in the commitment of environmental policy support up to a certain level has no impact on technology as the expected profit of the dirty type remains higher than the clean type. Thus, in line with Sengupta (2012), I find that marginal increase in environmental stringency may not always be sufficient for the monopoly to adopt cleaner technology. As the firm chooses to remain dirty with low levels of environmental policy support, the possible benefit from

[5] Environmental compliance as a strategic measure is well established in the corporate management and organization literature. For details, see Kassinis & Vafeas (2006), Flammer (2013), Babiak & Trendafilova (2011). Even though the current monitoring technology might not reveal the environmental damage being averted, the firms will have an incentive under strategic compliance to signal their actual production type.

the regulation is forfeited. Therefore, low levels of environmental policy support turn out to be ineffective in terms of generating a higher consumer surplus. The pro-environmental party fails to capture the support of the environmentally conscious voters when the commitment of environmental policy support is below a threshold level. However, beyond a certain level of support committed, the clean type has a lower effective marginal cost than the dirty type. Due to incomplete information regarding the investment outcome, the firm continues to distort its price, but now the firm distorts the price downwards to signal its type to the environmentally conscious consumers. A separating equilibrium is established with a price decrease by the clean type. The lower price serves as a signal to the consumers and the political party, who update their prior beliefs based on the marginal costs. The environmentally conscious population is better off not only in terms of the improvement in the environmental quality of the product but also finds the same product at a lower price. This creates a sharp rise in the consumer surplus and consequently, the pro-environmental voters retain their support in favor of the pro-environmental party.

I define minimum effective subsidy as the lowest level of environmental policy support which could incentivize a polluting monopolist to adopt clean technology. As the pro-environmental party commits to this minimum effective subsidy, the polluting monopolist adopts cleaner technology, consequently retaining the support of the pro-environmental voters. The results confirm that the lower the environmental consciousness, higher is the environmental policy support necessary to motivate the firm to invest. That is, the minimum effective subsidy increases with the decrease in environmental consciousness of the consumers. With low environmental consciousness, the firms could observe that the party's commitments do not have substantial support from the voting consumers, and it might be less likely that the policy would be passed.

Much higher effort in terms of environmental policy support would be required from the pro-environmental party to motivate the firm to invest.

The rest of the paper is structured as follows. In section 2, we begin by setting up the full information model and analyzing the equilibrium. Section 3 offers an analysis under full information with the objective of finding the minimum environmental policy support required from the pro-environmental party to retain its niche voters. This section evaluates the cost of market imperfection in terms of the uncertainty in investment outcome. In section 4, incomplete information is introduced due to the lack in monitoring technology. Here, I analyze the effects on the commitments of environmental policy support due to the behavior of the firm who invests in clean technology. The difference in the extent of environmental policy support under full and incomplete information offers insight into the role of monitoring or other disclosure mechanisms. Section 5 concludes the paper with a discussion of the results and implications.

1.2 The Model

The model consists of three agents or groups of agents, which includes voting consumers, a polluting monopolist and two contesting political parties. The consumer and firm's structure are developed from the model presented in Sengupta (2012), where consumers have heterogenous environmental consciousness, in the sense, that some consumers have a higher willingness to pay for the environmentally higher quality product. The consumer's utility function is assumed to be quasi-linear in the good that the monopolist produces, such that, the utility from consuming the good produced via the dirty type of production (U_D) and the clean type of production (U_C) can be represented as follows:

$$U_D = I - \frac{(a-q)^2}{2}; \qquad U_C = I - \frac{(a-q)^2}{2\alpha} \qquad \dots\ (Eq{:}\ 1)$$

Here, the consumer's income: $I > 0,\ a > 0$ is the choke price and q is the good that the monopolist produces. The environmental consciousness index (α) is distributed uniformly on the interval [$\underline{\alpha}$,1], where $\alpha < 1$. In a first-order stochastic sense, lower value of $\underline{\alpha}$ indicates higher levels of environmental conscious of the consumers.[6] Further, the value of $\underline{\alpha}$ indicates the willingness to pay a premium for the cleaner product $-$ as the marginal utility from consuming the good produced by the clean type is higher than the dirty type: $\left(\frac{\delta U_C}{\delta q}\right) > \left(\frac{\delta U_D}{\delta q}\right)$ for $0 < \alpha < 1$.

The model includes a monopolist with an inherent dirty production technology that causes β levels of environmental damage per unit of output. The consumers and the regulator know the amount of environmental damage caused by the monopolist. The construction of the firm's environmental performance follows the literature where the clean type causes zero environmental damage whereas the dirty type causes some form of environmental damage (β) per unit of output. Although the consumers and the regulators are aware of the damage, it is not possible to observe immediately without the aid of monitoring technologies whether the product entails the damage in concern.[7] Abatement of this environmental damage by the clean type increases the utility of the environmentally conscious consumers, who are willing to pay higher for the cleaner production technique. Therefore, if the firm invests in cleaner technology, it could cater to these consumers who are willing to pay a higher price for their product. In the benchmark model, the cost for adoption of clean technology is assumed to be a fixed cost and set to zero ($f = 0$).[8] Although

[6] The assumption of uniform distribution is a simplification which dilutes the heterogeneity in terms of each voter but represents the mean of environmental consciousness across the population.

[7] Daughety & Reinganum (1995) utilize product safety of a monopoly's output as an element of vertical differentiation, where the firm has private information on the outcome of R&D and signals its type through prices. The consumers do not observe the actual vertical attribute of the product. The paper considers that there is no available means of measuring the product's safety attributes a priori.

[8] In a following section, an analysis with investment cost is presented.

investment is assumed to be costless, the abatement that it allows increases the cost of production at the margin. The marginal cost of the clean type (m_C) and the marginal cost of the dirty type (m_D) are such that: 0 < m_D < m_C and $a > m_C$.

I further restrict the model parameters to establish a scenario where the polluting monopolist does not have an incentive to adopt cleaner technology without external support. This scenario is presented to emphasize the role of environmental policy required in adoption of cleaner technology when the marginal cost of the cleaner technology is so high that firms do not find it profitable to adopt cleaner technology. This restriction requires that the marginal cost of the clean technology is sufficiently higher than the dirty type such that there is no incentive for the monopolist to adopt the cleaner technology, even if the environmental consciousness of the consumers is at the highest ($\rho \to 2$):

$$m_c > \sqrt{2}\left(\sqrt{2}a - (a - m_D)\right) \quad \ldots\ (Eq: 2)$$

In other words, this restriction allows the dirty type to charge a lower price and earn higher profits than the clean type, even if the level of environmental consciousness of the consumer is at its highest ($\underline{\alpha} \to 0$).

The information about the marginal cost of dirty and clean technology is also assumed to be common knowledge along with the level of environmental damage (β). The environmental regulations in such a setup tend to punish the dirty type by increasing the firm/firms' liabilities through taxes on the dirty type.[9] However, based on the results from Schumacher (2010) and Bansal & Gangopadhyay (2003), the choice on the type of environmental policy support in this

[9] For related literature in this application see: ((Sengupta, 2012); (Sengupta, 2015)). The results from using a subsidy instead of tax as in Sengupta (2012) replicates some of the results on firm's behavior but in a reverse fashion due to the use of subsidy. The results remain qualitatively similar.

model is assumed to be a subsidy as the objective is to support investment in clean technology.[10] Although the findings do not change qualitatively from the application of taxes (as in Sengupta (2012)), a tax break or a subsidy is more applicable in this analysis due to the direct measurement of consumer surplus of the voting consumers. Intuitively, the subsidy also imposes a cost on the regulator in terms of financing the policy and therefore, imposes a restriction on the extent of environmental support that can be committed.[11]

The regulator commits to an environmental policy support in the form of a subsidy such that the effective marginal cost of the clean type becomes:

$$X_C = m_C - s\beta \qquad \ldots\ (Eq{:}\,3)$$

where $s>0$ is the rate of subsidy commitment and β is the environmental damage abated per unit of output or the marginal external benefit of clean type production.[12] Observing the environmental policy support, the firm takes the decision to invest in the adoption of clean technology. The polluting monopolist decides to invest in clean technology based on the anticipated liability of implementation of the commitments on environmental regulation. Whether the investment is successful (with a probability of μ or not with a probability of $(1-\mu)$), is known to the firm but the other agents remain uninformed due to the lack of monitoring technology as discussed above.

[10] Schumacher (2010) studies the type of government intervention that consumers would approve of and finds that environmentally conscious consumers prefer a subsidy on the green goods and tax on the dirty goods. Further, Bansal & Gangopadhyay (2003) finds that uniform subsidy policy improves average environmental quality, whereas a uniform tax policy worsens it.

[11] The analysis in this paper focuses on the commitment of the minimum level of environmental policy support that would establish the partisanship. Finding the upper bound on the commitment is beyond the scope of this paper as it would require a trade-off for the political parties in terms of the amount that they would allocate on different instruments or different agendas.

[12] An important feature here is the abstraction from the explicit use of an environmental damage function. In the competitive investment analysis of similar models with incomplete information on environmental performance, Sengupta (2015) considers the cost of defecting from environmental regulation as an anticipated liability instead of formally incorporating an environmental damage function. The modification simplifies the scenario and allows the analysis to focus on the pricing choice of the firm.

When the polluting monopolist adopts cleaner technology successfully, it converts to a clean type, otherwise it remains dirty. The firm with dirty production anticipates that their production, which entails environmental damage, would be penalized once the damage becomes observable.[13]

The regulator could commit to several levels of subsidy to the firm with clean type of production technique. In the range of possible subsidy commitments, the subsidy rate s^R is defined as one where the marginal cost of the clean type is lowered to that of the dirty type. That is,

$$X_C = m_C - s^R\beta = m_D$$

$$\Rightarrow s^R = \frac{(m_C - m_D)}{\beta} \qquad \ldots\ (Eq{:}\ 4)$$

s^R is used in the model to distinguish between high and low levels of subsidy commitment. The level of subsidy commitment is defined as high when $s > s^R$ whereas the subsidy commitment is defined as low when as $s < s^R$. Effectively, the application of subsidies keeps the dirty type's marginal cost unchanged. The reduction in marginal cost of the clean type using a subsidy is to provide an incentive for the dirty type to adopt cleaner technology. Further, without the environmental policy support, the investment initiative would be irrational had the consumers' willingness to pay were the same for the dirty and the clean type's product. Therefore, the incentive for the monopolist to adopt cleaner technology is also motivated by the presence of environmentally conscious consumers, who would be willing to pay a premium for the cleaner output.

[13] The liability rule can be observed in some popular regulations and acts of the government like the Comprehensive Environmental Response, Compensation and Liability Act of 1980, Superfund Amendments of 1986, and EU's Environmental Liability Directive. Similar to Sengupta (2012) and Sengupta (2015), several other studies have utilized the liability structure, both theoretically and empirically. See Anton and Khanna (2002), Anton et al. (2004) and Segerson and Miceli (1998) for more applications.

In the case of full information, the consumers and the regulator can observe the actual production process of the monopolist. Intuitively, it implies that the monitoring technology is available and that it reveals the exact environmental performance of the firm's production technology. However, uncertainty still exists in terms of the outcome of the investment initiative. The firm compares the expected profit from the investment and decides whether to adopt cleaner technology. As the monopolist's demand is the market demand, the demand for the dirty product is represented by:

$$D^D(P) = a - P$$

The full information monopoly price (P_D^{FI}) and quantity (Q_D^{FI}) for the dirty product is obtained by the profit maximization exercise where:

$$Q_D^{FI}(P) = \frac{a - m_D}{2} \text{ and } P_D^{FI} = \frac{a + m_D}{2}$$

Given the uniform distribution over [$\underline{\alpha}$,1], the market demand for the clean product can be derived as:

$$D^C(P) = \frac{1}{(1 - \underline{\alpha})} \int_{\underline{\alpha}}^{1} (a - \alpha P)\ d\alpha$$

Let $\rho = \frac{2}{(1+\underline{\alpha})}$, then the market demand for the clean product can be written as:

$$D^C(P) = a - \frac{P}{\rho}$$

The market demand represents the heterogenous environmental consciousness as a mean level of consciousness among the voting consumers. As the lower value of $\underline{\alpha}$ represents higher environmental consciousness, higher value of ρ would indicate the same. The full information monopoly price (P_C^{FI}) and quantity (Q_C^{FI}) for the clean product is obtained by the profit maximization exercise where:

$$Q_C^{FI}(P) = \frac{a\rho - X_C}{2\rho};\ P_C^{FI} = \frac{a\rho + X_C}{2}.$$

The profit of the dirty type (Π_D^{FI}) and clean type (Π_C^{FI}) can be represented as follows:

$$\Pi_D^{FI} = \frac{(a - m_D)^2}{4};\ \Pi_C^{FI} = \frac{(a\rho - X_C)^2}{4\rho}$$

While the erstwhile models in the literature take the level of policy choice of the regulator as exogenous, this paper endogenizes the choice on the level of environmental support that can be implemented. To this end, the model includes two parties called the Green party and Brown party who are contesting in an election. The model in Sengupta (2012) is extended in terms of the voting ability of the consumers. The consumers decide to vote in favor of a party whose policy commitment increases their consumer surplus, with specific interest in that good produced by the monopolist. Thus, the quasi-linear structure of the model is retained. To capture the trade-off in the choice of vote, emphasis is laid on the consumer's ability to spend their income on other goods as well. When the level of environmental consciousness is low, the income remaining for other goods would be important for the voting decision. The model requires that the commitment towards environmental policy support should have a tangible effect on the voters to retain their allegiance in favor of the Green party. The model assumes that the Brown party adheres to the commitment of environmental policy support (s), such that, $s^0 = 0$. On the other hand, the Green party commits to an environmental policy support of $s \geq 0$ and that the political parties maintain a balanced budget where the expenditure on subsidies is balanced by taxes on income thereby imposing a restriction on the level of subsidy that may be committed.

Both the party's utility is positively related to the votes that they get from the consumers. However, they realize that increasing taxes could reduce the possible number of votes. The utility function of the Brown Party (U_B) and the Green Party (U_G) are as follows:

$$U_B = U_B\big(v(t)\big) \quad , \quad U_G = U_G\big(v(t)\big)$$

Where $v(t)$ denotes the votes that each party could get.

$$\frac{\delta U_B\big(v(t)\big)}{\delta t} < 0 \quad and \quad \frac{\delta U_G\big(v(t)\big)}{\delta t} < 0$$

The ideological position of the two parties is such that the marginal utility of Green Party from securing votes via subsidy to the dirty firm is higher than that of the Brown Party. This attribute of the political parties regarding environmental preference is assumed to be exogenous. The Brown Party does not have an incentive to increase taxes to subsidize the clean technology adoption given their partisanship position on the environmental issues.[14]

$$\left|\frac{\delta U_B\big(v(t)\big)}{\delta t}\right| < \left|\frac{\delta U_G\big(v(t)\big)}{\delta t}\right|$$

The Green party differentiates itself from the Brown party with the commitment of imposing a stricter level of environmental regulation, and it is assumed that the consumers and the firm believe that the political parties would impose the committed policies.[15]

[14] For example, in the United States, the state-level environmental policy commitments of the Democratic Party follow the national partisanship position, by presenting a relatively pro-environmental standpoint compared to the Republican Party.

[15]Although there exists criticism over candidates sticking to their commitment, I impose this assumption as a simplification in this basic model. In Callander (2008), a model of political competition between heterogeneously motivated candidates shows that convergence and divergence from the commitments depends on the candidates' inherent type. Further, Fredriksson, Wang & Mamun (2011) empirically tests the results to find similar outcomes using term limits for the candidates.

Let $\overline{CS}$ be the measure of the consumer surplus without environmental policy. Given a scenario of close election, it can be assumed that both parties are equally likely to win the election, that is, the probability of either party winning the election is one-half. Post commitment on environmental policy by the two parties, the consumers and the firm anticipate the effects such that the probability of victory of the Green Party can be summarized as follows:

$$\text{Prob}\ (Green\ Party\ wins) = \begin{cases} 0 & if\ \ CS < \overline{CS} \\ \frac{1}{2} & if\ \ CS = \overline{CS} \\ 1 & if\ \ CS > \overline{CS} \end{cases} \qquad (Eq:)$$

The commitment to the environmental policy support establishes partisanship to the targeted voters, but the effectiveness of the policy would depend on the increase in the consumer surplus.

1.3 Effective Policy Commitments under Full Information

In this model, the *minimum effective subsidy* is defined as the least amount of subsidy commitment required to retain the partisan votes from the single-issue voters. However, to increase the consumer surplus of those voters, it is necessary that the product from the clean type is available in the market. The polluting monopolist would adopt cleaner technology if the expected profit from investment is higher than remaining dirty. Given that the marginal cost of the clean type is higher than the dirty type, the monopolist would be better off adopting cleaner technology if the subsidy commitment is large enough to ensure that the expected profit is greater than remaining dirty. The minimum level of subsidy for which the monopolist would adopt cleaner technology depends upon the marginal cost of the clean type, the marginal cost of the dirty type and the choke price.

Proposition 1: *Under full information, commitment of a high level of environmental policy support ($s = s_{FI} > s^R$), is a sufficient condition for the pro-environmental party to secure the pro-*

environmental votes. Even if the subsidy commitment is low ($s = s_{FI} < s^R$), high environmental consciousness of the voting consumers could incentivize the polluting monopolist to adopt cleaner technology (Proof: See Appendix).

Under full information, let $s_{FI} > 0$ be the subsidy commitment from the Green party such that the expected profit from investment is at least greater than remaining dirty.[16] In this scenario, the subsidy commitment of $s_{FI} \geq s^R$ would ensure that the profit of the clean type is higher than the dirty type. In other words, the effective marginal cost of the clean type being less than the dirty type: $X_C \leq m_D$ is a sufficient condition for the monopolist to adopt cleaner technology. However, even if the effective marginal cost of the clean type is higher than the dirty type ($X_C > m_D$), the monopolist still has an incentive to adopt cleaner technology under full information. This is due to the presence of the environmentally consciousness consumers who are willing to pay more for the clean type's product ($\rho \in (1,2)$).

The result confirms that the polluting monopolist could adopt cleaner technology profitably without the commitment of $s_{FI} \geq s^R$, that is, when the effective marginal cost of the clean type is lower than the dirty type. Higher value of ρ indicates higher willingness to pay for the clean type and therefore, investment turns out to be lucrative for the polluting monopolist. The highest level of effective marginal cost, at which the monopolist could adopt cleaner technology:

$$X_C = \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)$$

Therefore, to achieve this level of X_C, the Green party needs to commit to a subsidy of:

[16] $\mu\Pi_C^{FI} + (1-\mu)\Pi_D^{FI} \geq \Pi_D^{FI}$

$$s_{FI}^{*} = \frac{1}{\beta}\left[m_C - \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)\right] \quad \text{... } (Eq{:}\ 2)$$

The Green party's objective to offer subsidy to the clean type is driven by the intent to capture the environmentally conscious voters. For the subsidy commitment to be effective, the consumer surplus from the clean type needs to be higher than the dirty type. If the monopolist does not adopt cleaner technology, there is no change in the consumer surplus as the political parties commit subsidy only to the clean type. In that case, the consumer surplus with the dirty type:

$$CS_D^{FI} = \frac{(a^2 - m_D^2)}{8}$$

And the consumer surplus with the clean type:

$$CS_C^{FI} = \frac{(a^2\rho^2 - X_C^2)}{8\rho}$$

This would require the effective marginal cost of the clean type: $X_c \leq \sqrt{\rho(a^2(\rho - 1) + m_D^2)}$. To achieve this level of effective marginal cost, the Green party needs to commit a subsidy s_{FI}^{C}, which we define as the least amount of subsidy that needs to be committed for the consumers to experience an increase in the surplus:

$$s_{FI}^{C} = \frac{1}{\beta}\left[m_C - \sqrt{\rho(a^2(\rho - 1) + m_D^2)}\right] \quad \text{... } (Eq{:}\ 3)$$

I find that $s_{FI}^{*} \geq s_{FI}^{C}$ under the condition that $\rho \in (1,2)$. This ensures that the minimum effective subsidy is the lowest subsidy commitment that is required to incentivize the polluting monopolist to adopt cleaner technology. Where $s \geq s^R$ is the sufficient condition for the partisanship to hold and generate voter support, s_{FI}^{*} turns out to be the minimum effective subsidy under full information.

The full information scenario presents uncertainty as the market imperfection in the form of the probability of success in the investment outcome. The scenario is built up on the restriction that the polluting monopolist needs some form of support from the government to adopt clean technology profitably. Note that $s_{FI}^{*} \geq s_{FI}^{C}$, indicates that a lower level of subsidy commitment would have ensured consumer support in terms of the consumers being better off materialistically. However, s_{FI}^{C} would not guarantee adoption of clean technology. The difference arises from the probability of success of the investment outcome. Although investment is costless in the benchmark model, the expected profit from the investment is lower due to the uncertainty. The additional amount of subsidy being committed above s_{FI}^{C} can be considered as the cost to influence adoption of cleaner technology. In the next section, we introduce asymmetric information regarding the type of the monopolist once the investment initiative has been undertaken. Breaking down the analysis into two segments under full and asymmetric information helps in comparing the outcomes and to present a case for the need for monitoring or any other form of mandatory disclosure initiatives. In many industries, the information as well as the technology for monitoring environmental damage is either very expensive or missing. This paper offers a theoretical perspective on the debate over the requirement in improving the technology in terms of monitoring or developing other programs catering to revelation of firm’s environmental performance.

1.4 Effective Policy Commitments under Asymmetric Information

I consider a three-player, three-stage Bayesian game. In the first stage, the Green Party commits to a certain level of stringency of environmental regulations (subsidy to the clean type), which is higher than the Brown Party. Observing the commitment, consumers decide to vote and the polluting monopolist decides whether to adopt cleaner technology. In the second stage, nature draws the type (clean or dirty) the polluting monopolist would take upon investment efforts, from a distribution that assigns probability μ to the clean type and (1-μ) to the dirty type. The political parties and the consumers observe the initiative of the firm to adopt cleaner technology but are uninformed about the actual nature of environmental performance of the firm. In the third stage, the consumers observe the price, update their beliefs, and decide whether to buy. The Green party observes the price, update their beliefs, and grants the minimum effective subsidy to the clean type and nothing if the monopolist is a dirty type.

The solution concept used is the Perfect Bayesian Equilibrium (PBE) where out of equilibrium beliefs satisfy the Cho-Kreps Intuitive Criterion. The equilibrium is contingent on the firm's belief that electoral contestants stick to their agendas and the consumers' belief about the firm's production technology. The consumers' belief on the firm's production technology is developed from the marginal cost of each type – which is common knowledge. Post the investment initiative, the prior belief of the consumers and the Green party is that the firm is of clean type with a probability of μ and dirty type with probability of 1-μ. Based on this prior knowledge, the consumers as well as the political parties, can interpret the price signals from the firm. The PBE enables to set up distinct separating equilibrium where the monopolist not only distorts prices under different levels of subsidy commitment but the effectiveness of the electoral commitments in garnering voter support depends critically on the pricing distortions over a range of subsidy commitments.

1.5 Firm's Reaction to Environmental Policy Commitments

This section is dedicated to the analysis of the firm's reaction to the environmental policy support being committed by the political parties under incomplete information. Effectively, this section adds to the market imperfection due to uncertainty in investment outcome and introduces incomplete information regarding the firm's type post investment. The firm behaves differently under this lack of information as the consumer and the regulators may not be able to observe its type. As the dirty type may have incentive to mimic the clean type, the clean type distorts its price to ensure that imitation is unprofitable. This deviation from the full information price hurts the clean type's profit and increases the requirement of environmental policy support.[17] The polluting monopolist observes the commitments being made for the implementation of the policy. The commitment is observable by all agents and the firm takes the decision on adopting the clean technology based on the level of environmental policy support that has been committed.

Under incomplete information, when the environmental policy commitment is low ($s \leq s^R$), the effective marginal cost of the clean type is greater than the dirty type ($m_D \leq X_C$). This indicates that the full information price of the dirty type would be lower than the clean type. In this case, a pooling strategy from the clean type can be considered sub-optimal as the consumers remain unaware of the environmental quality.[18] Even though investments are assumed to be costless in the benchmark model, pooling is costly. With pooling, the clean type is not only losing out on the environmentally conscious consumers who have a higher willingness to pay for the environmentally cleaner product but also missing out on the subsidy committed by the Green party. In a separating equilibrium, the clean type signals its type through prices, adhering to their respective incentive compatibility conditions (ICC). As the electoral commitment on environmental policy support (s) is increased, the gap between the marginal cost of each type is reduced and therefore it becomes difficult for the clean type to credibly signal its type. When the environmental policy commitment is high ($s \geq s^R$), a similar situation arises when the difference

[17] This problem could also be catered to by labeling, improvement in monitoring technologies and other forms of disclosure mechanism. However, we focus on subsidy as the only tool in this model and bring on the debate in the choice of tool later in this paper.

[18] This presents a case for disclosure of environmental performance for the clean type.

between the marginal costs is low. Technically, the firm would have to bear the cost of distorting its price such that the dirty cannot mimic the clean type. This distortion in prices affects the consumer surplus and alters the effectiveness of the environmental policy.

Proposition 2: *(i) When the commitment of environmental policy support is low* $(s \leq s^R)$, *the clean type charging a price higher than or equal to the full information price is the unique separating equilibrium that satisfies the intuitive criteria. (ii) When the commitment of pro-environmental policy support is high* $(s \geq s^R)$, *the clean type charging a price lower than or equal to the full information price is the unique separating equilibrium that satisfies the intuitive criteria. (Proof:* See Appendix A.2)

ICC of the clean type requires that when the clean type can be better off without mimicking the dirty type's price: $\pi(C, 1, P_c) > \pi(C, 0, P_D^{FI})$. In this range of prices, the clean type does not earn a higher profit when it imitates a dirty type, and this is possible when the clean type charges a price P_c such that the ICC of a clean type is satisfied. With the dirty product, if the monopolist mimics the clean type's product and charges the clean type's price, it could cater to a greater demand (inclusive of the environmentally conscious consumers) with a higher price. However, a higher price would hurt the dirty type as the quantity demanded is lower. When $s \ll s^R$, the difference in marginal cost is large ($m_D \ll m_C$) and this will render a greater loss in terms of quantity sold in the market if the dirty type imitates the clean type. As the subsidy commitment (s) increases, the gap between the effective marginal costs closes in. In such a situation it becomes harder for the clean type to effectively reveal its type to its targeted consumers. The dirty type has an increasing incentive in terms of mimicking the clean type and capturing the consumer base. However, if the clean type sticks to its ICC, the dirty type might receive lower profits relative to charging its full information price. Thus, the dirty type resorts to the full information price.

When the full information price of the clean type is greater than the highest price that the dirty type could charge within its ICC ($P_c^{FI} \geq P^U$), then the clean type charges P_c^{FI}. In this range, the clean type does not need to distort the price as the higher price can effectively signal its type to the consumers. With the increase in the level of subsidy commitment, the effective marginal cost of the clean type decreases and there would be a situation under low levels of subsidy commitments, that the full information price of the clean type becomes lower the higher limit of the dirty type's ICC ($P_c^{FI} < P^U$). There is a range of prices where both the ICC of the clean type and dirty type overlap $\left(P^U < \overline{P} \;\; and \;\; P^L < \underline{P}\right)$. The scenario provides an incentive for the dirty type to imitate the clean type. Therefore, when the level of subsidy commitment is low ($s \leq s^R$), to reveal its type, the clean type must charge a price higher than the maximum price that the dirty type could charge (P^U). Notice that the clean type would not charge a price below the ICC of the dirty type as $P^L < \underline{P}$. In such a situation, the clean type charges P^U or greater to signal its type. The clean type makes an upward distortion in the price to reveal its type. Charging a price higher than P^U would suffice the condition that the clean type can credibly signal its price but it would not be profitable for the clean type as a higher price would deem less quantity being sold. Therefore, the equilibrium pricing strategy which satisfies the intuitive criteria with low levels of subsidy commitment is $max\{P_c^{FI}, P^U\}$.

Under similar arguments, when the level of subsidy commitment is high ($s \geq s^R$), the effective marginal cost of the clean type is lower than that of the dirty type. However, there could be possible overlaps in this range of subsidy commitments as the minimum price that the dirty type may charge within its ICC is less than the upper bound of the price strategy of the clean type, and also the full information $\left(P^L \leq \overline{P} \, and \; P^L \geq \underline{P}\right)$. The clean type would charge the full information price if it is lower than the minimum price that the dirty type could profitably charge to mimic the clean type ($P_c^{FI} \leq P^L$). However, when the full information price of the clean type is more than the lower limit of the pricing strategy of the dirty type ($P_c^{FI} \geq P^L$), the clean type vertically distinguishes its product by charging P^L. The clean type charges at most P^L where lowering the price would only result in giving away possible mark-ups. Therefore, the equilibrium pricing strategy with a high level of subsidy commitment is $min\{P_c^{FI}, P^L\}$.

1.5 Profit Distortions under Environmental Policy Commitments

The movement of price, by the clean type, away from the P_c^{FI} under low and high levels of subsidy commitment is a signaling distortion to reveal its type to its customers. P^U and P^L serve as the minimum upward and downward signaling distortions in this case, respectively. The equilibrium pricing strategy for the clean type can be summarized as:

$$P_c^* = \begin{cases} max\{P_c^{FI}, P^U\} \ if \ \ s \leq s^R \\ min\{P_c^{FI}, P^L\} \ if \ \ s \ > s^R \end{cases} \qquad \ldots (Eq: 4)$$

Proposition 3*: (i) When the commitment of environmental policy support is significantly low: $s \ll s^R$ or significantly high: $s \gg s^R$, there is no signaling distortion and the market outcome is as under full information. (ii) There exists a level of subsidy commitment $\underline{s}$ such that $\underline{s} \leq s \leq s^R$, there is an incentive for the clean type to distort prices above the full information price to signal its type. (iii) There exists a level of subsidy commitment $\overline{s}$ such that $s^R \leq s \leq \overline{s}$, there is an incentive for the clean type to distort prices below the full information price to signal its type. (Proof:* See Appendix_A3)

Note that under a low level of subsidy commitments, when $P_c^{FI} \geq P^U$, there exists a $\underline{s}$ such that:

$$s \geq \underline{s} = s^R - \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_d^2)}. \qquad \ldots (Eq: 5)$$

Here $\underline{s}$ serves as the least subsidy commitment for which the monopoly starts to distort the price. For any $s < \underline{s}$, there is no price distortion by the clean type. Note that $s < \underline{s} < s_{FI}^{*}$, which implies that the clean type begins to distort the price for a support level lower the minimum effective subsidy in case of full information[19]. Consequently, the price distortion makes the subsidy ineffective in this range of marginal cost. Let us define this distortion in price as ΔP where $\Delta P = P^{U} - P_{c}^{FI}$. The price distortion intrigues the Green Party as the magnitude of this distortion affects consumer surplus. Specifically, the clean type distorts the price upwards, that is, the equilibrium price in this range of low commitments $\left(\underline{s}, s^{R}\right)$ lie above the full information price. Further, the upward distortion increases with the increase in the level of subsidy. This is unfavorable for the Green party in the sense that the subsidy is less than effective in generating consumer surplus in the range of low subsidy commitments. On the other hand, when the subsidy commitment is high, the clean type distorts the price downwards as the full information price lies in the range of the ICC of the dirty type. With high levels of subsidy commitment, it is to be noted when $P_{c}^{FI} \leq P^{L}$, there exists a $\overline{s}$ such that:

$$s \leq \overline{s} = s^{R} + \frac{1}{\beta}\sqrt{(\rho - 1)(a^{2}\rho - m_{d}^{2})} \qquad \ldots\ (Eq{:}\,6)$$

In this case, $\overline{s}$ serves as the highest subsidy commitment for which the monopoly distorts the price; beyond which the clean type charges the full information monopoly price. When the level of commitment is high, ΔP can be defined as the difference between P^{L} and P_{c}^{FI}. The results show that within this range of subsidy commitments $(s^{R}, \overline{s})$, there is a downward distortion of prices but the magnitude of distortion weakens as the subsidy rate increases.

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[19] As $\sqrt{(\rho - 1)\left(a^{2}\rho - m_{d}^{2}\right)} > \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_{D})\right)$

As the commitment on environmental policy support increases from s^0, the effective marginal cost decreases and moves closer to the marginal cost of the dirty type until $s = s^R$. Beyond s^R, the effective marginal cost is lower than the marginal cost of the dirty type and it moves farther away from it as the commitment gets stronger. The closer the effective marginal cost of the clean type is to the marginal cost of the dirty type, the harder it is for the clean type to credibly signal its type. This leads to the large distortions in the price charged by the clean type as the marginal costs of each type get closer to each other[20]. These distortions in price may not be profitable for the clean type and could adversely alter investment incentives for the firm at certain levels of subsidy commitment.

Proposition 4: *(i) When the commitment of environmental policy support is low* $(s \leq s^R)$, *there is no incentive for the firm to adopt cleaner technology. There is no change in the consumer surplus and subsidy commitment can be rendered ineffective. (ii) When the commitment of environmental policy support is high* $(s \geq s^R)$*, the monopoly has an incentive to adopt cleaner technology. Consumer surplus increases due to the downward price distortion making the subsidy commitment effective. (Proof:* See Appendix A.4)

If the monopolist does not get an incentive to adopt cleaner technology with the level of subsidy committed by the Green Party, then the subsidy is ineffective in terms of generating voter support. In that case, the monopolist remains dirty and the consumer surplus is unchanged. The subsidy should be sufficiently high to make the monopolist take the investment decision. To investigate the investment choice, we need to evaluate the profit of the monopolist under different levels of

[20] This explains why ΔP is increasing in the range $(\underline{s}, s^R)$ and decreasing in $(s^R, \overline{s})$, reaching a maximum around s^R where the effective marginal cost of the clean type exactly equals that of the dirty type. Also note that ΔP is undefined at $s = s^R$.

subsidy commitments. Let Δ_π be the measure of distortion in profit of the monopoly. We can break down the profit distortion according to the subsidy commitment such that, when the level of subsidy committed is low $\left(\underline{s}, s^R\right)$,

$$\Delta_\pi = \pi^U - \pi_C^{FI} < 0 \;\; and \;\; \frac{\partial \Delta_\pi}{\partial s} < 0 \;\; \forall \;\; s \in \left(\underline{s}, s^R\right);$$

where π^U refers to the profit of the clean type when it charges P^U instead of the full information price. The marginal effect of increasing the subsidy commitment results in an increase in losses for the clean type when it continues to distort the price upwards to P^U . When the level of subsidy committed is high $(s^R, \overline{s})$,

$$\Delta_\pi = \pi^L - \pi_C^{FI} < 0 \;\; and \;\; \frac{\partial \Delta_\pi}{\partial s} > 0 \;\; \forall \;\; s \in (s^R, \overline{s})$$

where π^L refers to the profit of the clean type when it charges P^L instead of the full information price. Now the marginal increase in subsidy commitment leads to a decrease in losses. Note that when there is price distortion, the clean type sacrifices its profit to credibly signal its type. Greater is the magnitude of price distortion (ΔP), greater is the loss due to signaling.[21] Considering that monitoring or any other form of disclosure of environmental performances are absent, investment could be an option for the firm only if the expected profit of the firm from investment is greater than the full information profit of the dirty type.

When the level of subsidy committed is low, the effective marginal cost of the clean type is always higher than the dirty type. Even in the range of low subsidy commitment, there could be higher profits for the clean type as we observed under the case of full information. However, under

[21] Both Mahenc (2008, 59-68) and Sengupta (2012, 468-480) advocate for this loss in profit as the willingness to pay for mandatory disclosure or eco-labels.

incomplete information, when the effective marginal cost: $X_c < m_D$ and the subsidy rate: $s > \underline{s}$, the clean type distorts the price upwards to P^U to signal its type and incurs a loss due to deviation from the full information price. As a result:

$$\pi(D, 0, P_D^*) > \pi(D, 1, P_C^*) \ \ for \ \ s \in (\underline{s}, s^R).$$

The firm does not have any incentive to adopt cleaner technology when the level of subsidy commitment is low, even though investment is costless. The subsidy is ineffective due to price distortion in the range of abatement support: (s^0, s^R), effectively imposing a restriction on the Green Party on the level of subsidy commitment which could be effective in generating voter support. Although the subsidy commitment: $s^0 < \underline{s} < s^R$ signals partisanship over the environmental agenda, low levels of commitment might be limited in their capacity to provide a tangible benefit to the voters. The voting consumers observe the level of subsidy committed but they also realize that the commitment would not induce the monopolist to adopt the cleaner technology. Consumer surplus without adoption of cleaner technology remains the same as it was before the application of subsidy.

On the other hand, when the level of subsidy committed is high, the decision to adopt of cleaner technology does not immediately follow from the level of subsidy committed. $(\pi_C^{FI} - \pi_D^{FI}) - \Delta_\pi > 0$ determines if the investment is profitable and the condition holds for some level of subsidy commitment where $s^R < s < \overline{s}$ (See <u>Appendix A.4.ii</u>). Let Δ_I measure the incentive for the monopolist to invest in clean technology. The incentive depends upon the additional profits that the clean type can make over the dirty type and the loss in profits due to signaling.

$$\Delta_I = \mu[\Delta_\pi + (\pi_C^{FI} - \pi_D^{FI})] \quad \text{where } \Delta_\pi = \pi^L - \pi_C^{FI}$$

$$\Rightarrow \Delta_I > 0 \text{ if } (\pi_C^{FI} - \pi_D^{FI}) > \Delta_\pi.$$

However, when the level of environmental policy support committed is high: $s > s^R$, then: $\pi_C^{FI} > \pi_D^{FI}$ and $\left|\frac{\partial \Delta_\pi}{\partial s}\right| < 0$. Further, when the subsidy commitment is so high that $s > \overline{s}$, the profit distortion is zero, i.e., $\Delta_\pi = 0$. Thus, the minimum effective subsidy lies between the range: $s \in (s^R, \overline{s}\,)$. Given the parameters, let s_{II}^* be the minimum subsidy required to motivate the monopoly to invest in cleaner technology under incomplete information. Then,

$$s_{II}^* = \overline{s} - \phi = s^R + \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_d^2)} - \phi \qquad \ldots (Eq: 7)$$

where $\phi > 0$. The incentive to adopt cleaner technology under high levels of subsidy increases. The probability of successful investment (μ), the abatement rate (β), and most importantly, the environmental consciousness index ($\underline{\alpha}$) plays an important role. A greater level of environmental consciousness increases the willingness of the consumers to pay a premium for the cleaner product. Consequently, the profit of the clean type (π_C^{FI}) increases relative to that of the dirty type (π_D^{FI}), increasing the incentive of the monopolist to adopt of cleaner technology. In effect, when the subsidy commitment is high, there exists a particular subsidy rate, that could be sufficiently high for the clean type to be able to differentiate from the dirty type and be able to cater to a larger market at a lower price. Therefore, ϕ represents a host of factors including the marginal cost of each type, the abatement rate and most importantly, the environmental consciousness index:

$$\phi'(\rho) > 0 \; and \; \phi''(\rho) > 0 \qquad \ldots (Eq: 8)$$

This implies that higher environmental consciousness would require lower levels of subsidy commitment from the Green party. $s_{II}^* = \overline{s} - \phi(\rho)$ would be least that the Green Party needs to commit, to increase the consumer surplus and retain the support of the pro-environmental voters. With high levels of subsidy commitment ($s^R < s_{II}^* < \overline{s}$), the firm continues to distort the price but now the firm distorts the price downwards. This downward distortion makes the subsidy more than effective in the sense that it increases the consumer surplus by more than the amount that the subsidy itself would trigger (had the monopolist charged the full information price). Therefore, the minimum subsidy commitment required to trigger clean technology adoption under incomplete information would be sufficient to increase the consumer surplus.

1.6 Environmental Policy Commitments with Costly Investment

When the investment is costly, the subsidy commitment needs to be increased to cover the cost of market imperfections not only due to the uncertainty but also due to the cost of investment initiative. Let the cost of adopting clean technology be an exogenously assigned fixed cost: $f > 0$. As investment is costly, it decreases the net expected profit of the polluting monopolist under both scenarios of full and incomplete information. The political parties and consumers can observe the cost of investment but cannot observe whether the investment was successful. The Green party would consider the cost of investment and update their commitments on environmental policy support such that, the minimum effective subsidy under full information and costly investment (s_{FI}^{**}):

$$s_{FI}^{**} = \frac{1}{\beta}\left[m_C - \sqrt{\rho}\left(\sqrt{\rho}a - \sqrt{(a - m_D)^2 + 4f}\right)\right] \qquad \dots (Eq: 9)$$

The minimum effective subsidy depends on the magnitude of the fixed cost. Due to costly investment, the political parties need to commit to higher levels of subsidy to generate similar profit levels for the investing firm. Even under full information, the cost of investment magnifies due to the uncertainty in the investment outcome. If the fixed cost: $f > 0$ is sufficiently high, the subsidy commitment would be required to be increased. However, when the level of environmental consciousness is high, it increases the net profit of the monopolist and provides greater incentive to adopt cleaner technology. Under incomplete information, the subsidy required for investment is higher than under full information due to the cost that the clean type needs to incur for signaling its type. Now, with costly investments, it depends on the fixed cost. The minimum subsidy required to incentivize a polluting monopolist to adopt cleaner technology under incomplete information and costly investments is ambiguous, as it depends on the size of the investment cost. The incentive to innovate Δ_I becomes:

$$\Delta_I = \mu[\Delta_\pi + (\pi_C^{FI} - \pi_D^{FI}) - f] \qquad \ldots (Eq{:}\ 10)$$

The minimum effective subsidy in that case (s_{II}^{**}) could lie within the bound of the distortions $(s^R < s_{II}^{**} < \overline{s})$ or it could go beyond the upper bound $(s^R < \overline{s} < s_{II}^{**})$ if the cost of investment (f) is too high.

Table 1 illustrates the minimum subsidy commitment required under different scenarios. At the first level, the Green party marginally increasing their level of support relative to the Brown party may express their ideological position on the issue of environmental agenda but it may not be sufficient to secure the pro-environmental votes, even under full information. The voters vote based on tangible gains that they observe from the political commitments. Effectively, the Green party needs to commit to a minimum effective subsidy of $s_{FI}^{*} > 0$, under a full information scenario, that is, when the monitoring technology is advanced or there could be other credible means of direct disclosure of environmental performance. Under incomplete information, the Green party needs to increase the environmental policy support above s_{FI}^{*}, as the clean type distorts its price above the full information price to signal its type. The clean type begins to distort the price for a level of environmental policy support: $\underline{s} < s_{FI}^{*}$, which implies that under no instance would the clean type find it profitable to adopt of cleaner technology under incomplete information when $m_D < X_C$. However, when if the Green party could increase the subsidy commitment to $s_{II}^* > s^R$, it could motivate clean technology adoption from the monopolist and retain its niche voters. When the investment becomes costly, it becomes harder for the monopolist to adopt clean technology profitably. Therefore, the subsidy requirement is higher than the situation without the investment cost.

Comparison between the minimum effective subsidy under full information and incomplete information reveals the cost incurred by the firm due to the lack of monitoring or other credible forms of disclosure mechanisms. The results resonate with the findings of Mahenc (2008) and Sengupta (2012), who argue that the loss in profitability from signaling distortions provides an indirect measure of the willingness to lobby for imposition of mandatory disclosure. Adding on to the earlier findings, this study offers an analysis from a regulatory perspective. In this paper, the results indicate that the Green party could commit to improvements in monitoring technology instead of relying on the subsidy commitments, as it could establish the partisanship and secure its niche voters at a lower cost to their party budget (See Figure 1). The difference between s_{FI}^* and s_{II}^* represents the additional spending on environmental agenda, which the Green party needs to incur due to the lack in proper disclosure mechanisms. If the cost of developing the monitoring technology is less than the additional support required, it would be beneficial to the Green party to commit to improvements in monitoring technology instead of relying on the subsidy commitments only. When monitoring technology is costly, subsidy policy has the potential to generate more than expected benefits to the consumers for a certain range. Although this additional benefit does not explicitly imply greater benefits to the Green party in this model, intuitively, it could bring about stronger allegiance from the pro-environmental voters. In this paper, however, I focus on voter retention, where the tangible gain is a binary variable in the voting choice of the single-issue voters.

Conclusion

Using a simple voting framework, I seek to establish the influence of the environmental consciousness of voting consumers on economic and political outcomes at two levels. First, I investigate the influence of environmentally conscious voters on the electoral commitments of a pro-environmental party. Second, the model establishes a connection between the latter agents via firms that are affected due to the partisanship over environmental agenda. The model works in a backward induction technique where the rational agents evaluate the effect of the implementation of the committed policies at a future date. The model posits that the voters can predict what level of subsidy would drive this investment but they remain unaware of the investment outcome. Their vote strictly depends upon the expected tangible benefits from the adoption of cleaner technology. The benefits to the voters are measured in terms of the consumer surplus resulting from the commitment on environmental policy support. Although the environmental consciousness index imposes favoritism on the population's voting choice, the rational voters are triggered through the possible improvement in their consumer surplus via effective subsidy commitments.

Under different scenarios, I find specific levels of subsidy commitment that are effective in terms of generating voter support. The specific level of subsidy serves as the minimum that the Green Party needs to commit to generate voter support. The results show that the inclusion of investment cost does not qualitative change the findings from the zero investment cost scenarios. But high investment costs could render the subsidy requirement to be too high to be borne by the regulators. Single-issue voters provide ground for party sorting on the agendas and the consequent political polarization. In this aspect, the United States presents a strong case to study the implications in this model. Several issues representing the concept of single-issue voting over liberal and conservative ideas have been relevant in most elections in United States' history but environmental agendas have surged in importance over the last few decades.[22] Considering various policy measures taken by the pro-environmental parties to cater to the environmentally conscious voters, this model predicts that high environmental consciousness requires lower levels of subsidy commitment to trigger voter support. The result in this study suggests that partisanship over environmental agendas is easier to establish in states with higher environmental consciousness. Thus, allowing for a larger range of effective subsidy commitments. Pacca et al., (2021) investigates the influence of lobbying, electoral incentives, and US state governors' party affiliation on environmental expenditures. They find that Democratic governors spend more on environmental issues on average. However, in states where polluting industries are economically important (oil-abundant states), Democratic governors tend to allocate lesser resources towards environmental protection. As the environmental consciousness is low in the oil-abundant states, the Democrats would need to resort to much higher level of environmental support to motivate the firms to adopt pro-environmental initiatives. However, this may not be supported by the voters who bank heavily on the fossil fuel deposits for livelihood.

[22] In the early 1990s, the Republicans began to question the legitimacy of the extreme anthropogenic impacts on the environment, and its consequent effect on living standards (Jacques et al., 2008). During Bill Clinton's term, the 1992 Rio Earth Summit took place and issue of ozone depletion was given high importance but the Center's support towards environmental consciousness was highly criticized by the Republicans on the grounds of legitimacy and evidence, especially on the issue of climate change and the role of human interference ((Demeritt 2006, 453-479); (McCright & Dunlap 2003, 348-373)).

CHAPTER 2: Political Polarization and Environmental Innovation:

Insights from US State-Level Patent Applications (1980-2019)

Dibyajyoti Sinha[23]

2.1 Introduction

The decentralized political structure of the United States (US) allows states autonomy to form their environmental policies and regulations – often diverging from those established nationally.[24] For example, when the US backed out of the Paris Climate Accord in 2017, states such as New York, California, and Washington allied to challenge the federal government's stance.[25] The then-New York Governor, Andrew Cuomo, declared (in a post on Twitter) on June 1, 2017, that "*Withdrawing from the Paris Accord is reckless. I'm signing an Executive Order affirming NY's role in fighting climate change*." Several other states joined the alliance in the following weeks, demonstrating their independent stand on environmental policymaking.

In this paper, I examine whether and how the state leadership's independent stand on environmental policymaking influences the development of cleaner technologies in that state. Specifically, I explore how the development of clean technology, measured by environmental patent applications, is affected by the state governor's party affiliation and voters' environmental preferences. To this end, I leverage the growing political polarization in the US to establish

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[24] The state's autonomy in terms of policy liberalism has been found to be persistent in the United States (Caughey & Warshaw, 2016). Other than state's decision on the level of spending or tax implementation, this departure can also be observed in terms of secondary policy issues like environment, gun laws, possession and use of cannabis, and reproductive rights, consequently affecting electoral incentives and policymaking at the state level (Bouton et al., 2021).

[25] For more details see www.USClimateAlliance.org.

environmental policy divergence and investigate whether this divergence leads to any difference in initiatives to develop cleaner technology at the state level.[26] In other words, I study how innovative activity in environmental technology changes if a Democratic or Republican party controls the state's governance.

The influence of state policies on innovation has not received much attention in the literature due to the centralized nature of patenting regulations in the US.[27] However, I find considerable variation in environmental patenting activity across states. For instance, from 1980 to 2019, in North Dakota and Delaware, the average annual environmental patent applications were 0.38 and 9.63 per 100,000 residents, respectively, while Michigan recorded 4.26 (see Figure 2). Primarily, the electorate's environmental consciousness may drive varying demands in different states, prompting firms to develop environmentally higher quality products or adopt a cleaner production process.[28] Further, these disparities could also arise due to state-level environmental policies and regulations influenced by local industry requirements and resource dependency.[29] As a result, each state exhibits idiosyncratic trajectories in environmental patenting activity with or without government interventions.

[26] The Democrats have been taking a pro-environmental position in U.S. politics, with the early 1990s being noted as the inception (Demeritt, (2006); McCright & Dunlap, (2003)). Since then, the partisanship over environmental policy has been observed to be increasing – not only in the Congress but also among the population in general (McCright, Xiao & Dunlap, 2014).

[27] The U.S. Patent and Trademark Office (USPTO) is a part of the Department of Commerce, which is regulated at the federal level. It is responsible for granting patents to inventors and companies, and for enforcing patent laws and regulations nationally. As a result of the centralized structure, the enforcement of the property rights would apply in all states regardless of which state the patent is being filed.

[28] Sengupta (2015) shows that an increase in environmentally conscious consumers lead to more competitive investments in cleaner technology. The results follow from the increased demand for environmentally higher quality products and in the anticipated liability of future regulations.

[29] Brouhle et al., (2023) finds that environmental patenting is most strongly driven by the technological capacity of the firm along with factors such as environmental innovation opportunities, the regulatory environment, and firm-specific characteristics.

I construct a state-level dataset for US environmental patents to explore if *state* policies and political affiliations affect innovative activity.[30] I evaluate the influence of governors (as state leaders with substantial autonomy) on clean technology developments by implementing a sharp Regression Discontinuity Design (RDD) on US gubernatorial elections.[31] The results suggest that when a Democratic governor runs a state, innovative activity in the environmental technology domain increases. Notably, this trend emerges post-1992, coinciding with the increased polarization over environmental policy in the US between the two parties. On average, the tenure of a Democratic governor observes approximately an 11% surge in environmental patent applications, corresponding to an annual increase of around 15 new patent filings in that state.[32] At the same time, there is no evidence of increased innovative activity in all sectors combined. Democrats do not induce, and in some specifications depress, across-the-board innovation enhancements relative to Republican tenures. The results suggest that firms may be strategically allocating their resources to sectors that align with the policy priorities of the governing party.

Given the centralized nature of patent regulation in the US and interstate trade dynamics, concerns may arise regarding interstate spillovers influencing the baseline results. For instance, regulations on automobile emissions in New York might impact innovation in Michigan's automobile industry, especially when Michigan's manufacturers aim to sell to consumers in New

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[30] For a detailed review of the impact of state level policymaking (and political identity) on economic outcomes, see Potrafke (2018). For a detail review of the theoretical and empirical literature related to regulations and innovation, see Jaffe (2000), Hall & Harhoff (2012).

[31] The environmental policy divergence is proxied by the political affiliation of the governor. When the governor of a particular state is a Democrat, I assume the state experiences pro-environmental changes on an average. However, this pro-environmental treatment changes when a Republican governor takes over. As a result, the standard difference in difference technique is not applicable in this case. I use a Regression Discontinuity Design (RDD) similar to Fredriksson et al. (2011), Beland & Boucher (2015), Pacca et al. (2021), and Bonnet & Olper (2024) which evaluates the role of governors in the state level environmental policymaking in the US.

[32] These counts of patent applications, though eventually successful, does not guarantee that the market has adopted the technology. Rather the application counts represent successful initiatives or investments in the research and development of cleaner technology.

York. To address this issue, I conduct several robustness tests. To begin with, I additionally include population-weighted Democratic-governed states in my analysis (as a measure of pro-environmental policies in the rest of the nation) and find no significant change in my baseline results. The exclusion of Delaware, a state known for favorable corporate and income tax policies, also does not notably alter the estimates. Additionally, analyzing a sub-sample of smaller firms (less likely to operate in multiple states) yields similar directional impacts to baseline estimates, albeit smaller in magnitude (3-6%). The smaller magnitude is likely due to the resource constraints of smaller firms, which often find it challenging to invest in new technologies and adapt to stricter regulations. The above findings suggest that my baseline estimates are not an artifact of interstate spillovers.

The mechanism at work can be broadly categorized into two folds. First, the state government initiates new environmental policies or changes the stringency of the regulations that firms in that state must adapt to operate.[33] Further, an increase in innovative activities may also stem from anticipating policy implementation.[34] In other words, innovators may not wait for stricter policies to be officially implemented. Instead, they may respond to a pro-environmental party being instated in state leadership. This response is in the expectation that the pro-environmental party will likely implement more stringent policies relative to the other party candidates. Second, it is crucial to recognize that although environmental policy and regulations may initiate environmental

[33] Theoretically, stricter environmental regulations increase the cost of operation for (dirty) firms (Porter & Linde, (1995); Palmer et al., (1995)). Therefore, environmental stringency increases the demand for cleaner technology for the existing firms, leading to higher counts of environmental patents (Jaffe & Palmer, (1997); Johnstone et al., (2010); Johnstone et al., (2012)). The impact of environmental regulation on innovation (Jaffe et al., 1995) and specifically environmental innovation using patent data in specific sectors such as automobiles, comply with latter findings (Pickman, (1998); (Lee et al., (2011)). For a detailed review on the literature related to environmental regulations and innovation, see Popp (2019).

[34] This is due to the anticipated liability of (future) environmental policy implementation by the regulator. Specifically, Segerson and Miceli (1998) have noted that the expectation of regulatory actions motivates firms to proactively engage in voluntary arrangements with regulatory authorities to reduce pollution.

innovation, it is ultimately a firm-level decision.[35] The firm's decision to operate in a particular state and invest in the development of new technology is driven by the demand for environmentally higher quality products. That is, firms could invest in clean technology without the government's intervention due to their profit motivation arising from consumers' demand for green products and cleaner production processes.

As the voters in a state are also the consumers, the tastes and preferences of the state's electorate could matter for environmental innovation, along with environmental policy and its anticipation. The strength of environmental advocacy groups, the energy sector's economic and environmental importance, and the constituents' environmental preferences may affect policymaking at the state level. These factors can moderate (or amplify) the impact of political party changes, as postulated by Yu (2005) and empirically tested by List & Sturm (2006), Pacca et al. (2021), and Bonnet & Olper (2024). I investigate heterogeneity in these dimensions by estimating the impact of Democrats over sub-samples split by the percentage of environmentally conscious electorate and the state's dependency on fossil fuels. Consistent with Pacca et al. (2021), I find that the impact of Democratic governors (on environmental patents) is more prominent in states with pro-environmental attributes like the preponderance of green voters and less dependency on fossil fuels for the state's economy.

One may argue that the voters' preferences primarily drive the Democratic governors' positive influence on environmental innovation. For example, an increase in environmental consciousness among voters would increase firms' investments in green technology, consequently contributing

[35] In this context, Palmer et al., (2015) adds that firms might relocate or stop operating due to stricter environmental regulations. More recently, in an interview with the Wall Street Journal on Dec 8th, 2020, Elon Musk said that the primary reason for Tesla moving from California to Texas is that Texas offers favorable taxes and regulations for the business.

to the victory of a Democratic Party candidate. In that case, the state would experience spurred green innovation before the election of a Democrat.[36] I demonstrate that a Democrat's victory does not necessarily follow increased environmental patents in the previous years in a particular state. My empirical results suggest that the implementation and commitment of a supportive environmental policy framework primarily facilitates such endeavors. The state electorate's environmental sentiment is largely responsible for inducing demand for innovation in environmental technology. However, due to the increasing environmental policy divergence, changes in the state leadership appear to maneuver the incentives for the innovating firms.

I provide ample evidence supporting the independent effect of Democratic governors on environmental patenting activity, over and above the contribution of the environmental consciousness of the electorate. The main results indicate that environmental patent applications increased during the tenure of a Democratic governor. Further, in an extension analysis, I show that Republican governors tend to veto bills related to energy and natural resources more than their Democratic counterparts (although Democratic governors' likelihood to enact new green bills does not differ significantly from Republicans). I also show that the number of government employees in the environmental sector increases when the state's governor is a Democrat. The latter result, coupled with the findings of Pacca et al. (2021) (who show an increase in state's environmental spending in Democratic states), suggests augmented stringency or enforcement of environmental protection by Democratic governors. My empirical results indicate that local state-level stringency in environmental regulations and the anticipation of their implementation induce innovative activity in environmental technology.

[36] It might be important to consider that environmental politics is considered a secondary policy issue in the US, catering to specific portion of the population. On most occasions, it may not be a critical policy agenda to turn around the election results.

2.2 Data and Methodology

I construct the primary dataset in the following steps. First, I collect information on US domestic patent applications from the USPTO databases.[37] This data includes the year of application, the location of the primary patent holder, and the classification of the patent (including both the United States Patents Classification (USPC) and International Patent Classification (IPC)). Note that all patent applications used in this analysis are eventually granted. If granted patent counts used in the innovation literature serve as a proxy for technological advancement, the patent applications I use are officially registered as a contribution to improving cleaner technology in the future.[38] Effectively, innovative activity (patent applications) today represents the long-term prospects of developing environmental technology. Second, I use the classifications listed under the US Green Technology Pilot Program (2009) and the list of International Patent Classification (IPC) codes provided by Hascic and Migotto (2015) to identify environmental technology patents. Third, I combine the annual patent dataset for each state with the results of their gubernatorial elections and other state-specific information. A detailed description of the data and the constructed variables are discussed below, followed by the empirical strategy.

2.2.1 Data Description

The data set includes information on annual US domestic patents from 48 lower states in the US from 1980 to 2019.[39] I represent the *"year"* (i.e., patent filing year) and the "*state*" (i.e., the

[37] The data are available at https://patentsview.org/download/data-download-tables. This database consists of files linking patent IDs to their specific sectoral classification and the location of the patent holder. They are available for different classification schemes followed domestically and internationally and schemes developed for global concordance.

[38] See Jaffe & Palmer, (1997); Johnstone et al., (2010); Johnstone et al., (2012).

[39] I use the years 1980 to 2019, due to the data availability. I exclude years after 2019 due to uncertain affects during the COVID years. Further, Hawaii and Alaska have not been included due to heavy dependence on federal funds.

location) of a patent by the patent's year of application and the location of the patent's assignee (typically a firm or institution).[40] The following example describes how I classify a patent's state and year. Say, in the year 2000, an inventor from Iowa applied for a patent, which was eventually adopted by a firm that operates in California. In this case, the patent is counted among those in California in 2000, even though the inventor may be living in a different state, and the grant date may be after 2000. I use this strategy to focus on the patent fillings, such that the application counts represent innovative activity. The choice of the year and state variables are detailed below.

I consider the location of the patent's assignee instead of the location of the inventor because firms tend to adapt to the policies of the states in which they operate. On the other hand, inventors in one state can transfer patent rights to firms in other states – where there is greater demand for such technologies. The objective is to trace the demand for such technologies. I assume that changes in the political environment for a firm in a particular state induce demand for specific technologies. This assumption follows the literature on firms' reaction to environmental regulation, which postulates that if governments could affect the costs associated with using environmental resources, firms' demand for improvements in production technology would increase. Consequently, an increase in the investment and development of patents directed to the environmental technology domain can be expected.[41] Therefore, patenting activity is the prerogative of the firms and institutions that react to regulatory changes that are implemented or those that are anticipated to be implemented.

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[40] It is to be noted that large corporations tend to operate in multiple states, and they usually file for their domestic patents in the states where their headquarters is located. Due to this reason, the effect of state-level policy on patenting activity in the location (state) of operation is expected to be underestimated, whereas the patenting activity in the headquarters state would be overestimated. To counter this problem, I check the model's robustness to smaller firms, that are likely to operate and headquarter in the same state.

[41] See Jaffe et al., (1995); Jaffe & Palmer, (1997); Johnstone et al., (2010); Johnstone et al., (2012).

I consider the patent application year and not the grant year because the objective is to analyze the short-run reaction of the firms to political changes. However, there are several other technical advantages of implementing this strategy. First, patent applications are usually filed early in the research process. Second, anticipatory effects of environmental liabilities could significantly influence firms to adopt environmental self-regulation (Segerson & Miceli, 1998). As a result, firms might not necessarily postpone their actions until stricter policies are implemented. Instead, they may proactively respond to the prospective policy changes when a pro-environmental party assumes control of the state's governance. Therefore, firms might seek intellectual property rights well in advance of the official policy implementation. Lastly, in terms of empirical advantage, considering the application year helps avoid the endogeneity issues related to the patent grants (political, examiner, industry-specific, etc.) (Griliches, 1990).

I consider a patent to be an environmental patent if, (1) its United States Patents Classification (USPC) is included in the classifications listed under the US Green Technology Pilot Program (2009) or (2) its International Patent Classification (IPC) codes are listed by Hascic and Migotto (2015).[42] The outcome variable in the main analysis is the log of environmental patents per 100,000 residents in a state each year, computed using states' population, obtained from the Annual Census publications.[43]

[42] The USPC classification of environmental patents is listed in Table 2.

Information about this program is available at https://www.federalregister.gov/d/E9-29207. This program, implemented in 2009, reduced the cost of application and review time for environmental patents. The codes of all patents included in this program are considered environmental patents. The classifications presented in Hascic & Migotto (2015) list a series of classifications in the International Patent Classification (IPC) and CPC codes, which can be considered as environmental patents. I find a significant overlap in the patents under the two classifications.

[43] Carlino et al. (2007) show that locations with higher population density in the United States are associated with higher levels of innovation and growth. Therefore, using per capita patent measures control for the effect of population.

Table 3, where the sample means and the descriptions of the variables are presented, shows that the share of environmental patent applications is about 6.28% of the successful patent applications. Out of all patent applications, an average US state has about 1,619 successful applications annually. Among these successful applications, the state average of environmental patents stands at approximately 91 counts each year. Each state's average counts of environmental patents per 100,000 residents between 1980 and 2019 is demonstrated in Figure 2. From the figure, it can be observed that there is substantial geographic variation in environmental patenting activity across states.

One of the critical limitations in empirical studies on the effect of environmental policy at the state level in the US is the lack of data on the measures of environmental stringency for the required period in this analysis. The existing measures are not helpful in this analysis due to the length of 40 years and the breadth of 48 states covered.[44] Therefore, to represent the stringency of the state's policies on environmental issues, I rely on the information related to the state's political scenario. Specifically, the governor's party affiliation is used to proxy for the environmental policies in that state. This application is contingent on the assumption that there is a growing political polarization in the US over the environmental agenda between the two major parties – the Democrats and the Republicans. I collect data on governors' political parties and the results of the gubernatorial elections from Dave Leip's Atlas of US Elections.[45] Besides the governor's political identity, I use the data on gubernatorial elections to calculate the winners' victory margin.[46] I

[44] The Pollution Abatement Cost and Expenditure (PACE) survey took place annually from 1973 to 1994. However, the U.S. Census Bureau discontinued the survey after 1994 due to budget constraints. Recognizing the importance of this data, the EPA provided funding to conduct the survey in 2000 which differed significantly from previous surveys, making it challenging to conduct a longitudinal analysis (Becker & Shadbegian, 2005).

[45] They are available at https://uselectionatlas.org/RESULTS/.

[46] Only the races where the winner and the runner-up candidate are members of either the Democratic or Republican Party are considered in the analysis. I exclude from my analysis the races/states where a third party or independent

hypothesize that states governed by Democrats are more likely to implement pro-environment policies. The assumption is also supported by the literature, which demonstrates the pro-environmental nature of the policies implemented by Democratic party governors (Beland & Boucher (2015); Pacca et al. (2021); Bonnet & Olper (2024)).

The above data are used for the main analysis, where I investigate the role of the governor's party affiliation in environmental patenting activity. For an extended analysis and robustness, I collect data on the state's political and environmental characteristics, like the partisan control of the state legislature, the environmental sentiment in each state, and their dependency on fossil fuels for the state's economy. I evaluate how these factors may affect the trends in environmental patenting activity in the state, and whether they affect the environmental policy to any level.

To evaluate the role of partisan control in the state government on policymaking, I obtained data on the number of Democratic, Republican, and Independent party members in the state legislature and the state senate.[47] The dataset includes the number of state legislators and senators who are Democrats and Republicans. Specifically, I use the percentage of Democrats in the House and Senate to determine the control of partisanship at the state legislature. A trifecta (control of the executive branch and both legislative chambers) can be expected to ease the policymaking process for the incumbent governors. For example, a Democratic trifecta should allow a pro-environmental Democratic governor to pass an environmental policy with less opposition.[48] Furthermore, Table 2 and Table 4 suggest

candidate wins or obtains second place. Out of 1,920 observations between 1980 and 2019, there are 40 instances where such a situation has occurred.

[47] These data are obtained from Carl Klarner Dataverse from 1980 to 2015; I refer to the Ballotpedia website for the remaining years. The data on State Partisan Balance can be found in the following website: https://dataverse.harvard.edu/dataset.xhtml?persistentId=hdl:1902.1/20403 and that of Ballotpedia is available at https://ballotpedia.org/Historical_partisan_composition_of_state_legislatures. The State Partisan Balance dataset from Carl Klarner Dataverse is currently updated to 2015.

[48] In many cases, achieving the passage of climate-related bills requires a Democratic trifecta (Bromley-Trujillo et al., 2016; Trachtman, 2020).

that the victory of a Democratic governor is correlated with the presence of partisan control in both the House and the Senate. However, the correlation may not hold for the House when looking at close elections.[49]

The difference in environmental policies between the Democrats and Republicans is also apparent in the US Congress, as depicted in Figure 3. In Figure 2, the blue (red) solid [dashed] line shows the national average "Environmental Voting Scores (EVS)" of Democrats (Republicans) in the Senate [House of Representatives] over time. The EVS data are obtained from the League of Conservation Voters (LCV) website, which computes a value for each member of Congress, indicating how they voted on issues related to the environment each year.[50] For example, a Democratic representative in the House from West Virginia has an average score of 58 – much less than the national average for a Democratic representative (73). Nonetheless, the average score for a Republican representative from West Virginia is 18, which indicates that within a given state, Democrats would be more pro-environmental than their Republican counterparts.

Figure 3 shows that Democratic House and Senate representatives have been more environmentally friendly than Republicans throughout the sample period. In addition, the gap between them has increased since the early 1990s. Specifically, 1992 was a crucial year for the shift in political dynamics regarding environmental policy (McCright et al., 2014). According to McCright et al. (2014), the Democratic Party aligned itself with the growing concern over

[49] The results in Table 4 presents the OLS estimates with Democratic governor as the dependent variable on all the variables listed, for different samples of victory margins. The estimates include state and year fixed effects.

[50] The link to these data is https://scorecard.lcv.org/members-of-congress. LCV scores utilize the votes on the most critical environmental issues of the year, including energy, climate change, public health, environmental and racial justice, worker protection, democracy, public lands, and wildlife conservation, and spending for environmental programs. For details on methodology, see https://scorecard.lcv.org/methodology. The EVS range between 0 and 100, where higher numbers imply pro-environmental voting. Among several others, the recent works using LCV data include Blundell et al. (2021) and Liao & Junco (2022).

environmental sustainability, effectively differentiating itself from the Republicans in the early 1990s.

I use several proxies to capture the effect of the state electorates' environmental inclination. First, I utilize the EVS data to construct an aggregate state-level score. The EVS of each Senate and House member is available annually and indicates the state and the political party that they represent. I generate the state-level score by averaging the individual voting records of all representatives. The state's environmental score in Congress mimics the relative position of the voters' environmental consciousness and proxies the lobbying efforts in environmental policymaking. Table 3 shows that the aggregate environmental voting score (both in the Senate and the House) is higher for states with Democratic governors, indicating an association of the Democratic party with pro-environmental sentiments in the state. Second, industries where the cost of adopting cleaner technology is high, or industries in those states dependent on fossil fuels like coal or oil, would tend to lobby against environmental policies.

Further, I use List and Sturm's (2006) 1987 membership of the largest US environmental organizations (Sierra Club, National Wildlife Federation, and Greenpeace) as a proxy of the share of green voters in a state. In addition, I include the state's annual coal and crude oil production in my analysis, which are obtained from the Energy Information Administration (EIA). Higher per capita oil and coal production indicate the state's economic reliance on these resources, capturing the potential lobbying influence on environmental policymaking. Lastly, I obtain annual data on the state governments' full-time employment in the environmental sector to evaluate possible increments in environmental monitoring and regulation during different party regimes in a particular state.[51]

2.2.2 Methodology and Empirical Specification

There have been several instances in US politics where a shift in the political identity of the governor followed a dynamic change in environmental policy.[52] A line of research has scrutinized the role of state governments in shaping environmental policies and their effects in the United States (Fredriksson et al., 2011; Beland & Boucher, 2015; Pacca et al., 2021). Fredriksson et al. (2011) contend that Democratic governors wield no significant influence on state environmental policy compared to their Republican counterparts. They argue that Democratic governors lacking re-election incentives tend to curtail the expansion of environmental spending. However, Pacca et al. (2021) present contrasting evidence by incorporating lobbying dynamics into environmental politics in a more recent study. They assert that Democratic governors increase per capita environmental expenditures, particularly in states susceptible to pro-environmental lobbying, and this effect intensifies in the post-1992 era. Moreover, Beland and Boucher (2015) found diminished air pollution levels during the tenure of Democratic governors, indicating the influence of pro-environmental governance in addressing environmental challenges. Further establishing the nexus between political leadership and environmental initiatives, Olper and Bonnet (2024) reveal

[51] These data are obtained from U.S. Census Bureau, Annual Survey of State and Local Government Employment and Census of Governments. They are available at https://www.census.gov/programs-surveys/cog/data/historical-data.html

[52] In 2019, New Mexico, a traditionally Republican state, enacted a significant increase in its Renewable Portfolio Standards (RPS) after the election of a Democratic governor. In contrast, Kentucky, which saw a change from a Democratic to a Republican governor, shifted its energy policy focus towards supporting coal and reducing environmental regulations.

that Democratic governors positively influence state-level adoption of renewable energy, underscoring the significance of pro-environmental governance at the local level.

Although Democratic governors are more likely to implement relatively pro-environmental policies than Republican governors, the states that Democrats govern may differ from Republican-run states in aspects other than these policies. The sample averages in Table 2 indicate that the Democratic governors are more likely to be elected in pro-environmental states. While the EVS in the House shows that the Democratic states lead the Republican states by 6%, the difference in the Senate is considerably large (10%). Likewise, residents in states that rely more heavily on the fossil fuel industry could be more likely to vote against the pro-environmental policies. I also suspect unobserved state-specific shocks that affect both the election outcomes and the level of patenting activity. For these reasons, comparing the environmental patents in these states does not necessarily lead to the causal effect of policies. Therefore, following the empirical literature investigating the governors' effect on environmental policy-making (Fredriksson et al., 2011; Beland & Boucher, 2015; Pacca et al., 2021), I use a Regression Discontinuity Design (RDD) to address the endogeneity issue.

Below is my baseline specification:

$$\mathrm{Y_{st}} = \alpha + \beta_1 \mathrm{D_{st}} + \mathrm{F}(\mathrm{mv_{st}}) + \delta_t + \phi_s + \varepsilon_{st} \qquad \ldots\ldots (Eq.1),$$

where $\mathrm{Y_{st}}$ represents the log of environmental patent counts per 100,000 residents in the state "s" in year "t". The treatment is the dummy variable, $\mathrm{D_{st}}$, indicating whether the state had a Democratic governor in that year. The running variable is the Democratic governor's margin of victory – indicating the cut-off at zero. $\mathrm{F(mv)}$ represents the different polynomial functions of the margin of victory. I fit a line in the baseline specification and use higher-order polynomials in alternative regressions. Further, ϕ_s and δ_t capture the state and year fixed effects, and ε_{st} is the error term. The model compares the environmental patenting activity in Democrat-governed states to that in their Republican-governed counterparts, focusing on the states in which the winner of the gubernatorial election has a small margin of victory. The identifying assumption is that winning Democrats (Republicans) could have easily lost to their competitors if a small share of voters, who supported them due to reasons orthogonal to the outcome, cast their votes for other candidates. Thus, in this design, the barely-winning Democrats are the counterfactuals to the barely-winning Republicans.

Although RDD does not require covariates to be included, they can improve the point estimates' precision and demonstrate the robustness of the model to the inclusion of additional controls. I include year and state-fixed effects in the analysis following Fredriksson et al. (2011), Pacca et al. (2021), and Bonnet and Olper (2024). Fredriksson et al. (2011) and Pacca et al. (2021) use state and year-fixed effects in their RD design to estimate the effect of Democratic governors on environmental expenditure per capita. State-fixed effects enable comparisons within each state, isolating the influence of time-invariant factors such as state-specific resources, culture, and economic conditions. Similarly, year-fixed effects account for national-level trends, like aggregate economic conditions and federal policy changes, which could confound the analysis. This control is particularly crucial given the potential impacts of the changes in the federal government and policy uncertainty, which affect all states in that year. Figure *4* demonstrates the increase in environmental patents per capita and shows substantial variability in environmental patent applications year-on-year. Although there is a long-term trend, year-specific productivity shocks have affected the short-run trends on several occasions.

2.3 Results

Results from the baseline model with various specifications in estimating eq.(1) are presented. The dependent variable is the log application counts of environmental patents per 100,000 people in the state annually. The tables present estimations of the baseline model, including 1^{st} to 4^{th}-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable – Democrat. The estimations implement a triangular kernel to emphasize the observations with smaller victory margins. I cluster the standard errors at the state level as the economic environment for the individual firms in the same state is likely to be correlated. Lastly, regarding the validity of the RDD specification, selection into treatment would imply that the Democratic governors can manipulate their victory. Although such an instance is unlikely in an election, I test that party affiliation is not manipulated across the cut-off using a McCrary density test. Figure 5 demonstrates the result of the McCrary density test to validate the RDD.

The results from the full sample (1980 – 2019) show that the Democratic governors did not affect environmental patent applications. However, the post-1992 period shows a significant increase. Table 5 compares the estimates from the baseline model with the sub-sample of the post-1992 period. This comparison follows the evidence of increasing polarization between the Democrats and the Republicans over environmental policy from the early 1990s. The increasing polarization over environmental policy is expected to result in an environmental policy divergence, where Democratic governors commit or implement stricter policy measures than their Republican counterparts. This finding is in line with Pacca et al. (2021). The study shows that Democratic governors not only increased environmental spending compared to Republican governors, but the difference in magnitude further increased in the post-1992 period. I start with a bandwidth of 14% as it provides sufficient data to compute the RDD estimates for the post-1992 period. In Figure 7, I present the estimates with closer bandwidths (6-8%) for all years. In those closer elections, the estimates are also significant for the pre-1992 sample. This result follows the intuition that anticipations are crucial in innovative activity in a politically contentious domain. When elections are tight, it becomes difficult to anticipate which party will win the elections, diluting the pre-election anticipations. Further, the results are robust to the inclusion of additional controls.[53]

The results in Table 6 include covariates used in Besley & Case (1995), List & Sturm (2006), Fredriksson et al. (2014), Pacca et al. (2021), and Bonnet & Olper (2024) – like population above 65 years, population below 17 years, and the log of per capita personal income. The latter literature argues that these population proportions and income variables control the heterogeneity in state-level policymaking. The estimated coefficients in Table 5 and Table 6 indicate that in states where elections are closely contested, the victory of a Democratic governor instead of a Republican one would observe an increase in environmental patents by approximately 11-18% (bandwidth of 14%). A back-of-the-envelope calculation shows that this increase (11%) is commensurate with the increase in state-level counts by approximately 15 patents on average from the state-level average of 91 counts. Note that the average level of environmental patents per 100,000 people in a state is about 1.34. Further, to verify if the discontinuity at the cut-off is only attributable to the treatment, I show that the baseline covariates are continuous at the threshold (See Figure 7).[54]

[53] In Figure 6, using a non-parametric approach, I also represent the above findings diagrammatically and compare the effect of the Democratic governor when there is a state trifecta for the Democrats. I find a more substantial effect in states that observed a Democratic trifecta, indicating a couple of effects. A Democratic trifecta makes the passage of state bills on environmental policy easier. Further, a Democratic trifecta indicates a political stronghold. It strengthens firms' anticipatory reaction to the expected pro-environmental laws or increased environmental stringency.

[54] The balance among the covariates is also evident from Table 4, where I show that the above-listed covariates are balanced across different bandwidths of victory margins.

In support of the main findings, I conduct analogous regressions utilizing the count of non-environmental patents per 100,000 residents within a state. Non-environmental patents encompass all patents that are not categorized under environmental patents. The findings in Table 7 depict the RD estimates for non-environmental patents as the dependent variable, incorporating various polynomial specifications and victory margin selections. The outcomes suggest that the influence of Democratic governance on non-environmental patents tends towards either a negative effect or neutrality. The reallocation of resources towards environmental technology or the departure of polluting firms from the market could potentially explain this observed decline. Nevertheless, the stringent policies enacted under Democratic administrations may inadvertently prompt the exit of incumbent polluting firms, attributed to their inability to finance the necessary innovation or comply with heightened regulatory standards. In contrast, the laissez-faire, low-tax environment fostered by Republican governance may attract investment in non-environmental technological advancement, thus contributing to the negative estimates observed. The negative coefficients signify that across-the-board patenting activity tends to be more robust under Republican gubernatorial leadership. The results indicate diminished private sector investments in technological innovation during Democratic regimes within a state. However, the targeted emphasis on environmental technology manifests in an increase in successful environmental patent applications under Democratic governance.

I check the robustness of the model to the exclusion of possible outliers. One such case is that of the state of Delaware. Although Delaware does not host many manufacturing or chemical industries (most likely affected by environmental regulations), corporations choose to incorporate in Delaware because of its favorable legal framework and low income and corporate taxes. As a result, Delaware has the highest per capita environmental patents at 9.6 per 100,000 residents (see

Figure *2*). Firms operating in other states likely incorporate their headquarters in Delaware, consequently overestimating Delaware's treatment effect, which the Democratic party, post-1992, has always governed. Table 9 presents the result of estimating equation 1, excluding the state of Delaware. I find that results remain robust regarding the direction of the effect, and there is little to no change in the magnitude. Therefore, Delaware's large environmental patent count per capita does not temper the estimates of the model.

An essential consideration in assessing state policies' impact on innovation lies in evaluating the spillover effects of environmental regulations. Particularly, the stringency of environmental policies in Democratic states may spur innovation in states where firms are headquartered rather than only the state where they operate. Given that large firms often operate across multiple states, with headquarters potentially differing from operational sites, the exclusion of Delaware does not ensure that all firms patent in the states where they operate. I include a population-weighted measure to address this concern and test the model's robustness to such spillovers. This measure compares states' population with Democratic governors to the total population across all states that year, aiming to capture interstate spillovers stemming from Democratic governance elsewhere. Results from Table 10 demonstrate that estimates remain robust even with the inclusion of population weights, with the estimates exhibiting a marginal increase in magnitude relative to the baseline estimates.

To further address the issue related to the treatment's location and the location of the patent, I consider the patenting activity of "*smaller firms*." The literature on firm size and innovation indicates that smaller firms have fewer resources to research and develop new technologies and, consequently, engage in lesser patenting activity (Phan & Siegel (2005); Link & Scott (2003); Coad et al. (2016)). It is also observed that smaller firms in specialized sectors often opt for state-level patent filings to comply with local environmental regulations and demonstrate adherence to industry standards within the state (Merges & Nelson, 1990). Further, De Rassenfosse et al. (2013) highlight that smaller firms are often cost-sensitive when it comes to patent filings and choose state or regional protection to manage expenses efficiently. I used data on firms with less than ten, five, and two patents in the 40 years of my analysis. This strategy follows the finding in the literature that smaller firms innovate less and are more likely to file for patents in the same state of their operations.

Table 11 and Table 12 present estimations of the effect of the Democratic governorship on smaller firms with less than 5 patents in 40 years. Unlike larger firms, which are major contributors to innovation, smaller firms exhibit lower elasticity to innovation incentives due to capital constraints. Consequently, one might anticipate a smaller magnitude of effect for smaller firms. The results suggest a positive effect of pro-environmental policies post-1992, consistent with findings for the total sample of firms. However, the magnitude of this effect diminishes to 3% - 6%.[55] Furthermore, I examine the robustness of this specification by including smaller firms in non-environmental patent analysis, as presented in Table 12. The results reveal a notable adverse effect on non-environmental patents among smaller firms, indicative of resource reallocation towards environmental technology. This finding aligns with the discussed theoretical predictions on stricter environmental regulations and that Republican leaders are more likely to implement a low-tax pro-market policy. Resource constraints would make the negative effect on smaller firms more significant. Comparing the results from the full sample and smaller firms shows that the

[55] I obtain similar results for firms with less than 10 patents from 1980-2019 and for firms which appear only once in all the years under consideration. I find that the direction of causality remains consistent across bandwidths with a marginal increase in the magnitude relative to firms with less than 5 patents.

effect on smaller firms is not only negative but that the results are robust across specifications for all years and post-1992, which is not the case for the sample including all firms.

2.4 Extended Analysis: Heterogenous Effects

The United States federal system grants significant authority to individual states when it comes to formulating policies related to climate and energy (Karapin (2020); Rabe (2011)). Pacca et al. (2021) show that contrary to the electoral incentives as in List & Sturm (2006), lobbying at the state level plays a crucial role in determining the environmental policy choice of the state governors. They find that the state's pro-environmental attributes, like the presence of green voters, encourage the increment in environmental spending at the state level. On the other hand, as states rely on employment opportunities and tax revenues generated by the fossil fuel industry, they tend to make concessions to those corporations.[56] Their findings are furthered by Bonnet & Olper (2024), which finds evidence of lobbying efforts in determining the deployment of renewable energy capacity in a state.

As an exogenous proxy for lobbying, I use several variants to capture the possible pro-environmental or anti-environmental policy effects. The proxies considered in this analysis include the environmental voting score (EVS) of the representatives at the House and Senate, the number of green voters in the state, the amount of oil reserves across states, and the production of coal per capita. To examine the possible effects of lobbying, I consider deriving a pro-environmental slant for the states under consideration. I consider states with lower than median coal and oil production per capita to have a more pro-environmental slant than those with production per capita greater

[56] For example, Cecil H. Underwood, a Democratic governor of West Virginia from 1997 to 2001, supported coal-friendly policies, including opposition to stricter environmental regulations, due to the state's heavy economic reliance on the coal industry (McGinley, 2004).

than the median. This demarcation follows from List & Sturm (2006) and also the construction of interaction terms for heterogenous RDD applications in Pacca et al. (2021) and Bonnet & Olper (2024). The application is intuitively plausible because states with high dependency on fossil fuel production, like coal, would tend to lobby against the imposition of stricter environmental standards. This nature is also evident in the EVS data from Congress. I divide the states in terms of higher percentage of green voters and higher EVS in the Senate and the House.

Figure 9 presents the non-parametric results for states with relatively higher pro-environmental characteristics to capture the plausible lobbying effects at the state level. All figures present the analysis from the sub-sample of post-1992 years. I begin by comparing the states where there is a difference in states' reliance on oil and coal. In states where there is a high dependency on oil, Democratic governors tend to have a negative impact on environmental patents. However, when the reliance on oil is low, there is evidence of Democratic governors increasing environmental patent applications.

Fredriksson et al. (2011) show that brown states have a slant in favor of anti-environmental policies; therefore, it can be expected that the influence of Democratic governors on environmental patents is either not significant or negative. I find that the effects in states where reliance on coal is high, there is no effect on Democratic governors. However, in states with less coal production and expectedly less lobbying against pro-environmental policies, I find that Democratic governors significantly increase applications in environmental patents (see Figure 9. ii). These findings are also in line with Pacca et al. (2021). Specifically, they use political contribution amounts from "Money in State Politics" to show that in states where polluting industries contribute significantly to their Gross State Production (GSP), the electorate lobbies against pro-environmental government. Lobbying leads to Democrats restraining their commitments and policy implementation to cater to the local demands. A pro-environmental slant in the states enables the Democratic governors to implement their pro-environmental policies without political hindrance and, therefore, observes significantly higher environmental patents. The effects of the variables indicating the states' pro-environmental electorate, like green voters, and the environmental voting score (EVS) from the Senate and the House are presented in the following figures. There is a positive and significant influence on environmental patents from states where the state representatives in the House have a higher environmental voting score and from those states where the percentage of green voters is relatively higher. Surprisingly, there is no effect in states where the representative senator voting is pro-environmental. This is possibly due to a small representation (2 people) from each state at the Senate.

2.5 Discussion: Politics to Environmental Patents

The presence of a Democratic governor in a state may impact patent applications in the environmental domain through various mechanisms. The literature focusing on the effect of party affiliation of the state governors on environmental policy (environmental spending) and environmental outcomes (air quality) suggests that Democratic governors demonstrate pro-environmental attributes. However, the channel through which party affiliation and environmental polarization affect innovative activity is not evident.

The mechanism may be classified into two broad channels. First, the democratic governors influence firms via policies that directly affect the costs of polluting firms. Firms react to policy changes or in anticipation of policy stringency. Further, the anticipatory effects of environmental liabilities could "*significantly influence firms to adopt environmental self-regulation,*" – suggesting that regulatory signals and market forces influence firms' innovation decisions (Segerson & Miceli, 1998). Democratic governors signaling a commitment to environmental sustainability create market expectations of future regulatory stringency and consumer demand for green products. In this line of thought, it is the Democratic governors' victory and their control over the state's environmental regulation that induces environmental innovation. Second, a higher prevalence of environmentally conscious voters would imply the selection of a pro-environmental governor in the state and thus complement the investments in environmental technology. In this line of thought, firms assess their potential market for environmentally higher quality products based on the consumers' environmental consciousness (Sengupta, 2015).

Empirical evidence favoring policy-induced development of environmental technology since Jaffe and Stavins (1995) suggests that government support and funding play a crucial role in stimulating innovation in environmental technologies at the national level. It can be expected that Democratic governors may induce environmental stringency or allocate resources towards R&D in green technologies through grants, subsidies, and tax incentives, encouraging firms to pursue patent protection for their innovations.[57] Such policies create a regulatory environment that fosters the development of environmentally friendly technologies, prompting firms to invest in research and development to comply with regulations and gain a competitive edge. These national policymaking activities create an expectation about the pro-environmental party when they come to power at the state level.

To verify the influence of the Democratic governors, I investigate the number of environment and energy-related state bills enacted by the governors and those that have been vetoed.[58] Table 13 represents the results of the estimating equation (1) using the number of laws

[57] The policy variable – environmental spending – used in the previous literature does not indicate or provide a direct measure for the incentive of firms to invest in environmental technology.

[58] The data are obtained from the website of National Conference of State Legislatures which provides information of all state bills passed in the legislatures and further adopted, enacted and vetoed by state governors. Here is the link: https://www.ncsl.org/energy/energy-state-bill-tracking-archive-2008-2022.

enacted and vetoed by the state governors. Panel A presents estimates on the number of laws enacted during a governor's tenure, and it shows that there is no effect of Democrat governors on the number of environmental and energy-related laws enacted in the state. However, in Panel B, I find that the presence of a Democratic governor significantly reduces the number of energy and environment-related bills vetoed. The results indicate that Republican governors diverge from the Democrats in environmental policy, vetoing significantly more bills in the environmental domain.[59]

Due to potential bias in assessing the level of stringency of these bills, I further investigate other policy stringency measures taken by the state governors. Note that Beland and Boucher (2015) found a decrease in air pollution levels under the administration of Democratic governors. This result can be connected to the findings of Innes and Mitra (2015), who demonstrated a notable decline in inspection rates in the year after the election of Republican representatives, thus indicating a relaxation of environmental stringency. I obtained data on the state governments' employment, specifically environmental employment, to proxy for policy stringency. I run a similar estimation as equation 1, with the outcome variable being full-time employment in the environmental sector for every 100,000 state residents annually. Table 14 shows an increase in the level of environmental employment and non-environmental employment when the governor of the state is a Democrat. However, the percentage increase in employment in the environmental domain is not only larger in magnitude than the non-environmental employment, but the estimates are consistent across all bandwidths. Additionally, note that the effect is more substantial in the years

[59] I only use the counts of such bills. Information on the extent of policy impact or level of stringency that each of these bills entails is not available in the form to be used in an empirical analysis.

post-1992, indicating that increasing polarization induces divergence in environmental stringency at the state levels.

I omit the year in which the elections occur to check if the results remain valid to the exclusion of the policy uncertainty of economic agents before the election period.[60] Consider the following illustration to support the requirement of this analysis. Suppose the incumbent governor of a state is a Republican and that most gubernatorial elections occur around November. At the beginning of the year, the innovating firms can be expected to comply with Republican governance. However, as previously discussed, economic agents react quickly in terms of innovative activities due to anticipatory effects, and the application of patents occurs early in the patenting process. Due to these effects, the market response could be erratic in the quarters preceding the election, especially when the elections are close, and anticipation is difficult. At the end of the year, if the elected governor is a Democrat, the market would begin to comply with the expected policies. As a result, given the combinations of possible scenarios, it is difficult to estimate the patenting behavior in election years, and the exclusion of it is expected to provide more robust results. Further, for closer victory margins (6%), where predictions of election results are complicated, I found that the increase in environmental patent applications is significant for all years (see table 7).

Table 15 and Table 16 present the result of estimating equation 1, excluding the election years for respective states. The results remain robust, excluding ambiguous behavior during the election year. For closer elections, I find the estimates show a significant effect of Democratic

[60] Canes-Wrone & Park (2012) argues that the policy uncertainty generated by elections encourages private actors to delay investments that entail high costs of reversal, creating pre-election reductions in the associated sectors. Further, Baker et al., (2016) finds that policy uncertainty tends to spike during periods of major political events, such as elections or changes in government leadership, and during times of economic crises or policy debates.

governors for the post-1992 years and the full sample. This effect also holds for smaller bandwidths of 7-10%. In Table 16, I run a placebo test, leaving out the election years for the expected ambiguous behavior. I check whether the current governor influenced the previous year's environmental patent application. I find some positive effects of the previous terms patents, but the results are not robust across the specifications. The positive effect is partly due to the incumbent Democratic governors in previous terms. Nonetheless, the magnitude of the effect is smaller than in the current year, complying with the central assertion that pro-environmental policies accelerate the initiatives in clean technology developments. Overall, the role of anticipation has been significantly negated by emphasizing closer elections, making it harder for economic agents to predict the election outcomes. In Figure 10, I present a non-parametric comparison of the current and lagged effects. There is a positive and significant effect in current years, demonstrating the impact of the incumbent Democratic governors in the current year compared to the previous year, where either Democratic or Republican governors may have been the governor.

Figure 10 further implements the mechanism through which the application of environmental patents may be affected. I repeat the non-parametric analyses using environmental employment per capita as the outcome variable. The results resound strongly with the findings of the potential lobbying effects in the states, as established in Figure 9. There has been a significant increase in state employment in the environmental domain, where the pro-environmental slant is strong. I find that states whose House and Senate representatives vote more in favor of environmental policies observe an increase in environmental employment when a Democratic governor wins the election. The same intuition follows for states less reliant on fossil fuels like coal and oil. Specifically, for states less reliant on coal, there is a significant increase in environmental employment. However, the effect is neutral for states heavily reliant on coal.

The empirical results suggest that the policy channel contributes to generating a difference in environmental patenting activity. The increase in stringency or the anticipated increase stringency when the Democratic party is in power in the state is notably more substantial than that when they are still contesting for it. However, the statistically insignificant yet positive effects before the elections render caution in completely revoking the pre-election effects arising from the innate pro-environmental slant of those states. Instead, the effects appear to be complementary. If the pro-environmental government wins the election, the governor acts as the facilitator for supporting further investments in the domain and provides a supportive environment. However, if the pro-environmental government does not win the election, firms do not expect to get similar support.

Conclusion

Most endeavors in constructing environmental patent data have been sector-focused or focused nationally. The data set used in this paper includes state-level patents from all industries. Using this comprehensive data, I find that the effect of Democratic governors on environmental patent applications has been positive in the post-1992 years. This finding coincides with the intensifying polarization between the Republicans and Democrats on environmental issues, indicating the effect of political polarization on the development of cleaner technology at the US state level.

The motivation for using application counts lies in understanding the short-run changes in the innovating firms' behavior. Specifically, the finding of a significant increase in environmental patent applications for a state during the tenure of a Democratic governor deems interest. It suggests that economic agents form their anticipations or beliefs from the commitments and actions of pro-environmental state leadership. While the engine for growth in environmental patenting activities is the pro-environmental slant of a state's electorate, I find that environmental policy commitments and regulatory stringency imposed by a Democratic governor further accelerate it relative to a Republican governor for that state.

This finding not only reflects the intensifying polarization between Republicans and Democrats on environmental issues but also highlights the tangible effects of this polarization on technological innovation aimed at sustainability. In a recent study in the context of the United States, Kirikkaleli et al. (2023) find that in the long run, patents in environmental technology cause a reduction in an ecological footprint. In that context, an increase in the count of environmental patents serves as a tangible measure of environmental policy outcome, which environmentally conscious voters could consider important in their voting choice. Although the states are heavily dependent on directions from the Environmental Protection Agency and limited in terms of the power of the purse to pursue extensive programs, the decentralized nature of the political system and the autonomy granted to the institutions allows states to pressure the center to act more conscientiously on environmental issues.

CHAPTER 3: Was the Green Technology Pilot Program (2009) successful in Knowledge Spillover in Green Technology?

Dibyajyoti Sinha[61]

3.1 Introduction

Fostering environmentally sustainable innovation has emerged as a pivotal goal for national and global environmental policies. Governments worldwide recognize the imperative of advancing “green” innovation to address environmental challenges while promoting sustainable development and economic growth (Smith, 2020). To accelerate progress in this area, numerous national intellectual property offices around the world (United States, United Kingdom, China, Japan, etc.) have implemented initiatives aimed at expediting the examination of “green” patent applications.[62] These programs share a common objective of prioritizing patents that advance environmentally beneficial technologies. By shortening the time for patent review (potentially from several years to just a few months), they aim to support quicker deployment and commercialization of green innovations (Jones, 2018).

On December 8, 2009, the United States Patent and Trademark Office (USPTO) announced the Green Technology Pilot Program (GTPP). It was designed to accelerate the examination of green technology patents. Specifically, the USPTO promised to reduce the review time by one year of the patent applications that satisfied certain criteria. Applications needed to be non-reissue, non-

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[62] For instance, the European Patent Office launched the PACE (Program for Accelerated Prosecution of Green Technology) program to fast-track patents related to environmental technologies (European Patent Office, 2012). Similarly, the Japan Patent Office has implemented the "Green Channel" initiative, streamlining the examination process for patents that contribute to environmental conservation and sustainability (Japan Patent Office, 2015).

provisional utility applications filed at the USPTO. Initially, only applications filed before December 8, 2009, were eligible, excluding any new applications filed after the program began. Additionally, eligible applications had to be classified within specific U.S. patent classifications (USPC) listed in the notice at the time of examination. They also needed to contain three or fewer independent claims, twenty or fewer total claims, and no multiple dependent claims. The program was initially planned to run for a year or until 3,000 grantable petitions were awarded. Ultimately, the program ran until the end of February 2012, when 3500 petitions were granted in total. Those petitions which entered after 3500 petitions were granted were not considered.

In this paper, I investigate whether the GTPP effectively stimulated the development of high-quality green technologies. The impact of fast-tracking review of patents on the quality of patents is ambiguous. On the one hand, fast-tracking green technology patents could improve the quality because inventors may invest more resources in developing these technologies. In particular, the shorter time for the review of applications increases the net present value of the patent. On the other hand, expedited reviews could result in unintended negative consequences. For example, quick reviews may impact the thoroughness of examination and potentially compromise patent quality. My analysis draws on existing literature that explores the relationship between expedited patent reviews and patent quality (Jaffe & Lerner, 2006; Frakes & Wasserman, 2017).

I use data on patent applications which participated in the GTPP to evaluate the effectiveness of the program. My analysis, using data from the USPTO's PatEx databases, shows that the number of green technology patent applications, as defined in the call for GTPP petitions, increases during the GTPP period. This effect, however, dies down a year after the program ended.

This result indicates that there has been a successful, though temporary, elevation in the trajectory of developments in cleaner technology.[63]

To estimate the impact of GTPP on the quality of patents, I use two measures. First, I use patent citations. The number of citations is considered as a measure of the quality of patents in terms of knowledge spillover. Further, I adjust the citation counts for the number of years since the patent was granted. Second, I use the probability of a patent being granted as a measure of quality. Specifically, this measure captures whether a successful petition in the GTPP increases the likelihood of that patent being granted. I find that, among the patent applications that petitioned to participate in GTPP, those that were successful were about 13 percentage points more likely to be granted relative to the unsuccessful petitions. Further, note that these effects are majorly driven by the small firms, as the large firms do not show any considerable change in the likelihood of patent grants conditional on the outcome of GTPP decisions. I find that if a petition is successful, the likelihood of the patent being granted increases by about 20 percentage points for small firms but there is no significant effect for large firms. These findings resonate with the results where I use patent citations as the quality measure. I find that, on average, patents with successful petitions tend to be cited more (about 20 percentage points), both by the applicant and the examiner. This increase could occur either because the program attracted higher quality applications or because participation in the program positively influenced the likelihood of the patents being granted.

[63] I use two separate definitions of "green" technology in this analysis. The first is the ex-ante listed classification codes in the call for GTPP petitions. The program initially required an application to be in one of those codes. However, this requirement is later relaxed to include other classifications. I show that the increase in the patent applications in this more broadly defined (ex-post approved) green technology classifications remain until the end of 2018.

In order to disentangle the mechanisms, I compare the successful petitions to an exclusive set of petitions which were rejected because the petitions were late.[64] Effectively, these petitions were not reviewed and therefore they were not rejected by USPTO because of their low quality. This analysis reveals that the average likelihood of patent grant for a successful petition remains higher than the those rejected due to late petition. However, these effects on the quality measures change when considering the period of GTPP after December 2010. In 2010, two crucial changes were made to the program. In May 2010, the environmental classification requirement was relaxed as it turned out to be too restrictive. The removal of the classification requirement was expected to increase the number of petitions but by the end of the year, the USPTO was far short of the targeted 3,000 successful petitions. In fact, only about 900 petitions were granted by November 2010. This led to the USPTO further dropping the criteria on the filing date, which restricted patent applications filed after December 8, 2009, to participate in the program.

I conduct the same analyses with a focus on Phase 3 (post December 2010 phase) of the program. I find that if the petition was successful in Phase 3, then the number of additional citations drops significantly (by more than 10 percentage points) relative to the citations to successful petitions in the earlier phases. This result is synchronous to the findings in the probability of grant and is consistent across several specifications. Specifically, when I compare the citations of successful petitions to the late petitions, I find that the patents with successful petitions in Phase 3 have lower citations than the rejected late petitions. In terms of patent grants, I find that petitions which were successful in the post December 2010 phase of the program are not very different from

[64] Note that the program ended after 3,500 successful petitions were granted. The remaining petitions were not considered by the USPTO.

the rejected late petitions. Therefore, success in the GTPP does not necessarily improve the likelihood of grant. There is a notable difference in quality in the different phases.

The above finding leads me to investigate the possible reasons behind the drop in quality measures in Phase 3 of the program. Not only did Phase 3 observe a higher number of petitions, but the proportion of petitions granted was also higher (see Figure 12). A possible explanation can be that examiners were rushed to meet the targeted number of petitions in Phase 3 which was missed by a large margin in the first two phases of the program. In that case, examiners workload would be higher because the data shows no increase in number of examiners in GTPP Phase 3. Therefore, I evaluate the effect of the examiners workload on patent quality by measuring the citations of those patents, whose GTPP petitions were reviewed when the examiner's review load was higher than their median load. The findings suggest a significant and negative effect of high desk-load on the patent quality. This effect is more prominent in Phase 3 of the program suggesting a possible rush to meet the target. The findings are in line with the empirical evidence from the literature of examiner review times and patent quality suggests that faster patent approvals can lead to an increase in patent grants but may not necessarily correlate with higher quality innovations (Hall & Helmers (2010); Frakes & Wasserman (2017)).

Overall, the results suggest that the GTPP boosted innovation in environmental technology (in terms of application counts) temporarily. This effect is significant given that the program itself was a pilot, and therefore, temporary in nature. However, the quality measures raise concern. There is no evidence that successful petitions are necessarily associated with patents with higher quality.

The rest of the paper is structured as follows: Section 2 provides a detailed overview of the GTPP, including its objectives, implementation, and subsequent modifications, followed by a discussion on the potential benefits of the program. Section 3 describes the data and methodology used in our analysis, highlighting the construction of the control group and the econometric models employed. Section 4 presents the empirical results, discussing the impact of the GTPP on patent grants and citations. Finally, Section 5 concludes the paper.

3.2 Program Overview: Green Technology Pilot Program (GTPP)

The GTPP was aimed at promoting environmentally beneficial technologies.[65] This program was designed to accelerate the examination of green technology patents, akin to the existing "Accelerated Examination" procedure. However, unlike other accelerated programs, the GTPP waived the fee typically required to attain "special status" or reduced review time. The program was slated to run for a year or until a targeted 3,000 grantable petitions were received, whichever came first. If fewer than 3,000 petitions were received by the end of the year, the program would terminate.

Several eligibility criteria were set forth to qualify for the program. Applications had to be non-reissued, non-provisional utility applications filed at the USPTO, or international applications that had entered the national stage. Initially, only applications filed before December 8, 2009, were eligible to participate in the program. This criteria excludes new applications filed after the program's inception. Furthermore, eligible applications needed to be classified within specific U.S. patent classifications (USPC) listed in the notice at the time of examination.[66] Additionally, they had to contain three or fewer independent claims, twenty or fewer total claims, and no multiple dependent claims. Further restrictions were more subjective, relying on the examiner's discretion to determine whether the patent substantially enhanced environmental quality through innovative

[65] The federal government notice is available here: Federal Register :: Pilot Program for Green Technologies Including Greenhouse Gas Reduction

[66] See here for the list of eligible classifications: Federal Register :: Pilot Program for Green Technologies Including Greenhouse Gas Reduction

technologies. As the program progressed, it became evident that the initial restrictions were overly stringent, prompting the USPTO to amend the GTPP to allow for more petitions. Figure 11 represents the timeline of patent filing dates of those applications which participated in the GTPP.[67] The figure shows that the earliest application dates for petitions were in January 2006. However, very few patents that were filed in 2006 or 2007 could participate in the GTPP because of yet another restriction, that is, the petition should have been filed before the First Office action of the examiners. In other words, if the examiners had already started reviewing the patent, then the application is no longer eligible to petition for the program.

Following an initial surge in petitions during the program's first month, the number of petitions declined sharply from December 2009 to May 2010 (see Figure 12). The blue shaded part of the bar indicates the proportion of the petitions granted whereas the yellow shaded part indicates petitions that were not granted. This decline can be attributed to challenges in defining and classifying "green" technology. Many submissions were dismissed or denied for not qualifying under the specified technology classification, which led the USPTO to broaden the eligibility criteria. From December 2009 to May 2010 (Phase 1), about 1000 petitions were made, averaging approximately 167 petitions per month. This contrasts with the 478 petitions made in December 2009 alone. When the classification restriction was removed in May 2010, there was an increase in petition filing leading to an additional 769 counts until November 2010 (Phase 2) (see Figure 12). Interestingly, the proportion of successful petitions also increased after this change – in Phase 1, 53% of the petitions were granted on average, however, in Phase 2, the average increased to 69%. There could be two possible reasons influencing this outcome. First, the erstwhile environmental classification was too restrictive, and the relaxation of which invited more quality

[67] Details on data construction and sources are discussed in section 3.3

petitions which need not restrict themselves to fit into the strict domain. Second, despite the increase in petitions following the removal of classification restrictions, participation in the GTPP was still below expectations. By November 2010, the program received 937 grantable petitions, which was far behind the anticipated 3,000 grantable petitions by December 2010. Consequently, on November 10, 2010, the USPTO announced further changes to the GTPP, extending the program's deadline to December 31, 2011, or until 3,000 petition applications were accepted. Further, it also allowed applications filed on or after December 8, 2009, to participate in the program. This extension led to a dramatic increase in requests, with an additional 3,725 petitions (including re-petitions from earlier dismissals) being filed from December 2010 to March 2012 (Phase 3), when the program ended. Notably, the grant rate remained almost the same as Phase 2.

USPTO Director David Kappos, at a press conference indicated that the Green Technology Pilot Program "*will see a significant savings in pendency*" by approximately twelve months.[68] Summary statistics in Table 18 indicate that this prediction was very precise. Petitions that were successful in the GTPP took about 330 days less to be granted compared to those that applied for the program but were not successful. There are numerous benefits associated with a reduced examination process for patents. Faster patent grants can lead to faster market entry, which can further lead to earlier adoption of eco-friendly technologies, contributing to environmental sustainability. Second, having a granted patent can enhance their ability to attract private capital, as investors are more likely to fund projects that have secured intellectual property rights (Lane, 2012). Consequently, fast-track schemes for green patents are anticipated to accelerate the diffusion of clean technologies via knowledge spillover, which is essential for broader

[68] The USPTO press release can be obtained here: https://dir.commerce.gov/node/11670.html

environmental and economic benefits (Dechezleprêtre et al., 2011). The expedited process can also reduce costs associated with prolonged patent examinations, making it more feasible for smaller firms to innovate and compete. These advantages align with the findings that indicate faster processing times can stimulate technological innovation and dissemination (Jaffe et al., 1993; Popp, 2006) .

There exists a trade-off in the sense that the time allocated to review patent applications could induce examiners to grant lower quality patents (Frakes & Wasserman, 2017), which could potentially hurt the intent of the program. Several instances point towards the idea that the GTPP was designed in order to provide sufficient time for review. The program was capped at 3000 petitions and resources were dedicated to employ examiners specifically for the review of the GTPP petitions. Interestingly, the number of claims for patent application was also restricted. For instance, the number of independent claims was restricted to 3, whereas the total number of claims was restricted to 20. Further, the program restricts the number of multiple dependent claims to zero. Claims define the boundaries of an invention and indicate what the property rights cover in legal terms. The number of claims therefore indicate towards the content matter of the patent and increases time to review a particular patent. Restricting the number of claims, therefore, is in the light of reducing the time burden of individual examiners. Considering that the USPTO had prescribed a list of USPC classification codes for eligibility also hints towards a reduction in review time. The latter is evident as most of the initial applications were dismissed on the grounds that they did not meet the classification codes criteria. Finally, considering that the resources were allotted to review 3000 petitions in one year, which finally ended up extending to a little more than two years, indicates that it is unlikely that the review process may not have been intended to rush, but Phase 3 of the program saw three times more petitions than Phase 1 and Phase 2 combined. However, the number of petitions reviewers, according to the data, was lower in Phase 3.

3.3 Data and Methodology

3.3.1 Data

The dataset consists of information about individual patent applications at the USPTO. This information is retrieved from the USPTO's Patent Examination Research Dataset (PatEx) database.[69] These data include the application number, the date of filing, and whether and when the patent was granted. It also includes information on the pre-grant publication of the patent, the inventor and their country of residence, the firms and an indicator for the size of their operation, and the examiner and examiner's technological unit.

The dataset consists of all patent applications at the USPTO from 1980 to 2018. The specific years from 2006 to 2013 are selected to evaluate the effectiveness of the GTPP which ran from December 2009 to March 2012. Although the program begins in December 2009, only those patents which were filed before December 8, 2009, were eligible to participate in the GTPP. Therefore, inclusion of those years in the data is essential in which the patent application was filed, and later those applications also petitioned under the GTPP. As the GTPP petition with the earliest filing date is in January 2006, it necessitates the inclusion of year 2006 in the analysis.[70] There are about 2.7 million patent applications from 2006 to 2013, and among them 67% are eventually granted (see Table 17). It takes on average about 1200 days or about 3.25 years for a patent review to be completed. The average number of claims in patent applications is about 19, and among them, independent claims average around 3. Note that these average figures for the number of

[69] The data are available at: Patent Examination Research Dataset (PatEx) | USPTO

[70] The following paragraph discusses how the information on patents which participated in the GTPP were retrieved.

claims fall within the eligibility criteria set forth in the GTPP. About half of the inventors are reside in the United States and a quarter of the patent applications come from small firms. The information on the small firms is deemed important as the small firms likely benefit more from the program than the larger firms who have relatively more resources to acquire patents from high quality inventors and appoint experienced attorneys.

The data on GTPP comes from the USPTO's Open Data Portal (ODP).[71] Applicants were required to file form PTO/SB/420 to participate in the GTPP.[72] This petition application form is classified under USPTO document code "PET.GREEN" in its Image File Wrapper (IFW) database.[73] The documents in the "cms_documents" folder identifies the petition application form ("PET.GREEN") and the decision notice ("PET.DEC") for each individual application. This includes about 6,500 petition application documents. From each document, I extract information related to the petition decision. I obtain the date in which the petition was filed, the name and technological unit of the petition examiner, the decision on the petition, and the reason for dismissal or denial of the petition.[74] Table 18 summarizes the data related to the application and decisions on the GTPP petitions.[75] I find that successful petitions in the GTPP were more likely to be granted on average. This might happen either due to the program receiving higher quality applications or because the program had some favorable effect in the eventual grant of the patents.

[71] All documents, allowed to make public and related to the patent applications can be retrieved from this database: https://beta-data.uspto.gov/search

[72] The form can obtained here: https://omb.report/icr/201005-0651-001/doc/17380701

[73] Link to the Image File Wrapper: https://www.uspto.gov/patents/apply/filing-online/efs-info-document-description

[74] Note that the petition examiner is different from the patent examiner.

[75] However, not all these applications are unique as some of the applications include multiple entries of the same information. Upon cleaning of the data, there are 5,497 unique entries which are either granted, dismissed or denied.

One of the key challenges in evaluating the effect of the program is that the total number of patent applications in the dataset is ~2.7 million, while that in the GTPP is about 4,500. Therefore, I use the participation conditions listed in the GTPP notice to construct a comparable group. First, I remove non-utility, reissue and provisional patents. Second, the GTPP defines a petition to be an eligible only if the application's United States Patents Classification (USPC) codes match the environmental technology classification listed in the notice. The PatEx dataset includes the USPC codes of all patent applications, including the main-class and the sub-class. However, 3% of the patent classification code from the data match this initial list published by the USPTO, and only 15% of the GTPP petitions had the exact USPC codes as listed in the program. I name the patent applications which fall under this classification as "listed codes". The summary statistics in Table 17 indicate that patent applications under the listed codes tend to have lower grant rates and take longer time to review on average. As discussed in section 2, many petitions which were non-compliant with the listed codes were rejected, and it led to a slowdown in the program application. This slowdown eventually led to the removal of the classification criteria in May 2010. Therefore, I further narrowed down the list of patent applications by using the USPC codes of those patents whose petitions were successful in this program. I name this variable "approved codes", which consists of the family of USPC codes which the examiners considered as a green patent. Table 17 shows that the approved codes restrict the sample to about 260,000 observations (~10% of the total applications) which are potentially a technological advancement in the environmental domain.

The information on the number of claims of a patent is derived from the USPTO PatentsView database.[76] The number of claims is subjected to review by the examiners, and are

[76] The data on claims can be obtained here: https://patentsview.org/download/data-download-tables

therefore, different from when the application is filed and when the patent is ultimately granted. The number of claims may change several times during the review period. However, the database provides information on the number of claims made during the pre-grant publication and when the patent is issued.[77] Table 17 shows that the average number of claims is typically lower in the granted patents and in the pre-grant publications. This is due to the review of the examiners who evaluate the validity of the claims and may suggest revision or removal. The number of claims holds importance as it draws the legal boundaries of the patent. The number of claims in a patent adds to the complexity and time required for thorough examination, thereby increasing the review time. Further, the number of claims indicates the dimensions of intellectual property rights within the patent and potentially draws a greater number of citations when the number of claims is higher in general. The number of claims has also been used as a measure of quality in the patent/innovation literature (Dechezleprêtre et al., 2013).

A common proxy measure for the quality of patents is the number of citations made to the patents, justified on the grounds that higher citations indicate the applicability and relevance of the patent being cited (Jaffe & Rassenfosse, 2019). Citations indicate the knowledge spillover from the patent, the information of which leads to the advancement of technology (Dechezleprêtre et al., 2013). I obtain information on the citations made to the patents from the USPTO's PatentsView database.[78] The data allows to distinguish between the citations made by the examiner and everyone else. Since the examiners in the GTPP are also examiners in the USPTO, there is a chance that the examiners could influence more referrals to the patents that passed the GTPP review. I construct the variable "forward" which measures the total citation counts made by other patents.

[77] The claims in both phases of the review are available in separate files for each year from which the number of independent, dependent and multiple dependent claims can be computed.

[78] The data on citations can be obtained here: https://patentsview.org/download/data-download-tables

Then, I use the identifier whether the citation was made by the examiner to create "forward examiner citation" variable. Lastly, I adjust all variations in the citation measures by the years since the patent issue. Table 17 summarizes the information on these variables and shows that the citation counts are relatively higher for those patents which participated in the GTPP.

The information on the inventor and assignee of the patent is also obtained from the USPTO's PatentsView database. While the inventor is typically an individual, the assignees are mostly firms and organizations which acquire the patents from the inventors. I mapped the information of the inventor and assignee of the patent to the list of patent applications in the PatEx database. Although more domestic inventors participated in the GTPP (74%), foreign-inventors were more successful (see Table 17 and Table 18). I also find that large firms tend to have more successful petitions even though smaller firms' participation in the GTPP was higher than their average trend in patent filings. It is to be noted that the proportion of domestic small firms which participated in the program (43%) was much higher than the foreign small firms' participation (18%), which again refers to the fact that patenting process itself might be costly and small firms from different countries may not have the resources to participate in the GTPP.

3.3.2 Empirical Strategy

To estimate the effectiveness of the program in terms of increasing green innovation, I estimate the following baseline specification for the sample of applications from the year 2005 to 2018:

$$\mathrm{Applications_{it}} = \alpha + \beta_{1it}.\,\mathrm{green\_code_{it}} + \beta_{2it}.\,\mathrm{green\_code} * \mathrm{year_{it}} + \varepsilon_{aikt} \ldots\ldots (\mathrm{Eq.}\,1)$$

The outcome variable is the number of applications in a given USPC subclass "i", in year "t". Note that there are about 60,000 unique subclasses in this panel, among which the listed codes and approved codes are represented by the "green codes" variable and interacted with the year. I estimate the effect on applications separately for the listed codes and approved codes. I also conducted an event study analysis to determine the contribution of the green classifications on the overall patent application trends, specifically after the inception of the GTPP.

To estimate the quality effects of GTPP, I estimate the following specification over the sample of patent applications that petitioned for the GTPP:

$$\begin{aligned}
Y_{aikt}|_{\text{petition applied}=1} \\
&= \alpha + \beta_1.\text{successful petition}_{aikt} + \beta_2 Z_{aikt} + \gamma_i + \phi_k + \delta_t \\
&+ \varepsilon_{aikt} \qquad \ldots\ldots (\text{Eq. } 2)
\end{aligned}$$

The outcome variable Y_{aikt} stands for quality measures like whether the patent was eventually granted or not, and citation measures including the adjusted forward citations, adjusted forward citations by patent examiners, and adjusted forward citations by non-examiners. The citation variables measure knowledge spillovers. The index "a" refers to an individual patent application, "i" to the broad technological field captured by the USPC class, "k" refers to the petition examiner and "t" refers to the month-year of the petition and application. The main independent variable is "successful petition", which is dummy for the success of the patent in the GTPP. The vector Z_{aikt} includes several controls related to the patent quality such as the number of independent and dependent claims and whether the patent's classification falls under the environmental classification listed in the program notice or, in short, the listed codes. ϕ_k is the USPC class fixed effects. δ_t captures the month and year fixed effects, and γ_i is the examiner fixed effects. This specification allows me to compare two identical patent applications (in that they both petitioned for GTPP and are in the same broad technological field reviewed by the same examiner in the same month), except that one of them was accepted into the accelerated GTPP program while the other was not. Thus, the identification assumption is that getting into GTPP conditional on the control variables is as good as random.

In Phase 3, not only the number of petitions but also the proportion of granted petitions was higher. This could be because the petitions in Phase 3 were of higher quality. To investigate whether this is indeed the case, in another specification, I include the interaction of Successful Petition dummy with Post-Dec2010 indicator, as displayed in the equation below:

$$\begin{aligned} \mathrm{Y_{aikt}}\big|_{\text{petition applied}=1} &= \alpha + \beta_1.\,\text{successful petition}_{\text{aikt}} + \beta_2.\,\text{PostDec2010} * \text{successful petition}_{\text{aikt}} \\ &+ \beta_3 \mathrm{Z_{aikt}} + \gamma_{\mathrm{i}} + \phi_{\mathrm{k}} + \delta_{\mathrm{t}} \\ &+ \varepsilon_{\text{aikt}} \qquad \ldots\ldots (\text{Eq. }3) \end{aligned}$$

The other possible explanation for the higher proportion of granted petitions in Phase 3 could be the examiner review times. Because the number of petitions increased dramatically in this period, the workload of examiners also rose, as no additional examiners were assigned to GTPP evaluations. The hypothesis is that the reduced review time affects the quality of the patent being granted. I test this hypothesis by running the regression below:

$$\begin{aligned} \mathrm{Y_{aikt}}\big|_{\text{petition applied}=1} &= \alpha + \beta_1.\,\text{successful petition}_{\text{aikt}} + \beta_2.\,\text{PostDec2010} * \text{successful petition}_{\text{aikt}} \\ &+ \beta_3.\,\text{PostDec2010} * \text{High Load} * \text{successful petition}_{\text{aikt}} + \beta_4.\,\text{PostDec2010} \\ &* \text{High Load}_{\text{aikt}} + \beta_5.\,\text{High Load} * \text{successful petition}_{\text{aikt}} + \beta_6.\,\text{High Load}_{\text{aikt}} \\ &+ \beta_7 \mathrm{Z_{aikt}} + \gamma_{\mathrm{i}} + \phi_{\mathrm{k}} + \delta_{\mathrm{t}} \\ &+ \varepsilon_{\text{aikt}} \qquad \ldots\ldots (\text{Eq. }4) \end{aligned}$$

where High Load indicates whether the examiner had more than the median number of petitions in her/his desk in a certain month. This variable is based on the number of petitions that were awaiting review by each examiner.

3.4 Results

3.4.1 Effects on Quantity

The application trends of the two plausibly environmental technology classification groups discussed above – the listed codes and approved codes – are illustrated in Figure 13 and Figure 14. The figures represent the number of patent applications filed in these classifications against all other patents, every quarter, from the year 2000 to 2018. Both figures indicate that there has been an increase in the number of applications in the field of green technology since the beginning of the sample period. The applications in these domain surpass the average trend in all other non-green patents during the GTPP. However, the increasing trend settles down over the next few years to catch up with the general patenting trends. In the light of this evidence, I investigate if the GTPP was successful in driving and sustaining the development of new technologies in the last decade. The estimation results from Eq. 1 is presented in Table 19 and the event study results are illustrated in Figure 15 and Figure 16, which shows the time coefficients of the listed codes and approved codes, respectively. As is evident from the results, the GTPP led to a temporary surge in the listed codes that were initially included in the notice. This is possibly due to the temporary nature of the program. However, for the approved codes, which includes a less restrictive set of USPC subclasses, the effect is significant and sustained until 2018. This result signifies that the program overall had a positive effect on the aggregate dissemination of green technology.

3.4.2 Effects on Quality

Table 20 and Table 21 presents estimates obtained from Eq. 2 and Eq. 3. These estimations include all patent applications that participated in the GTPP. All estimates control for the number of independent and dependent claims, a dummy capturing whether the patent classification is included in the listed codes, and a host of fixed effects including filing month, petition month, examiner and USPC class. Standard errors, clustered at the USPC class level, are included in parentheses. I also run regressions where I restrict citations made by patent applicants only, thus excluding citations added by patent examiners, which might not capture knowledge flows to individual applicants. Note that patent citations capture not only knowledge spillovers but also patent value, so our regressions include controls for patent value such as the number of claims.

The results indicate that the patents which were successful in the GTPP tend to have higher citations. The coefficients on the claims are positive and significant, indicating that patents with a higher number of claims also have higher citations. The average adjusted citation count for those patents which participated in the GTPP is 1.382. On average, the success at the GTPP increases the citation counts by 0.27 above those that were unsuccessful. However, when I compare the estimation results of the petitions that were successful in the post December 2010 period, I find that the latter tend to be of lower quality. Table 21 shows that patents with successful petitions still receive higher citations than unsuccessful ones but the effect on citation counts drop from 0.27 to 0.1 counts. These results are consistent for the examiner and non-examiner citation. Notably, examiners tend to cite more if the patent's classification falls under the listed codes of the GTPP even in the future when the program ended.

Table 22 presents the same estimation results from Eq. 2 and Eq. 3 but with a subsample of small and large firms. The results indicate that the full sample results are mostly drawn by the small firms participating the GTPP. The small firms receive relatively more citations when their GTPP petition is granted. However, the effect is smaller for larger firms. The post December 2010 effects are negative for the small firms and larger in magnitude. This finding indicates that there is little difference between the quality of the patent applications that were granted or denied GTPP petitions in Phase 3 of the program. These estimates are insignificant for large firms, though the direction of the estimates is similar to the small firms. The results suggest that success at GTPP might be more beneficial for the smaller firms than the larger ones.

Towards the end of the program about 250 petitions were denied because the program reached the target of 3,500 petitions (see Figure 11). These petitions were rejected without review. As the petitions were rejected without review, they serve as a strong comparison group for judging the quality of the patents that were successful in the program. The quality of these rejected petitions is unknown. Table 23 presents the estimates of regressing Eq. 3 with successful petitions and a subsample of unsuccessful petitions that were denied due to the program closure. The results show that the successful petitions were of higher quality than those rejected due to the deadline. However, upon comparing the successful petitions in Phase 3, it can be observed that the successful ones get cited less. Although of much smaller magnitude, the examiners tend to cite more of the patents that were rejected due to the deadline in the GTPP. The findings indicate that successful petitions in the GTPP may not have been of higher quality, especially in Phase 3 of the program.

To verify the findings in terms of quality, I also check for the likelihood of the patents being granted, conditional on participation in the GTPP. Table 24 presents the same estimation from Eq. 2 and Eq. 3 where the outcome variable is the likelihood of the patent being granted. The estimation results remain very similar to those of citation counts. This is true for the comparison of small and large firms as well (see Table 25). Therefore, the observed decline in quality measures during Phase 3 prompted an investigation into its potential causes. This phase not only experienced a surge in petition numbers but also saw a higher grant rate. One plausible reason is that examiners might have been pressured to meet the petition targets, which were significantly unmet in the initial phases.

3.4.3 GTPP Examiner Desk Loading

I assess the impact of examiner workload on patent quality by examining citations for patents reviewed during periods of high examiner load. High examiner load implies that an individual examiner had more than the median number of petitions on her desk in a given month. Note that the examiners desk-load was typically higher in Phase 3 of the program, that is, after December 2010 (See Figure 17). Table 26 presents the estimation results from Eq. 4. The outcome variable in Table 26 are the adjusted citation measures. Although high desk-load for the examiners does not significantly affect the citation measures alone, the petitions that were successful in the GTPP when examiners desk-load was high, tend to have significantly lower citations. This result is indicative of some evidence that the examiners might have been rushed in Phase 3 of the program. In this rush, some petitions which would have been otherwise rejected in Phase 1 or Phase 2 of the program, are accepted in Phase 3, thus leading to lower quality outcomes. The results align with empirical evidence suggesting that expedited patent approvals can lead to more grants but do not necessarily correlate with higher quality innovations (Hall & Helmers, 2010; Frakes & Wasserman, 2017). Table 27 presents the estimates of the estimation results from Eq. 4 including the interactions of the Phase 3 time-dummy. The results show negative and significant effects on successful petitions from Phase 3 that were passed when the examiner’s desk-load was high, thus strengthening the hypothesis. In Table 28, I present the estimation results on small and large firms to explore the effects of examiner desk-loading. The results are mostly insignificant though similar in direction to that in Table 22. Similar to the previous result, there is a negative effect on citations of successful petitions from Phase 3 that were passed when the examiner's desk-load was high.

Lastly, I check for the examiner load effects on the likelihood of the patent being granted, to find that successful petitions that were passed when examiner's desk-load was high has lower likelihood of getting granted relative to those that were successful when the examiner's desk-load was not high (see Table 29). Comparing with those petitions rejected due to the program deadline, I find that high desk-load reduces the probability of the grant as it was the case for patent citations.

Conclusion

I conduct an examination of the Green Technology Pilot Program (GTPP) implemented by the United States Patent and Trademark Office (USPTO) in 2009. I study the program's objectives, implementation, and the resulting patent quality using citations and grant likelihood. To understand the effects of the GTPP, I utilized patent data from USPTO's PatEx database. I focus on patent applications between 2006 and 2013, with particular attention to applications that participated in the GTPP. By examining patent quality through forward citations and grant probability, I aimed to uncover the implications of accelerated examination procedures on innovation outcomes.

The findings reveal that while the GTPP did lead to a temporary increase in the dissemination of green technology, there were notable concerns about patent quality. Successful petitions in the program were associated with higher grant rates and citation counts, especially for small firms. However, in Phase 3, when the program saw a surge in petitions, the quality of granted petitions declined. This suggests that the rush to meet petition targets may have compromised thorough examination. Therefore, I explore the hypothesis that increased examiner workloads during the program, particularly in Phase 3, might have led to rushed reviews and potentially lower patent quality. The results are indicative of an association of lower quality of patents with examiner workload. The implications highlight the need for balanced approaches that ensure both timely and thorough patent examinations to foster technological advancement. However, it is to be noted that the workload estimation is limited to GTPP only. These examiners may be working on other patents, the effort or workload of which is not discernable from the available dataset.

APPENDIX I: PROOFS

Appendix A.0: Restriction on clean technology adoption without environmental support:

Without any form of environmental support from the regulator, the polluting monopolist would adopt clean technology if the expected profit from the clean type is greater than remaining dirty:

$$\mu \Pi_C^{FI} + (1-\mu)\Pi_D^{FI} \geq \Pi_D^{FI}$$

$$\Rightarrow \Pi_C^{FI} \geq \Pi_D^{FI}$$

$$\Rightarrow \frac{(a\rho - m_C)^2}{4\rho} \geq \frac{(a - m_D)^2}{4}$$

If there is no environmental consciousness among the consumers, the marginal cost criteria ($m_C > m_D$) is sufficient to deter adoption of clean technology. To prove the statement, let us impose a restriction where $\rho \to 1$, such that the effect of higher willingness to pay for the clean type is removed. We get: $(m_D - m_c)(2a - m_C - m_D) \geq 0$, which implies that $m_C < m_D$ for this condition to hold as $2a > m_C + m_D$. Therefore, when the environmental consciousness is low, it is not profitable for the monopolist to invest in clean technology without regulatory support. However, when the environmental consciousness is high, there is incentive to adopt clean technology.

$$\Rightarrow (a\rho - m_C)^2 \geq \rho(a - m_D)^2$$

$$\Rightarrow a\rho - m_C \geq \sqrt{\rho}(a - m_D)$$

$$\Rightarrow m_C \leq \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)$$

If the marginal cost of the clean technology is sufficiently low, the polluting monopolist may invest in adopting the clean technology depending on the level of environmental consciousness of the consumers, the choke price, and the marginal cost of the dirty type. To focus on the scenarios where the role of environmental support is imperative, the model is restricted in the following manner:

$$a \geq m_C \geq \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right) \geq m_D$$

The marginal cost of clean technology is not only higher than the dirty type, but also the difference in the marginal costs are large enough to deter the polluting monopolist from adopting clean technology on its own.

Appendix A.1: Proof of Proposition 1.

The polluting monopolist would adopt clean technology if the expected profit from the clean type is greater than remaining dirty:

$$\mu \Pi_C^{FI} + (1 - \mu)\Pi_D^{FI} \geq \Pi_D^{FI}$$

$$\Rightarrow a^2\rho(\rho - 1) - \rho m_D^2 + 2a\rho(m_D - X_c) + X_C^2 \geq 0$$

If $(X_c - m_D) \leq 0$, then the expression holds true. $X_c \leq m_D$ implies that the effective marginal cost of the clean type is less than the dirty type and it turns out to be a sufficient condition for the monopolist to adopt cleaner technology. This is possible due to the followings conditions: *i)* $\rho \in (1,2)$, *ii)* $a > m_C > m_D$. To prove the statement, let us impose a restriction where $\rho \to 1$, such that the effect of higher willingness to pay for the clean type is removed. Even under this condition, we get: $(m_D - X_c)(m_D + X_c + 2a) \geq 0$. Thus, without any influence of environmental consciousness, $X_c \leq m_D$ is a sufficient condition for the polluting monopolist to adopt cleaner technology. However, $X_c \leq m_D$, may not be a necessary condition due to the higher willingness to pay for the cleaner product. The highest value of X_C for which the monopolist would adopt cleaner technology: $X_C = \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)$. Here, we make a restrictive assumption that the marginal cost of the clean type is sufficiently large: $m_c > \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)$. The expected profit from investment depends on the difference in the marginal cost $(m_D - X_c)$, and the relative size of the market and choke price (a). A lower difference in the marginal cost and higher choke price increases the expected profit from investment.

Therefore, to achieve the level of X_C, the Green party needs to commit a minimum subsidy of:

$$s_{FI} = \frac{1}{\beta}\left[m_C - \left(\sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)\right)\right]$$

Where $s_{FI} < s^R$, as $\sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right) > m_D$. The polluting monopolist could adopt cleaner technology profitably without the commitment of $s \geq s^R$. However, for the subsidy commitment to be effective, the consumer surplus from the clean type needs to be higher under the clean type than the dirty type. Therefore, we need to check if the subsidy to the clean type is sufficient for the consumers to experience an increase in their surplus.

$$CS^{FI}_{Clean} \geq CS^{FI}_{Dirty}.$$

$$\Rightarrow a^2\rho^2 - X_C^2 \geq \rho(a^2 - m_D^2)$$

$$\Rightarrow X_c = \sqrt{\rho(a^2(\rho - 1) + m_D^2)}$$

Again, to achieve this level of X_C, the Green party needs to commit a minimum subsidy of:

$$s^*_{FI} = \frac{1}{\beta}\left[m_C - \sqrt{\rho(a^2(\rho - 1) + m_D^2)}\right]$$

$s_{FI} \geq s^*_{FI}$ under the condition that $\rho \geq 1$. This ensures that the minimum effective subsidy is the lowest subsidy commitment required to incentivize the polluting monopolist to adopt cleaner technology. $s_{FI}^{*} \geq s^{R}$ is the necessary and sufficient condition for the partisanship to hold and generate voter support.

Appendix A.2: Proof of Proposition 2.

Proposition 1 follows from the following characterization of the equilibrium.

Lemma 1:

For any $s \leq s^{R}$, the unique separating equilibrium price are:

$$P_D^* = P_D^{FI} \quad and \quad P_C^* = max\{P_C^{FI}, P^U\}$$

where P_D^* and P_C^* are the equilibrium price charged by the dirty type and the clean type respectively, and

$$P^U = \frac{(a\rho + m_D)}{2} + \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}.$$

For any $s \geq s^{R}$, the unique separating equilibrium price are:

$$P_D^* = P_D^{FI} \quad and \quad P_C^* = min\{P_C^{FI}, P^L\}$$

where P_D^* and P_C^* are the equilibrium price charged by the dirty type and the clean type respectively, and

$$P^L = \frac{(a\rho + m_D)}{2} - \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}.$$

Proof

The ICC of the clean type requires that it does not earn higher profit when it imitates a dirty type, and this is possible when clean type charges a price P_c such that the ICC of a clean type is satisfied. ICC of the clean type requires that the clean type can be better off without mimicking the dirty type's price:

$$\pi(C,1,P_c) > \pi(C,0,P_D^{FI})$$

$$\Rightarrow (P_C - X_C)\left(a - \frac{P_C}{\rho}\right) > (P_D^{FI} - X_C)\left(\frac{a-m_D}{2}\right)$$

$$\Rightarrow P_c = P_C^{FI} \pm \frac{1}{2}\sqrt{(a\rho - X_c)^2 - \rho(a-m_D)(a+m_D-2X_C)}$$

The bounds of P_c are such that any price in this range yields greater profits for the clean type, over and above setting the full information price of the dirty type. $\overline{P}$ and $\underline{P}$ serve are the upper and lower bounds of the price (P_c) that the clean type could charge. Also, note that $P_C^{FI} \in \left(\underline{P}, \overline{P}\right)$.

$$P_c = \begin{cases} \overline{P} = P_C^{FI} + \frac{1}{2}\sqrt{(a\rho - X_c)^2 - \rho(a-m_D)(a+m_D-2X_C)} \\ \underline{P} = P_C^{FI} - \frac{1}{2}\sqrt{(a\rho - X_c)^2 - \rho(a-m_D)(a+m_D-2X_C)} \end{cases}$$

A dirty type has no incentive to mimic the clean type if the clean type charges a price such that the dirty type does not earn higher profit when it imitates a clean type. The incentive compatibility condition when the dirty type mimics the clean type:

$$\pi(D,0,P_d^{FI}) > \pi(D,1,P_c)$$

$$\Rightarrow (P_D^{FI} - m_D)\left(\frac{a-m_D}{2}\right) > (P_C - m_D)\left(a - \frac{P_C}{\rho}\right)$$

$$\Rightarrow P_c = \frac{(a\rho + m_D)}{2} \pm \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

The range of price under which the dirty type could imitate the clean type are:

$$P_c = \begin{cases} P^U = \frac{(a\rho + m_D)}{2} + \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)} \\ P^L = \frac{(a\rho + m_D)}{2} - \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)} \end{cases}$$

where $(\rho - 1)(a^2\rho - m_D^2) > 0$ as $\rho > 1$ and $a > m_D$. Note that when the subsidy commitment is low ($s \leq s^R$), $P^U < \overline{P}$ and $P^L < \underline{P}$. This implies that there is an overlap between the ICC of the clean type and the dirty type. The best response of the clean type is to charge the full information price: P_C^{FI}; however, the pricing strategy is limited by the bounds of the ICC. The clean type can either charge a price: $P_c \geq P^U$ or $P_c \leq P^L$ given that $P_c \in (\underline{P}, \overline{P})$. As the subsidy commitment (s) increases, P_C^{FI} decreases and beyond a certain level of s, $P_C^{FI} < P^U$. Specifically, $P_C^{FI} < P^U$ where:

$$X_C - m_D < \sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

The clean type charges $P_c = P_C^{FI} > P^U$ when the full information price is higher than P^U, or $P_c = P^U$ otherwise. On the other hand, as $P^L < \underline{P}$, the clean type cannot charge $P_c \leq \underline{P}$ as that would imply that the clean type finds it profitable to mimic the dirty type. The equilibrium price can be expressed as: $P_C^* = max\{P_C^{FI}, P^U\}$, for any $s \leq s^R$. Effectively, P^U serves as the minimum upward signaling distortion price for the given range of subsidy commitment. Similarly, when the subsidy commitment is high ($s \geq s^R$), $P^U > \overline{P}$ and $P^L > \underline{P}$. The clean type can charge a price: $P_c \leq P^L < P^U$ given that $P_c \in (\underline{P}, \overline{P})$. Note that when $P_C^{FI} > P^L$:

$$X_C - m_D > \sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

the clean cannot reveal its type by charging a higher price than P^L. The clean type charges $P_c = P_C^{FI}$ when the full information price is lower than P^L, or $P_c = P^L$ otherwise. The equilibrium price can be expressed as: $P_C^* = min\{P_C^{FI}, P^L\}$, for any $s \geq s^R$. Effectively, P^L serves as the minimum downward signaling distortion price for the given range of subsidy commitment.

The individual rationality constraint (IRL) of the dirty type ensures that the dirty type charges its full information price (P_D^{FI}) because it is common knowledge that the dirty type did not adopt cleaner technology and that the clean type would distort price to signal its type. Charging a price other than P_d^{FI} would only reduce the dirty type's profit: $\pi(D, 0, P_d^{FI}) \geq max{:}\, \pi(D, 0, P)$. The IRL of the clean type is satisfied if the price in signaling distortions lies within the ICC:

$\overline{P} \geq P^U \geq \underline{P}$ $\;when\;\; s \leq s^R$ and $\overline{P} \geq \mathrm{P}^{\mathrm{L}} \geq \underline{P}$ $\;when\;\; s \geq s^R$.

Appendix A.3: Proof of Proposition 3.

From Lemma 1, we have $P_C^* = max\{P_C^{FI}, P^U\}$, for any $s \leq s^R$. Note that the clean type distorts price when $P_C^{FI} \leq\; P^U$ for any $s \leq s^R$.

$$P_C^{FI} \leq\; P^U \Rightarrow \frac{a\rho + X_c}{2} \leq \frac{(a\rho + m_D)}{2} + \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

$$\Rightarrow s \geq s^R - \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

We define $\underline{s}$ as the minimum level of subsidy commitment, below which there is no signaling distortion by the clean type and $\underline{s} = s^R - \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$. We also have $P_C^* = min\{P_C^{FI}, P^L\}$, for any $s \geq s^R$. Under such circumstances, the clean type distorts price when $P_C^{FI} \geq P^L$ for any $s \leq s^R$.

$$P_C^{FI} \geq\; P^L \Rightarrow \frac{a\rho + X_c}{2} \geq \frac{(a\rho + m_D)}{2} - \frac{1}{2}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

$$\Rightarrow s \leq s^R + \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$$

We define $\overline{s}$ as the maximum level of subsidy commitment, above which there is no signaling distortion by the clean type and $\overline{s} = s^R + \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_D^2)}$.

When subsidy commitment is low, ΔP can be defined as the difference between P^U and P_c^{FI}:

$$\Delta P = P^U - P_c^{FI} > 0 \quad and \quad \left|\frac{\partial \Delta P}{\partial s}\right| > 0 \quad \forall \; s \in \left(\underline{s}, s^R\right).$$

$$\Rightarrow \Delta P = \frac{1}{2}\left(m_D - X_C + \sqrt{(\rho - 1)(a^2\rho - m_D^2)}\right) > 0$$

$$\Rightarrow \Delta P = \frac{1}{2}\left(m_D - m_C + s\beta + \sqrt{(\rho - 1)(a^2\rho - m_D^2)}\right) > 0$$

For any increase in the subsidy commitment: $s \in \left(\underline{s}, s^R\right)$:

$$\frac{\partial \Delta P}{\partial s} = \frac{\beta}{2} > 0.$$

When subsidy commitment is high, ΔP can be defined as the difference between P^L and P_c^{FI}:

$$\Delta P = P^L - P_c^{FI} < 0 \quad and \quad \left|\frac{\partial \Delta P}{\partial s}\right| < 0 \quad \forall \; s \in (s^R, \overline{s}).$$

$$\Rightarrow \Delta P = \frac{1}{2}\left(X_C - m_D + \sqrt{(\rho - 1)(a^2\rho - m_D^2)}\right) > 0$$

$$\Rightarrow \Delta P = \frac{1}{2}\left(m_C - s\beta - m_D + \sqrt{(\rho - 1)(a^2\rho - m_D^2)}\right) > 0$$

For any increase in the subsidy commitment: $s \in \left(\underline{s}, s^R\right)$:

$$\frac{\partial \Delta P}{\partial s} = -\frac{\beta}{2} < 0.$$

Note that the marginal effect of subsidy commitment on the price distortion is linear:

$$\frac{\partial^2 \Delta P}{\partial s^2} = 0.$$

Appendix A.4: Proof of Proposition 4.

<u>Profit Distortion:</u> Let Δπ be the measure of distortion in profit of the monopoly. We can break down the profit distortion according to the subsidy commitment such that, when the commitment is low $(\underline{s}, s^R)$,

$$\Delta_\pi = \pi^U - \pi_C^{FI}$$

$$\Rightarrow \Delta_\pi = (P^U - X_C)\left(a - \frac{P^U}{\rho}\right) - \frac{(a\rho - X_c)^2}{4\rho} < 0$$

$$\Rightarrow \Delta_\pi = -\frac{1}{\rho}(P^U - P_C^{FI})^2 < 0$$

For any increase in the subsidy commitment where $s \in (\underline{s}, s^R)$:

$$\frac{\partial \Delta_\pi}{\partial s} = -\frac{\beta}{\rho}(P^U - P_C^{FI}) < 0$$

$$\Delta_\pi = \pi^U - \pi_C^{FI} < 0 \ \ and \ \ \left|\frac{\partial \Delta_\pi}{\partial s}\right| > 0 \qquad \forall s \in (\underline{s}, s^R);$$

where π^U refers to the profit of the clean type when it charges P^U instead of the full information price. When the level of subsidy commitment is high: $(s^R, \overline{s})$,

$$\Delta_\pi = \pi^L - \pi_C^{FI}$$

$$\Rightarrow \Delta_\pi = (P^L - X_C)\left(a - \frac{P^L}{\rho}\right) - \frac{(a\rho - X_c)^2}{4\rho} < 0$$

For any increase in the subsidy commitment where $s \in (\underline{s}, s^R)$:

$$\frac{\partial \Delta_\pi}{\partial s} = \frac{\beta}{\rho}(P_C^{FI} - P^L) > 0 \quad as \quad P_C^{FI} > P^L$$

$$\Delta_\pi = \pi^L - \pi_C^{FI} < 0 \quad and \quad \left|\frac{\partial \Delta_\pi}{\partial s}\right| < 0 \;\; \forall \;\; s \in (s^R, \overline{s})$$

where π^L refers to the profit of the clean type when it charges P^L instead of the full information price.

Incentive to Adopt cleaner technology: Even in the range of low subsidy commitment, there are higher profits for the clean type if $X_c < \rho m_D$. However, for $X_c < \rho m_D$, the subsidy rate $s > \underline{s}$. For $s > \underline{s} > s^R$, the clean type distorts the price upwards to P^U to signal its type and incurs a loss due to deviation from P_c^{FI}.

As a result: $\pi(D, 0, P_D^*) > \pi(D, 1, P_C^*) \;\; for \;\; s \in (\underline{s}, s^R)$.

Let Δ_I measure the incentive for the firm to adopt cleaner technology. Then, under high subsidy commitments $(s^R, \overline{s})$:

$$\Delta_I = (\mu\pi^L + (1-\mu)\pi_D^{FI}) - \pi_D^{FI}$$

$$\Rightarrow \Delta_I = \mu(\pi^L - \pi_D^{FI}),$$

where π_D^{FI} is the dirty type's profit from charging the full information price.

$$\Delta_I = \mu(\pi^L - \pi_C^{FI}) + \mu(\pi_C^{FI} - \pi_D^{FI})$$

where π_C^{FI} is the profit earned by the clean type under full information, $(\pi_C^{FI} - \pi_D^{FI})$ measures the incentive to invest under full information and as defined above $(\pi^L - \pi_C^{FI}) = \Delta_\pi < 0$.

$$\Rightarrow \Delta_I = \mu[\Delta_\pi + (\pi_C^{FI} - \pi_D^{FI})]$$

$$\Rightarrow \Delta_I > 0 \;\; if \;\; (\pi_C^{FI} - \pi_D^{FI}) > \Delta_\pi.$$

Incentive to adopt cleaner technology under high levels of subsidy commitment is ambiguous and depends on the difference in profit of the clean type and dirty type under full information and the loss of profit due to signaling distortion. Because:

$$(\pi_C^{FI} - \pi_D^{FI}) > 0 \ \ if \ \ s > s^R$$

and

$$\left|\frac{\partial \Delta_\pi}{\partial s}\right| < 0 \ for \ \ s \in (s^R, \overline{s})$$

and

$$\Delta_\pi = 0 \ \ for \ \ s > \overline{s},$$

for some level of high subsidy commitment, the firm would have the incentive to adopt cleaner technology. Further, the effect of the increase in the commitment level on the measure of incentive to invest in cleaner technology under full information is positive and is given by:

$$\frac{\partial(\pi_C^{FI} - \pi_D^{FI})}{\partial s} = \frac{\beta}{2}\left(a - \frac{X_C}{\rho}\right) > 0$$

Therefore, the minimum subsidy commitment required to motivate the firm to innovate would be less than the upper bound of the distortion.

$$s_{II}^* = \overline{s} - \phi = s^R + \frac{1}{\beta}\sqrt{(\rho - 1)(a^2\rho - m_a^2)} - \phi; \ \phi > 0$$

Note that:

$$\frac{\partial(\pi_C^{FI} - \pi_D^{FI})}{\partial \rho} = \frac{1}{4}\left(a^2 - \frac{X_C^2}{\rho^2}\right) > 0$$

$$\frac{\partial^2(\pi_C^{FI} - \pi_D^{FI})}{\partial \rho^2} = \frac{X_C^2}{2\rho^3} > 0$$

which implies that the minimum effective subsidy required for investment decreases and that:

$$\phi'(\rho) > 0;\ \phi''(\rho) > 0.$$

<u>Measuring Consumer Surplus:</u>

The expected consumer surplus when the firm does not adopt cleaner technology:

$$CS_{Dirty} = (1-\mu)\frac{(a^2 - m_D^2)}{8}$$

The consumers are better off if the firm adopts cleaner technology if:

$$CS_{Clean} \geq CS_{Dirty}$$

$$\Rightarrow \frac{(a\rho - P^*)P^*}{\rho} \geq \frac{(a^2 - m_D^2)}{4}, where\ \rho = \frac{2}{1+\underline{\alpha}}.$$

Now consider $P^* = P_C^{FI}$. Such that:

$$a^2\rho^2 - {X_C}^2 \geq a^2 - m_D^2$$

$$\Rightarrow a^2(\rho^2 - 1) - (X_C - m_D)(X_C + m_D) \geq 0$$

Note that the monopolist adopts cleaner technology when the level of subsidy commitment is high: $s > s^R$. This aids the proof in two ways. First, $X_C - m_D < 0$ for $s > s^R$, which ensures that $CS_{Clean} \geq CS_{Dirty}$. Second, considering $s > s^R$, the clean type would distort the price downwards to $P_L < P_C^{FI}$ for $s^R > s > \overline{s}$. The downward distortion ensures that the consumer surplus would be greater than the clean type charging the full information price. And finally, higher environmental consciousness also increases CS_{Clean}.

$$\frac{\partial\left(CS_{Clean} - CS_{Dirty}\right)}{\partial\rho} = 2a^2\rho > 0$$

APPENDIX II: LIST OF TABLES

Table 1: Minimum Effective Subsidy – Scenario analysis

	Minimum Effective Subsidy	Subsidy Level	Complete Information	Incomplete Information	Costly Investment
1.	$s_{FI}^{*} = \frac{1}{\beta}\left[m_C - \sqrt{\rho}\left(\sqrt{\rho}a - (a - m_D)\right)\right]$	$s_{FI}^{*} \in (s, s^R)$	√		
2.	$s_{FI}^{**} = \frac{1}{\beta}\left[m_C - \sqrt{\rho}\left(\sqrt{\rho}a - \sqrt{(a - m_D)^2 + 4f}\right)\right]$	$s_{FI}^{**} > s_{FI}^{*}$	√		√
3.	$s_{II}^{*} = \bar{s} - \phi$, where $\phi > 0;\ \phi'(\rho) > 0, \phi''(\rho) > 0$	$s_{II}^{*} \in (s^R, \bar{s})$		√	
4.	Ambiguous. Depends on the size of investment cost.	$s_{II}^{**} > s_{II}^{*} > s^R$		√	√

Table 2: List of the Eligible Classifications in the Green Technology Pilot Program (2009)

A. Alternative Energy Production
1. Agricultural waste (USPC 44/589).
2. Biofuel (USPC 44/605; 44/589).
3. Chemical waste (USPC 110/235-259, 346).
4. For domestic hot water systems (USPC 126/634-680).
5. For passive space heating (USPC 52/173.3).
6. For swimming pools (USPC 126/561-568).
7. Fuel cell (USPC 429/12-46).
8. Fuel from animal waste and crop residues (USPC 44/605).
9. Gasification (USPC 48/197R, 197A).
10. Genetically engineered organism (USPC 435/252.3-252.35, 254.11-254.9, 257.2, 325-408, 410-431).
11. Geothermal (USPC 60/641.2-641.5; 436/25-33).
12. Harnessing energy from man-made waste (USPC 75/958; 431/5).
13. Hospital waste (USPC 110/235-259, 346).
14. Hydroelectric (USPC 405/76-78; 60/495-507; 415/25).
15. Industrial waste (USPC 110/235-259, 346).
16. Industrial waste anaerobic digestion (USPC 210/605).
17. Industrial wood waste (USPC 44/589; 44/606).
18. Inertial (*e.g.*, turbine) (USPC 290/51, 54; 60/495-507).
19. Landfill gas (USPC 431/5).
20. Municipal waste (USPC 44/552).
21. Nuclear power—induced nuclear reactions: processes, systems, and elements (USPC 376/all).
22. Nuclear power—reaction motor with electric, nuclear, or radiated energy fluid heating means (USPC 60/203.1).
23. Nuclear power—heating motive fluid by nuclear energy (USPC 60/644.1) Photovoltaic (USPC 136/243-265).
24. Refuse-derived fuel (USPC 44/552).
25. Solar cells (USPC 438/57, 82, 84, 85, 86, 90, 93, 94, 96, 97).
26. Solar energy (USPC 126/561-714; 320/101).
27. Solar thermal energy (USPC 126/561-713; 60/641.8-641.15).
28. Water level (*e.g.*, wave or tide) (USPC 405/76-78; 60/495-507).

29. Wind (USPC 290/44, 55; 307/64-66, 82-87; 415/2.1).

B. Energy Conservation

1. Alternative-power vehicle (*e.g.*, hydrogen) (USPC 180/2.1-2.2, 54.1).
2. Cathode ray tube circuits (USPC 315/150, 151, 199).
3. Commuting, *e.g.*, HOV, teleworking (USPC 705/13).
4. Drag reduction (USPC 105/1.1-1.3; 296/180.1-180.5; 296/181.5).
5. Electric lamp and discharge devices (USPC 313/498-512, 567-643).
6. Electric vehicle (USPC 180/65.1; 180/65.21; 320/109; 701/22; 310/1-310).
7. Emission trading, *e.g.*, pollution credits (USPC 705/35-45).
8. Energy storage or distribution (USPC 307/38-41; 700/295-298; 713/300-340).
9. Fuel cell-powered vehicles (USPC 180/65.21; 180/65.31).
10. Human-powered vehicle (USPC 180/205; 280/200-304.5).
11. Hybrid-powered vehicle (USPC 180/65.21-65.29; 73/35.01-35.13, 112-115, 116-119A, 121-132).
12. Incoherent light emitter structure (USPC 257/79, 82, 88-90, 93, 99-103).
13. Land vehicle (USPC 105/49-61 (electric trains); 180/65.1-65.8 (electric cars)).
14. Optical systems and elements (USPC 359/591-598).
15. Roadway, *e.g.*, recycled surface, all-weather bikeways (USPC 404/32-46).
16. Static structures (USPC 52/309.1-309.17, 404.1-404.5, 424-442, 783.1-795.1).
17. Thermal (USPC 702/130-136).
18. Transportation (USPC 361/19, 20, 141, 152, 218).
19. Watercraft drive (electric powered) (USPC 440/6-7).
20. Watercraft drive (human-powered) (USPC 440/21-32).
21. Wave-powered boat motors (USPC 440/9).
22. Wind-powered boat motors (USPC 440/8).
23. Wind-powered ships (USPC 114/102.1-115).

C. Environmentally Friendly Farming

1. Alternative irrigation technique (USPC 405/36-51).
2. Animal waste disposal or recycling (USPC 210/610-611; 71/11-30).
3. Fertilizer alternative, *e.g.*, composting (USPC 71/8-30).
4. Pollution abatement, soil conservation (USPC 405/15).
5. Water conservation (USPC 137/78.2-78.3; 137/115.01-115.28).
6. Yield enhancement (USPC 504).

D. Environmental Purification, Protection, or Remediation
1. Biodegradable (USPC 383/1; 523/124-128; 525/938; 526/914).
2. Biohazard, Disease (permanent containment of the malicious virus, bacteria, prion) (USPC 588/249-249.5).
3. Biohazard, Disease (destruction of malicious virus, bacteria, prion) (USPC 588/299).
4. Carbon capture or sequestration (USPC 95/139-140; 405/129.1-129.95; 423/220-234).
5. Disaster (*e.g.*, spill, explosion, containment, or cleanup) (USPC 405/129.1-129.95).
6. Environmentally friendly coolants, refrigerants, etc. (USPC 252/71-79).
7. Genetic contamination (USPC 422/1-43).
8. Hazardous or Toxic waste destruction or containment (USPC 588/1-261).
9. In atmosphere (USPC 95/57-81, 149-240).
10. In water (USPC 210/600-808; 405/60).
11. Landfill (USPC 405/129.95).
12. Nuclear waste containment or disposal (USPC 588/1-20, 400).
13. Plants and plant breeding (USPC 800/260-323.3).
14. Post-consumer material (USPC 264/36.1-36.22, 911-921; 521/40-49.8).
15. Recovery of excess process materials or regeneration from the waste stream (USPC 162/29, 189-191; 164/5; 521/40-49.8; 562/513).
16. Recycling (USPC 29/403.1-403.4; 75/401-403; 156/94; 264/37.1-37.33).
17. Smokestack (USPC 110/345; 422/900).
18. Soil (USPC 405/128.1-128.9, 129.1-129.95).
19. Toxic material cleanup (USPC 435/626-282).
20. Toxic material permanent containment or destruction (USPC 588/all).
21. Using microbes or enzymes (USPC 435/262.5).

Source: *https://www.federalregister.gov/d/E9-29207*

Table 3: Summary Statistics

Variables	Description	All States	Republican States	Democratic States
Total Patents (count)	Annual patent applications in a state.	1618.73	1596.98	1641.73
Env. Patents (count)	Environmental patent applications in a state per year.	90.88	90.57	91.21
EPS	Share of Environmental Patents out of total.	0.06	0.06	0.06
Total Patents (per 100k)	Annual successful patent applications per 100,000 people in a state.	22.54	21.93	23.17
Env. Patents (per 100k)	Annual environmental patent applications per 100,000 people in a state.	1.34	1.21	1.48
Democrats in State House (%)	Percentage of members in the State House who belong to the Democratic party.	0.06	-0.027	0.157
Democrats in State Senate (%)	Percentage of members in the State Senate who belong to the Democratic party.	0.06	-0.029	0.159
Green Voters (%)	Percentage of state population having membership in environmental organizations (1987).	0.84	0.8	0.88
Env. Score (House)	House Representatives' scores derived from voting on environmental issues averaged yearly for a state.	45.25	42.26	48.41
Env. Score (Senate)	Senator scores derived from voting on environmental issues averaged yearly for a state.	47.56	42.95	52.43
Coal production	Annual coal production in million BTUs per 100,000 people in a state.	317.63	276.93	360.65
Crude Oil production	Annual crude oil production in million BTUs per 100,000 people in a state.	69.71	77.38	61.61
Population < 17 years (%)	Percentage of population below 17 years of age.	0.19	0.2	0.19
Population > 65 years (%)	Percentage of population above 65 years of age.	0.13	0.13	0.13
Per Capita Income	Per capita personal income of individuals in a state for a given year.	29103.45	30352	27783.86

Table 4: Effect of Democratic Governors on the Covariates

Variables	Full Sample	Margin of Victory (24%)	Margin of Victory (14%)
Col. 1	*Col. 2*	*Col. 3*	*Col. 4*
Total Patents (per 100,000 residents)	1.71 (2.74)	0.76 (2.19)	0.21 (1.87)
Environmental Patents (per 100,000 residents)	0.46 (0.25)	0.32* (0.14)	0.32 (0.17)
Green Voters (%)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Democrats in State House (%)	0.08*** (0.02)	0.07** (0.02)	0.03 (0.02)
Democrats in State Senate (%)	0.08*** (0.02)	0.08*** (0.02)	0.06* (0.03)
Environmental Score (Senate)	5.11* (1.95)	4.96* (2.15)	5.40* (2.58)
Environmental Score (House)	0.93 (1.06)	-0.07 (1.10)	-1.16 (1.36)
Coal Production (per 100,000 residents)	-45.41 (44.01)	-47.86 (46.42)	-17.12 (22.79)
Crude Oil Production (per 100,000 residents)	2.33 (10.75)	9.03 (5.60)	7.48* (3.25)
Population > 65 years (%)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Population < 17 years (%)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Ln (Personal Income pc)	0.00 (0.01)	0.01 (0.00)	0.01 (0.01)

NOTES: The table represents the correlation of Democratic Governor with the variables listed in column 1 for the full sample and sub-samples with closer margins of victory. In column 2, the estimates are listed for the full sample followed by sub-samples of 24% margin of victory in columns 3 and 14% margin of victory in column 4. The choice of 14% and 24% margin of victory is owing to the range of bandwidths used in the main estimations. Standard errors are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Impact of Democratic governor on Environmental Patent applications per capita
(Regression Discontinuity Estimates – Without Additional Covariates)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth =14%	0.03 (0.04)	0.08*** (0.03)	0.05 (0.05)	0.10* (0.06)	0.09 (0.08)	0.16** (0.08)	0.13 (0.10)	0.18 (0.11)
Bandwidth =16%	0.03 (0.04)	0.08** (0.03)	0.04 (0.05)	0.11** (0.05)	0.08 (0.08)	0.13* (0.08)	0.13 (0.10)	0.23** (0.10)
Bandwidth =18%	0.02 (0.04)	0.07** (0.03)	0.04 (0.05)	0.10** (0.05)	0.06 (0.07)	0.14* (0.07)	0.11 (0.09)	0.18* (0.10)
Bandwidth =20%	0.02 (0.03)	0.07** (0.03)	0.03 (0.05)	0.09** (0.04)	0.06 (0.07)	0.14** (0.07)	0.10 (0.09)	0.17* (0.09)
Bandwidth =22%	0.02 (0.03)	0.07** (0.03)	0.03 (0.05)	0.09** (0.04)	0.05 (0.07)	0.12* (0.06)	0.09 (0.09)	0.18** (0.09)
Bandwidth =24%	0.01 (0.03)	0.06* (0.03)	0.04 (0.05)	0.11** (0.04)	0.04 (0.06)	0.09 (0.06)	0.09 (0.09)	0.19** (0.09)
Full Sample	0.02 (0.03)	0.04* (0.03)	-0.01 (0.04)	0.03 (0.03)	0.01 (0.05)	0.07 (0.04)	0.05 (0.06)	0.12** (0.06)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. No additional coefficients are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Impact of Democratic governor on Environmental Patent applications per capita
(Regression Discontinuity Estimates – Robustness to Additional Covariates)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth=14%	0.04	0.11***	0.05	0.12**	0.08	0.18**	0.11	0.18*
	(0.04)	(0.03)	(0.05)	(0.05)	(0.08)	(0.08)	(0.10)	(0.10)
Bandwidth=16%	0.04	0.09***	0.05	0.13***	0.07	0.16**	0.12	0.25***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.10)	(0.10)
Bandwidth=18%	0.03	0.09***	0.04	0.12***	0.06	0.16**	0.10	0.21**
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth=20%	0.03	0.08***	0.04	0.11**	0.06	0.16**	0.09	0.20**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth=22%	0.03	0.08***	0.04	0.11**	0.05	0.14**	0.09	0.20**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)	(0.09)	(0.09)
Bandwidth=24%	0.02	0.07**	0.04	0.12***	0.04	0.10*	0.09	0.21**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.09)
Full Sample	0.03	0.05*	-0.01	0.04	0.01	0.07	0.04	0.12**
	(0.02)	(0.02)	(0.04)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Impact of Democratic governor on Environmental Patent applications per capita
(Regression Discontinuity Estimates – Close Elections, All years)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
Bandwidth= 6%	0.09**	0.09**	0.23***	0.19***	0.20***	0.13**	0.24***	0.17**
	(0.04)	(0.04)	(0.07)	(0.06)	(0.07)	(0.06)	(0.08)	(0.07)
Bandwidth = 8%	0.06*	0.06*	0.13*	0.11*	0.23***	0.19**	0.22**	0.17**
	(0.04)	(0.04)	(0.07)	(0.06)	(0.08)	(0.08)	(0.09)	(0.08)
Covariates	NO	YES	NO	YES	NO	YES	NO	YES

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5 and 7 (2,4,6 and 8) are obtained from a regression that does not include (does include) covariates used in previous literature dealing with the impact of state governors on environmental outcomes. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Impact of Democratic governor on Non-environmental Patent applications per capita
(Regression Discontinuity Estimates – Non-environmental Patents)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth =14%	-0.14**	-0.07**	-0.23**	-0.12**	-0.28**	-0.04	-0.16	0.12
	(0.06)	(0.03)	(0.11)	(0.06)	(0.14)	(0.08)	(0.14)	(0.08)
Bandwidth =16%	-0.14**	-0.06*	-0.24**	-0.10*	-0.30**	-0.10	-0.24	0.10
	(0.07)	(0.03)	(0.11)	(0.05)	(0.14)	(0.08)	(0.16)	(0.09)
Bandwidth =18%	-0.15**	-0.06*	-0.22**	-0.08*	-0.32**	-0.10	-0.26	0.00
	(0.07)	(0.03)	(0.11)	(0.05)	(0.15)	(0.08)	(0.16)	(0.10)
Bandwidth =20%	-0.15**	-0.06*	-0.20*	-0.08	-0.32**	-0.11	-0.31*	-0.04
	(0.07)	(0.03)	(0.11)	(0.05)	(0.14)	(0.07)	(0.17)	(0.09)
Bandwidth =22%	-0.15**	-0.06*	-0.18*	-0.06	-0.30**	-0.12*	-0.33*	-0.06
	(0.06)	(0.03)	(0.11)	(0.05)	(0.14)	(0.07)	(0.17)	(0.09)
Bandwidth =24%	-0.15**	-0.06*	-0.16	-0.04	-0.28**	-0.12*	-0.34**	-0.07
	(0.06)	(0.03)	(0.11)	(0.04)	(0.14)	(0.07)	(0.17)	(0.09)
Full Sample	-0.07	-0.04	-0.19**	-0.10**	-0.19*	-0.05	-0.15	0.01
	(0.05)	(0.03)	(0.08)	(0.04)	(0.11)	(0.05)	(0.14)	(0.06)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of non-environmental patents per 100,000 residents in a state for a given year. Non-environmental patents are all patents without the environmental classifications discussed. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Impact of Democratic governor on Environmental Patent applications per capita (*Regression Discontinuity Estimates – Excluding Delaware*)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth =14%	0.04	0.09***	0.05	0.13***	0.08	0.16**	0.13	0.25***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.10)
Bandwidth =16%	0.03	0.09***	0.05	0.12***	0.07	0.16**	0.11	0.21**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth =18%	0.03	0.08***	0.05	0.11**	0.06	0.15**	0.10	0.20**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth =20%	0.03	0.07**	0.05	0.11**	0.06	0.13**	0.10	0.20**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)	(0.09)	(0.08)
Bandwidth =22%	0.02	0.06**	0.05	0.12***	0.05	0.10*	0.09	0.21**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.08)
Bandwidth =24%	0.03	0.05*	0.00	0.03	-0.01	0.05	0.04	0.10*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)
Full Sample	0.04	0.09***	0.05	0.13***	0.08	0.16**	0.13	0.25***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.10)

NOTES: The table presents estimates obtained from equation 1 excluding the state of Delaware. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Impact of Democratic governor on Environmental Patent applications per capita
(Regression Discontinuity Estimates – Robustness to Population Weights)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth=14%	0.07*	0.12***	0.03	0.13**	0.07	0.19**	0.10	0.19*
	(0.04)	(0.03)	(0.05)	(0.05)	(0.08)	(0.08)	(0.10)	(0.10)
Bandwidth=16%	0.02	0.10***	0.03	0.13***	0.05	0.16**	0.10	0.26***
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.10)
Bandwidth=18%	0.01	0.09***	0.03	0.12***	0.05	0.17**	0.09	0.21**
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth=20%	0.02	0.08***	0.02	0.11**	0.05	0.16**	0.08	0.20**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth=22%	0.01	0.08***	0.03	0.11**	0.04	0.14**	0.08	0.21**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)	(0.09)	(0.09)
Bandwidth=24%	0.01	0.07**	0.03	0.12***	0.03	0.11*	0.08	0.22**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.09)
Full Sample	0.03	0.05*	0.00	0.03	-0.01	0.06	0.04	0.10*
	(0.03)	(0.02)	(0.03)	(0.03)	(0.05)	(0.04)	(0.06)	(0.06)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Impact of Democratic governor on Environmental Patent applications per capita
(*Regression Discontinuity Estimates – Firms with less than 5 patents from 1980 to 2019*)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth =14%	0.00	0.03***	0.00	0.03**	0.00	0.04**	0.00	0.06**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bandwidth =16%	0.00	0.02***	0.00	0.03**	0.00	0.04**	0.00	0.05**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bandwidth =18%	0.00	0.02**	-0.00	0.03**	-0.00	0.03**	-0.00	0.04*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bandwidth =20%	0.01	0.02**	-0.00	0.02*	-0.00	0.03*	-0.00	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
- Bandwidth =22%	0.00	0.02**	-0.00	0.02*	-0.01	0.02	-0.00	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Bandwidth =24%	0.00	0.02**	-0.00	0.02	-0.01	0.02	-0.00	0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Full Sample	-0.00	0.00	0.00	0.01	-0.00	0.01	-0.01	0.01
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). Firms with less than a total of 5 patents in the 40 years of the sample indicate smaller firms that are more likely to apply for patents in the same state of operation. All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Impact of Democratic governor on Non-environmental Patent applications per capita (*Regression Discontinuity Estimates on Non-environmental Patents of Firms with less than 5 patents*)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth =14%	-0.08***	-0.05***	-0.13***	-0.09***	-0.15***	-0.10***	-0.17***	-0.15***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Bandwidth =16%	-0.07***	-0.04**	-0.12***	-0.09***	-0.15***	-0.09***	-0.16***	-0.11***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)
Bandwidth =18%	-0.05***	-0.03	-0.12***	-0.10***	-0.14***	-0.08***	-0.16***	-0.11***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Bandwidth =20%	-0.04**	-0.02	-0.11***	-0.09***	-0.14***	-0.10***	-0.15***	-0.10***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Bandwidth =22%	-0.03*	-0.01	-0.10***	-0.09***	-0.14***	-0.11***	-0.14***	-0.09**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Bandwidth =24%	-0.03*	-0.00	-0.09***	-0.07***	-0.14***	-0.12***	-0.14***	-0.09**
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
Full Sample	0.00	0.02	-0.04*	-0.02	-0.08***	-0.06**	-0.09***	-0.08***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of non-environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). Firms with less than a total of 5 patents in the 40 years of the sample indicate smaller firms that are more likely to apply for patents in the same state of operation. All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13. Impact of Democratic governor on Environmental Bills (*Regression Discontinuity Estimates – Environmental Bills from 2008 to 2019*)

	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	Bandwidth=14%		Bandwidth=18%		Bandwidth=22%		Bandwidth=26%	
	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
PANEL A: Governor's Enactment on State Energy and Environmental Bills								
Enacted	1.56	-0.70	-0.82	-1.51	-0.32	-0.18	0.21	-1.31
	(1.71)	(1.99)	(2.29)	(1.71)	(1.92)	(1.78)	(1.63)	(2.00)
Enacted (non-zero)	0.04	-0.00	0.05	0.07	0.04	0.05	0.05	-0.02
	(0.06)	(0.07)	(0.05)	(0.07)	(0.04)	(0.07)	(0.04)	(0.08)
PANEL B: Governor's Veto on State Energy and Environmental Bills								
Vetoed	-0.84	-0.41	-0.08	-0.27	-0.53	0.26	-0.49	-0.04
	(0.55)	(0.65)	(0.82)	(0.65)	(0.44)	(1.08)	(0.42)	(0.74)
Veto (non-zero)	-0.33**	-0.45***	-0.24**	-0.40***	-0.08	-0.40***	-0.10	-0.30***
	(0.13)	(0.13)	(0.10)	(0.14)	(0.11)	(0.12)	(0.11)	(0.10)

NOTES: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the number of state bills enacted or vetoed by the governor in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) represent a linear (quadratic) fit. Col. 1 & 2 represents a bandwidth of victory margin =14%, Col. 3 & 4 represents a bandwidth of victory margin =18%, Col. 5 & 6 represents a bandwidth of victory margin =22%, and Col. 7 & 8 represents a bandwidth of victory margin =26%. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14. Impact of Democratic governor on Environmental Employment per capita (*Regression Discontinuity Estimates – from 1980 to 2019*)

	LOG OF ENVIRONMENT EMPLOYMENT				LOG OF NON- ENVIRONMENT EMPLOYMENT			
	Linear fit		Quadratic fit		Linear fit		Quadratic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth=14%	0.05**	0.07***	0.08**	0.06***	0.01	0.02**	0.01	0.03***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Bandwidth=16%	0.05*	0.06***	0.08**	0.08***	0.01	0.02**	0.01	0.03***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Bandwidth=18%	0.04*	0.06***	0.07**	0.08***	0.01	0.02**	0.01	0.02**
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Bandwidth=20%	0.04*	0.06***	0.07**	0.08***	0.01	0.02**	0.01	0.02*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Bandwidth=22%	0.04*	0.06***	0.07**	0.08***	0.01*	0.02***	0.01	0.02*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Bandwidth=24%	0.04*	0.06***	0.06**	0.08***	0.01*	0.02***	0.01	0.02*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)
Full Sample	0.03*	0.04***	0.03	0.06***	0.00	0.01***	0.01	0.01**
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.00)	(0.01)	(0.01)

NOTES: The table presents estimates obtained from equation 1. Columns 1-4 show the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental employment per 100,000 residents in a state for a given year whereas Col 5-8 represents the log of non-environmental employment . Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). All specifications include 1st to 2nd-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1, 2, 5 & 6) and quadratic fit (col.3, 4, 7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15. Impact of Democratic governor on Environmental Patent applications per capita
(Regression Discontinuity Estimates – Excluding Election Years from 1980 to 2019)

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth=16%	0.07*	0.12***	0.08	0.13**	0.10	0.15**	0.12	0.13
	(0.03)	(0.03)	(0.05)	(0.05)	(0.08)	(0.08)	(0.10)	(0.10)
Bandwidth=18%	0.06*	0.10***	0.08	0.15***	0.09	0.15**	0.13	0.22**
	(0.04)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.10)	(0.10)
Bandwidth=20%	0.05	0.09***	0.07	0.15***	0.09	0.16**	0.12	0.19**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.09)
Bandwidth=22%	0.04	0.09***	0.07	0.14***	0.09	0.17***	0.11	0.17**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.06)	(0.09)	(0.08)
Bandwidth=24%	0.04	0.08***	0.06	0.13***	0.08	0.16***	0.11	0.19**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.09)	(0.08)

NOTE: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). The years in which elections occur for a particular state are excluded. All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16. Impact of Democratic governor on Lagged Environmental Patent applications per capita *(Regression Discontinuity Estimates – Excluding Election Years from 1980 to 2019)*

	Linear fit		Quadratic fit		Triple fit		Quartic fit	
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8
	All years	Post-1992	All years	Post-1992	All years	Post-1992	All years	Post-1992
Bandwidth=16%	0.06	0.07**	0.08	0.12**	0.09	0.12	0.12	0.20**
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.08)	(0.09)	(0.10)
Bandwidth=18%	0.04	0.06*	0.07	0.11**	0.07	0.13*	0.10	0.15
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.09)	(0.10)
Bandwidth=20%	0.03	0.05	0.06	0.10**	0.07	0.14*	0.08	0.13
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)	(0.09)
Bandwidth=22%	0.02	0.04	0.06	0.10**	0.07	0.12*	0.08	0.16*
	(0.03)	(0.03)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)	(0.09)
Bandwidth=24%	0.01	0.03	0.06	0.11**	0.06	0.10	0.09	0.18*
	(0.03)	(0.03)	(0.05)	(0.05)	(0.06)	(0.06)	(0.08)	(0.09)

NOTE: The table presents estimates obtained from equation 1. Each cell shows the estimates of a separate regression measuring the effect of a Democratic governor on the log of lagged environmental patents per 100,000 residents in a state for a given year. Statistics in columns 1,3,5, and 7 (2,4,6 and 8) are obtained from a regression that includes observations from the years 1980 to 2019 (1993-2019). The years in which elections occur for a particular state are excluded. All specifications include 1st to 4th-order polynomial functions of the Democratic margin of victory and its interaction with the treatment dummy variable Democrat. The polynomial orders are represented by linear (col.1 & 2), quadratic (col.3 & 4), triple (col.5 & 6), and quartic fit (col.7 & 8). A triangular kernel is implemented. The estimations include state and year-fixed effects. Additional coefficients used in Fredriksson et al. (2014) and Pacca et al. (2021), like population above 65 years, population below 17 years, and the log of per capita personal income, are included. Standard errors, clustered at the state level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17. Summary Statistics (*Full sample*)

Variables	Description	All Patents	Approved Codes	Listed Codes	Applied to GTPP
Observations		2,711,765	258,690	83,712	4,472
	Outcome Variables				
Patent granted	Whether the patent is granted (dummy)	0.67	0.65	0.58	0.75
Forward citation	Citations by future patents (count)	12.61	12.36	11.53	17.81
Forward citation (examiner)	Citations by future patents by examiners (count)	3.31	3.54	3.07	4.49
	Control Variables				
Time for patent review	Time in patent review (days)	1198.68	1213.67	1240.3	989.49
Total claims (pre-grant)	Claims made in the pre-grant publication (count)	18.97	18.96	19.34	20.66
Total claims (granted)	Claims made in the granted patents (count)	16.39	16.36	16.29	16.13
Independent claims (pre-grant)	Independent claims made in the pre-grant publication (count)	3.16	3.11	3.12	3.43
Independent claims (granted)	Independent claims made in the granted patents (count)	2.57	2.5	2.36	2.31
Domestic Inventor	Inventor is from United States (dummy)	0.47	0.43	0.48	0.74
Small Firms	Defined by USPTO (dummy)	0.24	0.22	0.29	0.36

NOTE: The table presents the means of the key variables used in the analysis. The data sources are discussed in Section 3.

Table 18. Summary Statistics (*GTPP participants*)

Variables	Successful Petition	Unsuccessful Petition	Difference in Means
Col. 1	Col. 2	Col. 3	Col. 4
	3,494	929	--
	Outcome Variables		
Patent granted	0.77	0.66	0.11***
Forward citation	18.21	16.08	1.82
Forward citation (examiner)	4.44	4.59	-0.21
	Control Variables		
Time for patent review	917.53	1263.11	-329.04***
Total claims (pre-grant)	21.05	19.08	1.78***
Total claims (granted)	16.1	16.16	-0.15
Independent claims (pre-grant)	3.47	3.26	0.21
Independent claims (granted)	2.31	2.29	0.00
Domestic Inventor	0.72	0.79	-0.06***
Small Firms	0.35	0.41	-0.05**

NOTE: The table presents the mean of the variables for the patent applications that participated in the GTPP. Col.2 represents the mean for the subset of the petitions that were successful in the program. Col.3 represents the mean of the subset of the petitions that were not successful in the program. Col.4 presents the estimates of the difference in means, where the outcome variables are the variables listed in Col.1 and the independent variable is a dummy=1 if the petition application was successful. USPC class fixed effects have been implemented. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19. Effect of GTPP on Green Technology Patent Applications over time

	Listed Code	Approved Code
	Col. 1	Col. 2
Green code * year2006	-2.921**	-0.04
	(1.406)	(0.022)
Green code * year2007	-1.492*	0.1
	(0.713)	(0.004)
Green code * year2008	-0.613	0.22
	(0.555)	(0.312)
Green code * year2010	2.601**	0.67**
	(1.345)	(0.416)
Green code * year2011	4.861***	0.804***
	(2.011)	(0.198)
Green code * year2012	5.169**	0.836**
	(2.062)	(0.311)
Green code * year2013	5.81**	0.889**
	(2.809)	(0.422)
Green code * year2014	6.021***	0.601
	(2.581)	(0.422)
Green code * year2015	5.222***	0.003
	(1.792)	(0.515)
Green code * year2016	4.661**	-0.191
	(2.661)	(0.641)
Green code * year2017	3.951***	-0.233
	(1.503)	(0.22)
Green code * year2018	4.039**	0.12
	(1.101)	(0.896)
Constant	9.722***	0.2**
	(4.002)	(0.019)

NOTE: The table presents the estimates of the regression equation Eq.1. The outcome variable is all patent applications. The unit of observation is a subclass consisting of several applications in year. USPC class fixed effects have been implemented. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20. Effects of the GTPP on Adjusted Forward Citations

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3
Successful Petition	0.272**	0.044**	0.227**
	(0.119)	(0.022)	(0.110)
Dependent Claims	0.012**	0.002**	0.009**
	(0.005)	(0.001)	(0.004)
Independent Claims	0.030**	0.002	0.028**
	(0.013)	(0.001)	(0.013)
Listed Code	0.207	0.087**	0.120
	(0.201)	(0.044)	(0.177)
Constant	0.761***	0.234***	0.527***
	(0.123)	(0.021)	(0.112)
Observations	4323	4323	4323
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 includes all forward citations. Col. 2 includes citations made by the examiners. Col. 3 includes citations made by applicants, inventor, attorney or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21. Effects of the GTPP on Adjusted Forward Citations (*Interaction with Post December 2010 Phase of the Program*)

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3
Successful Petition	0.526***	0.094***	0.432**
	(0.194)	(0.032)	(0.178)
Successful * Post Dec2010	-0.427*	-0.083**	-0.343*
	(0.217)	(0.037)	(0.195)
Dependent Claims	0.012**	0.002**	0.009**
	(0.005)	(0.001)	(0.004)
Independent Claims	0.029**	0.002	0.027**
	(0.013)	(0.001)	(0.012)
Listed Code	0.191	0.084*	0.107
	(0.201)	(0.044)	(0.177)
Constant	0.820***	0.246***	0.574***
	(0.117)	(0.022)	(0.105)
Observations	4323	4323	4323
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 includes all forward citations. Col. 2 includes citations made by the examiners. Col. 3 includes citations made by applicants, inventor, attorney, or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22. Effects of the GTPP on Adjusted Forward Citations (*Small Firms vs Large Firms*)

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
	Small Firms			Large Firms		
Successful Petition	0.814**	0.107*	0.707*	0.446*	0.073	0.373
	(0.401)	(0.058)	(0.360)	(0.265)	(0.044)	(0.248)
Successful * Post Dec2010	-0.863*	-0.151	-0.712	-0.407	-0.064	-0.344
	(0.510)	(0.109)	(0.435)	(0.295)	(0.052)	(0.278)
Dependent Claims	0.008**	0.002*	0.006*	0.014*	0.005**	0.010
	(0.004)	(0.001)	(0.003)	(0.008)	(0.002)	(0.007)
Independent Claims	0.012	-0.001	0.013	0.063**	0.007*	0.056**
	(0.013)	(0.002)	(0.012)	(0.031)	(0.004)	(0.028)
Listed Code	0.317	0.125	0.192	-0.066	0.046	-0.112
	(0.337)	(0.086)	(0.297)	(0.204)	(0.046)	(0.183)
Constant	1.076***	0.245***	0.831***	0.710***	0.226***	0.483***
	(0.221)	(0.043)	(0.196)	(0.161)	(0.037)	(0.137)
Observations	1516	1516	1516	2705	2705	2705
Examiner FE	√	√	√	√	√	√
Application Year-Month FE	√	√	√	√	√	√
Petition Year-Month FE	√	√	√	√	√	√
USPC Class FE	√	√	√	√	√	√

NOTE: Columns 1-3 includes a subset of petitions from small firms. Columns 4-6 include a subset of petitions from larger firms. The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 and 4 includes all forward citations. Col. 2 and 5 includes citations made by the examiners. Col. 3 and 6 includes citations made by applicants, inventor, attorney or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 23. Effects of the GTPP on Adjusted Forward Citations (*Comparing with Petition Rejections without Review due to Program Deadline*)

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3
Successful Petition	2.142***	-0.195***	2.337***
	(0.814)	(0.074)	(0.793)
Successful * Post Dec2010	-2.305***	0.169**	-2.474***
	(0.860)	(0.080)	(0.832)
Dependent Claims	0.010**	0.002**	0.009**
	(0.004)	(0.001)	(0.004)
Independent Claims	0.033**	0.002**	0.030**
	(0.014)	(0.001)	(0.013)
Listed Code	0.195	0.068*	0.127
	(0.233)	(0.041)	(0.205)
Constant	0.587*	0.347***	0.241
	(0.350)	(0.041)	(0.326)
Observations	3642	3642	3642
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures the number of citations made to the patents which participated in the GTPP. The estimates compare the effect of successful petitions on citations relative to those petitions which were rejected because the target 3500 successful petitions were reached. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 includes all forward citations. Col. 2 includes citations made by the examiners. Col. 3 includes citations made by applicants, inventor, attorney, or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 24. Effects of the GTPP on the Probability of Patent being Granted

	All Petitions	All Petitions	Rejection without Review due to Program Deadline
	Col. 1	Col. 2	Col. 3
Successful Petition	0.106***	0.130***	0.770***
	(0.021)	(0.032)	(0.072)
Successful * Post Dec2010		-0.041	-0.724***
		(0.039)	(0.092)
Dependent Claims	0.001**	0.001**	0.001*
	(0.001)	(0.001)	(0.001)
Independent Claims	-0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)
Listed Code	-0.011	-0.012	-0.011
	(0.025)	(0.025)	(0.027)
Constant	0.643***	0.649***	0.527***
	(0.018)	(0.020)	(0.051)
Observations	4323	4323	3642
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures whether the patent application is ultimately granted. Col.1 and Col.2 includes all patent applications which participated in the GTPP. Col. 3 compares the effect of successful petition on patent grant relative to those petitions which were rejected because the target 3500 successful petitions were reached. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 25. Effects of GTPP on the Probability of Patent being Granted (*Small Firms vs Large Firms*)

	All Petitions	All Petitions	Rejection without Review due to Program Deadline	All Petitions	All Petitions	Rejection without Review due to Program Deadline
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
	Small Firms			Large Firms		
Successful Petition	0.195***	0.202***	0.210**	0.045	0.038	0.615***
	(0.049)	(0.049)	(0.083)	(0.045)	(0.045)	(0.126)
Successful * Post Dec2010	-0.047	-0.052	0.000	0.012	0.016	-0.667***
	(0.058)	(0.058)	(.)	(0.052)	(0.052)	(0.163)
Dependent Claims	0.001**	0.001**	0.001*	0.002**	0.002**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Independent Claims	0.000	0.000	0.000	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Listed Code	0.019	0.014	0.015	-0.016	-0.016	-0.018
	(0.051)	(0.049)	(0.048)	(0.023)	(0.023)	(0.023)
Constant	0.527***	0.525***	0.485***	0.716***	0.721***	0.681***
	(0.025)	(0.025)	(0.078)	(0.026)	(0.026)	(0.049)
Observations	1530	1516	1261	2730	2705	2303
	√	√	√	√	√	√
Examiner FE	√	√	√	√	√	√
Application Year-Month FE	√	√	√	√	√	√
Petition Year-Month FE	√	√	√	√	√	√

NOTE: The outcome variable measures whether the patent application is ultimately granted. Columns 1-3 includes a subset of petitions from small firms. Columns 4-6 include a subset of petitions from larger firms. Col.1,2, 4 and 5 includes all patent applications which participated in the GTPP. Col. 3 and 6 compares the effect of successful petition on patent grant relative to those petitions which were rejected because the target 3500 successful petitions were reached. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 26. Examiner Load Effects on Adjusted Forward Citations

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3
Successful Petition	1.235***	0.105	1.130***
	(0.382)	(0.088)	(0.371)
High Load	0.595	0.049	0.546
	(0.466)	(0.091)	(0.447)
Successful * High Load	-0.993***	-0.062	-0.931**
	(0.364)	(0.088)	(0.360)
Dependent Claims	0.012**	0.002**	0.010**
	(0.005)	(0.001)	(0.004)
Independent Claims	0.030**	0.002	0.028**
	(0.013)	(0.001)	(0.013)
Listed Code	0.206	0.087**	0.119
	(0.203)	(0.044)	(0.179)
Constant	0.175	0.186**	-0.011
	(0.481)	(0.088)	(0.463)
Observations	4323	4323	4323
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 includes all forward citations. Col. 2 includes citations made by the examiners. Col. 3 includes citations made by applicants, inventor, attorney, or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 27. Examiner Load Effects on Adjusted Forward Citations (*Interacted with Post December 2010 Phase of the Program*)

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3
Successful Petition	0.970**	0.133	0.837**
	(0.391)	(0.097)	(0.382)
High Load	0.492	0.036	0.456
	(0.558)	(0.107)	(0.538)
Successful * High Load	-0.462	-0.041	-0.421
	(0.376)	(0.103)	(0.369)
Successful * Post Dec2010	1.026	-0.129	1.155
	(0.825)	(0.173)	(0.814)
High Load * Post Dec2010	0.312	-0.046	0.358
	(0.750)	(0.178)	(0.717)
Successful * Post Dec2010 * High Load	-1.457*	0.048	-1.505*
	(0.786)	(0.178)	(0.784)
Dependent Claims	0.012**	0.002**	0.009**
	(0.005)	(0.001)	(0.004)
Independent Claims	0.029**	0.002	0.028**
	(0.013)	(0.001)	(0.012)
Listed Code	0.191	0.084*	0.107
	(0.204)	(0.044)	(0.180)
Constant	0.114	0.242**	-0.128
	(0.450)	(0.115)	(0.419)
Observations	4323	4323	4323
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 includes all forward citations. Col. 2 includes citations made by the examiners. Col. 3 includes citations made by applicants, inventor, attorney, or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 28. Examiner Load Effects on Adjusted Forward Citations (*Small Firms vs Large Firms*)

	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)	Adjusted Forward Citation	Adjusted Forward Citation (Examiner)	Adjusted Forward Citation (Non-Examiner)
	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
	Small Firms			Large Firms		
Successful Petition	0.787	0.230**	0.557	0.358	-0.143	0.501
	(0.485)	(0.102)	(0.427)	(0.493)	(0.164)	(0.500)
High Load	0.069	0.144	-0.075	0.054	-0.242	0.296
	(0.675)	(0.106)	(0.612)	(0.576)	(0.188)	(0.518)
Successful * High Load	0.029	-0.125	0.153	0.091	0.221	-0.130
	(0.556)	(0.107)	(0.488)	(0.540)	(0.182)	(0.546)
Successful * Post Dec2010	0.973	-0.350	1.323	1.432	-0.119	1.551
	(1.223)	(0.219)	(1.126)	(1.830)	(0.218)	(1.813)
High Load * Post Dec2010	1.273	-0.057	1.330	0.242	-0.085	0.327
	(1.261)	(0.253)	(1.144)	(0.786)	(0.246)	(0.748)
Successful * Post Dec2010 * High Load	-1.881	0.205	-2.087*	-1.851	0.049	-1.899
	(1.364)	(0.273)	(1.224)	(1.982)	(0.242)	(1.969)
Dependent Claims	0.008**	0.002*	0.006*	0.015*	0.004**	0.010
	(0.004)	(0.001)	(0.003)	(0.008)	(0.002)	(0.007)
Independent Claims	0.011	-0.001	0.013	0.063**	0.007*	0.056**
	(0.013)	(0.002)	(0.012)	(0.031)	(0.004)	(0.028)
Listed Code	0.300	0.125	0.175	-0.047	0.042	-0.089
	(0.333)	(0.085)	(0.294)	(0.199)	(0.047)	(0.178)
Constant	0.202	0.140	0.062	0.457	0.532***	-0.075
	(0.747)	(0.144)	(0.674)	(0.451)	(0.095)	(0.408)
Observations	1530	1530	1530	2730	2730	2730
Examiner FE	√	√	√	√	√	√
Application Year-Month FE	√	√	√	√	√	√
Petition Year-Month FE	√	√	√	√	√	√
USPC Class FE	√	√	√	√	√	√

NOTE: Columns 1-3 includes a subset of petitions from small firms. Columns 4-6 include a subset of petitions from larger firms. The outcome variable measures the number of citations made to the patents which participated in the GTPP. The number of citations has been divided by the years since the patent was granted to derive adjusted counts. Col. 1 and 4 includes all forward citations. Col. 2 and 5 includes citations made by the examiners. Col. 3 and 6 includes citations made by applicants, inventor, attorney or anyone other than the examiners. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

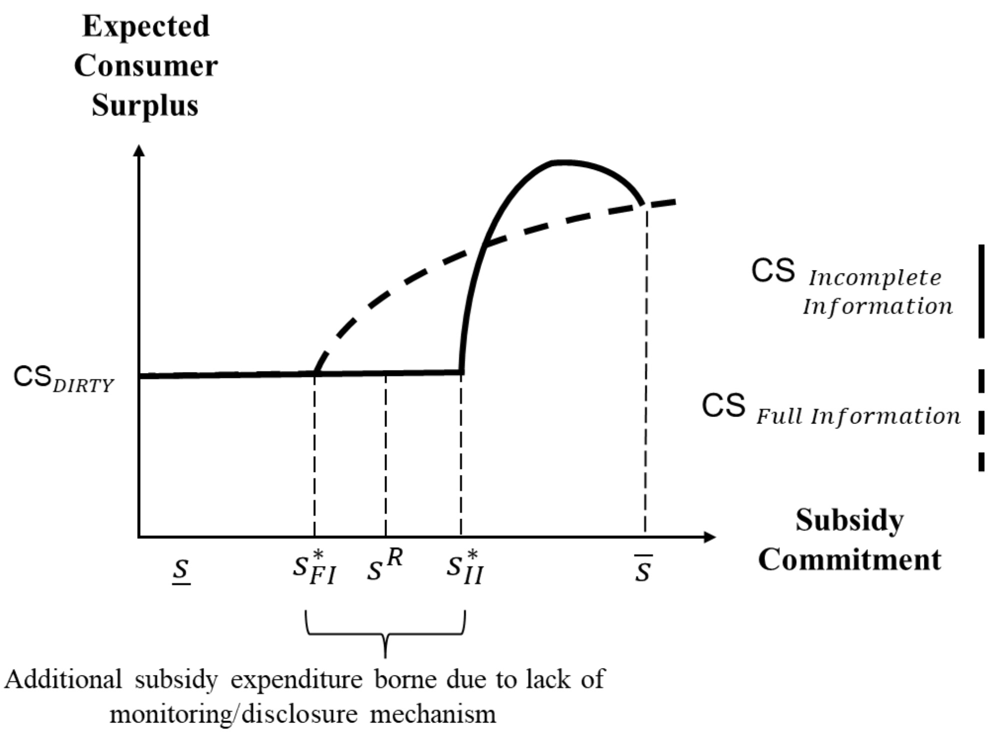
Table 29. Examiner Load Effects on the Probability of Patent being Granted

	All Petitions	All Petitions	Rejection without Review due to Program Deadline
	Col. 1	Col. 2	Col. 3
Successful Petition	0.345**	0.235	0.818***
	(0.139)	(0.155)	(0.097)
High Load	0.171	0.027	0.501**
	(0.144)	(0.156)	(0.239)
Successful * High Load	-0.246*	-0.116	-0.589***
	(0.142)	(0.159)	(0.215)
Successful * Post Dec2010		0.517**	-0.184
		(0.232)	(0.235)
High Load * Post Dec2010		0.597***	0.027
		(0.215)	(0.105)
Successful * Post Dec2010 * High Load		-0.551**	
		(0.233)	
Dependent Claims	0.001**	0.001**	0.001*
	(0.001)	(0.001)	(0.001)
Independent Claims	-0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)
Listed Code	-0.011	-0.012	-0.012
	(0.025)	(0.025)	(0.027)
Constant	0.475***	0.206	0.138
	(0.141)	(0.128)	(0.166)
Observations	4323	4323	3642
Examiner FE	√	√	√
Application Year-Month FE	√	√	√
Petition Year-Month FE	√	√	√
USPC Class FE	√	√	√

NOTE: The outcome variable measures whether the patent application is ultimately granted. Col.1 and Col.2 includes all patent applications which participated in the GTPP. Col. 3 compares the effect of successful petition on patent grant relative to those petitions which were rejected because the target 3500 successful petitions were reached. Standard errors, clustered at the USPC class level, are included in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

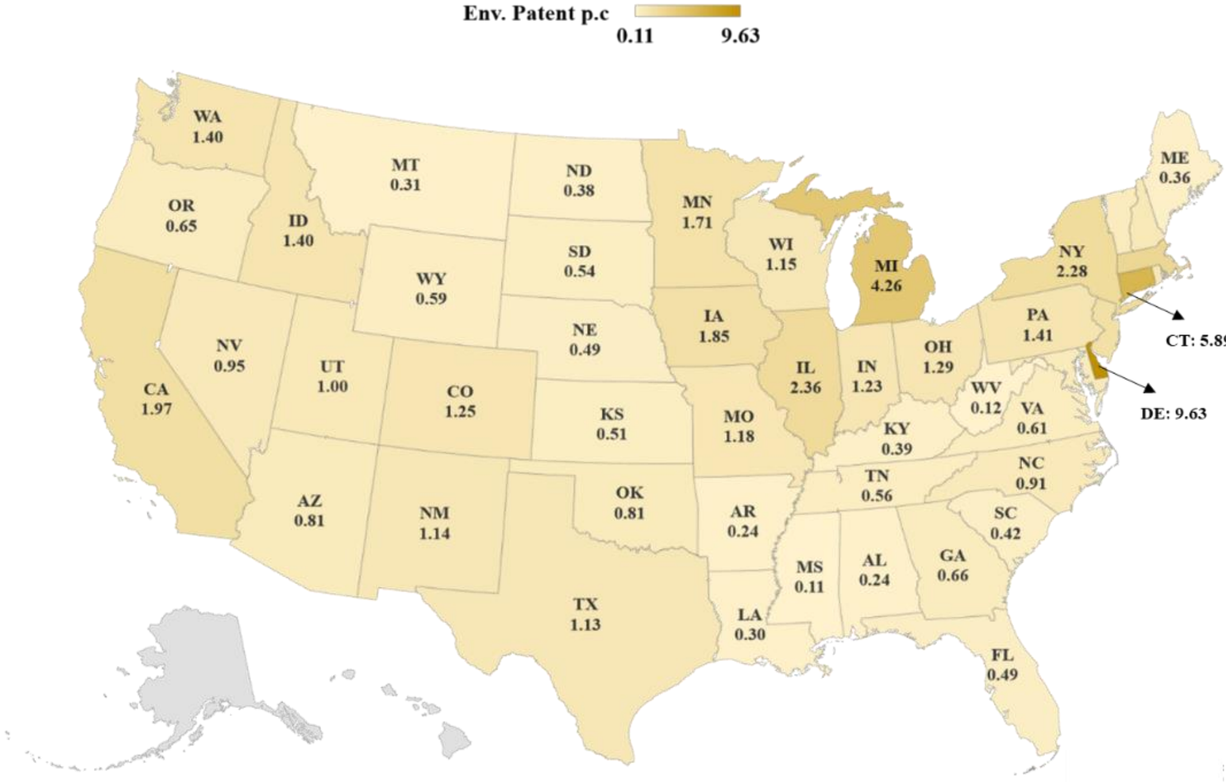
APPENDIX III: LIST OF FIGURES

Figure 1: Environmental policy support and consumer surplus with zero investment costs



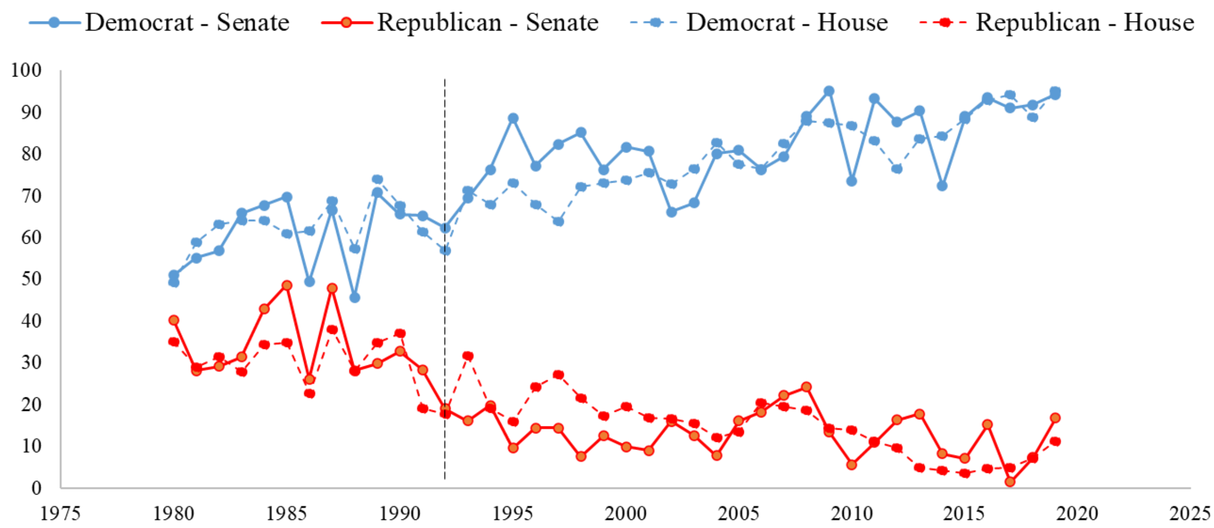
NOTE: The figure represents the geographical distribution of average per capita environmental patents across US states from 1980 to 2019. Deeper shades indicate a higher concentration of environmental patents. The data on patent counts and location are obtained from the website of the USPTO and further classified as environmental patents using the classifications listed in the Green Technology Pilot Program 2009 and Hascic & Migotto (2015). The average counts of environmental patents are represented by 100,000 residents of the respective states. The data on population is obtained from the Annual Census Publications.

Figure 2: Distribution of per capita environmental patents across us states from 1980 to 2019



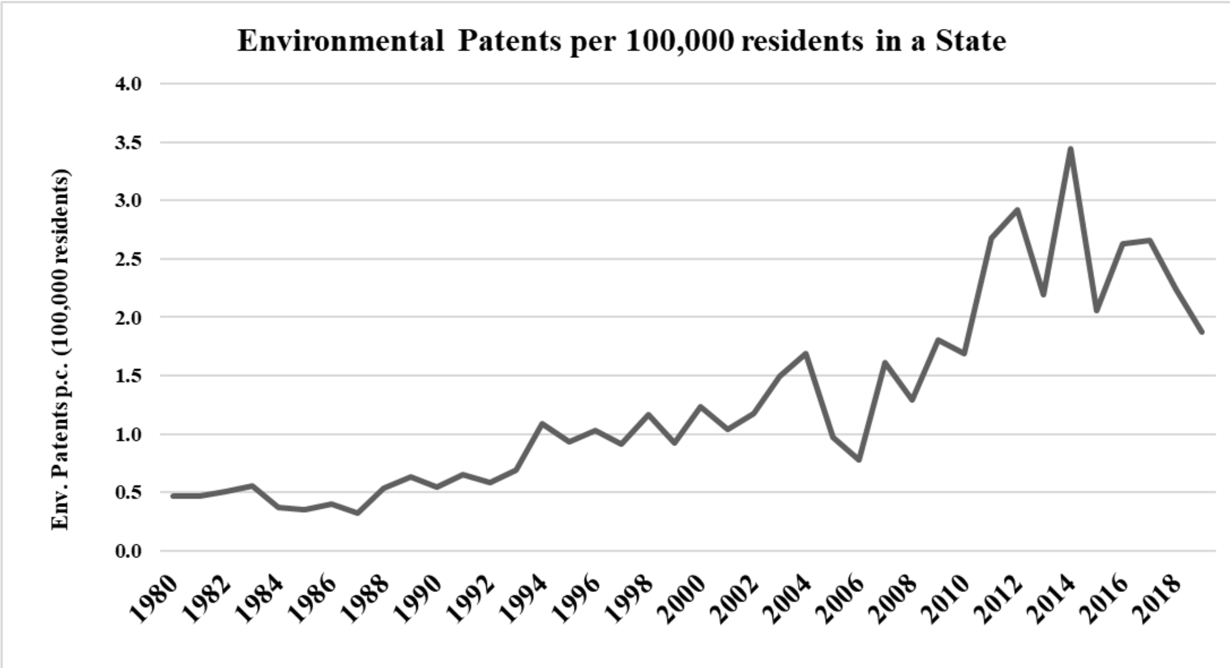
NOTE: The figure represents the geographical distribution of average per capita environmental patents across US states from 1980 to 2019. Deeper shades indicate a higher concentration of environmental patents. The data on patent counts and location are obtained from the website of the USPTO and further classified as environmental patents using the classifications listed in the Green Technology Pilot Program 2009 and Hascic & Migotto (2015). The average counts of environmental patents are represented by 100,000 residents of the respective states. The data on population is obtained from the Annual Census Publications.

Figure 3: Increase in political polarization over environmental policy in the congress



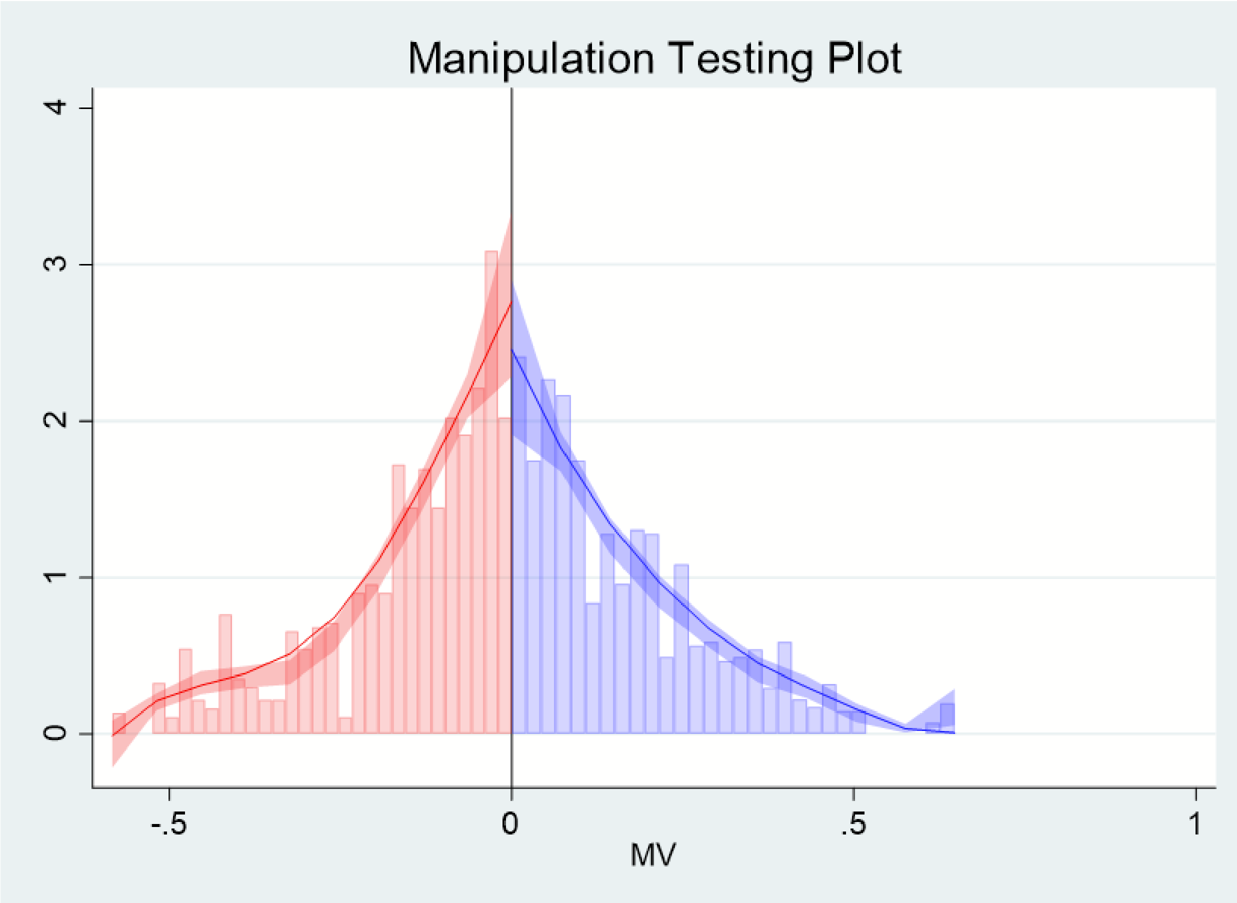
NOTE: The data are obtained from the League of Conservation Voters (LCV) website which computes a value for each member of Congress, indicating how they voted on issues related to the environment each year. (https://scorecard.lcv.org/members-of-congress)

Figure 4: National average of environmental patent applications per capita from 1980 to 2019



NOTE: The graph represents the national average of environmental patent applications per capita each year from 1980 to 2019. The data on patent counts are obtained from the website of the USPTO and further classified as environmental patents using the classifications listed in the Green Technology Pilot Program 2009 and Hascic & Migotto (2015). The average counts of environmental patents are represented by 100,000 residents of the respective states. The data on population is obtained from the Annual Census Publications.

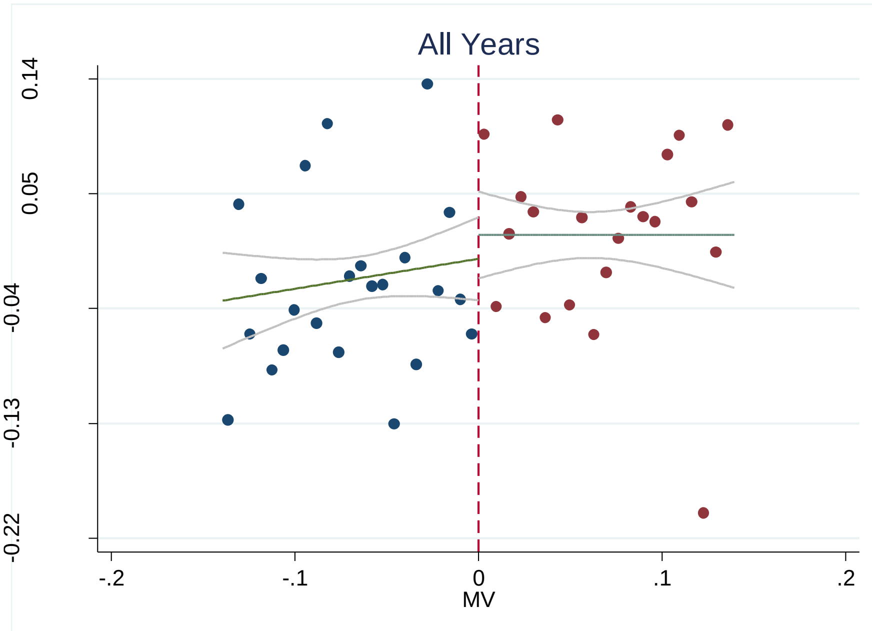
Figure 5: Test for manipulation of data around the cut-off

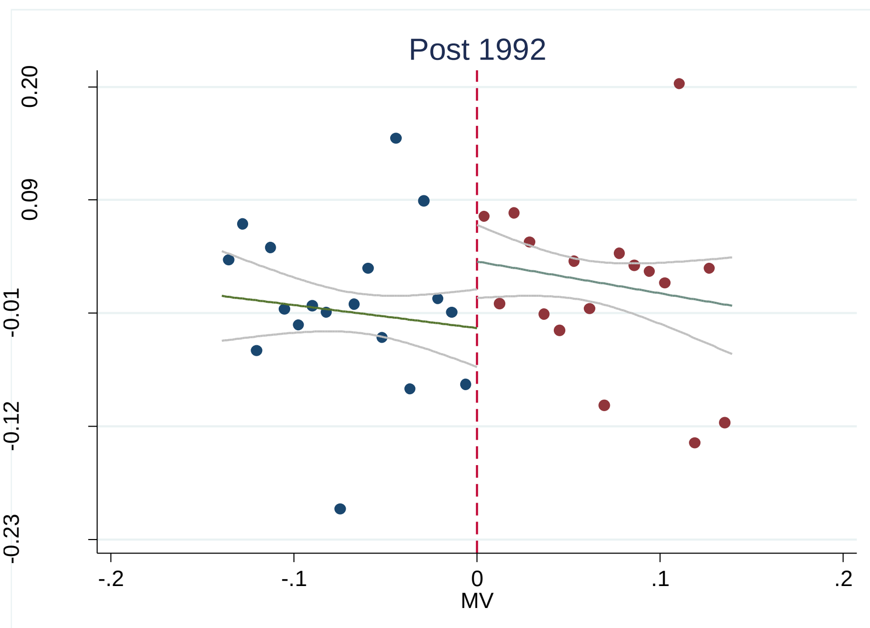


NOTE: The graph represents the results of the McCrary density test to demonstrate that there is no manipulation of running variables across the cut-off. The data on governors' political parties and the results of the gubernatorial elections are obtained from Dave Leip's Atlas of US Elections for the year 1980 to 2019 and includes 48 lower US states. Only those elections have been considered where the Republican or the Democratic governors ranked among the top two contestants.

Figure 6: Effect of state partisan control on the influence of democratic governors on environmental patent applications

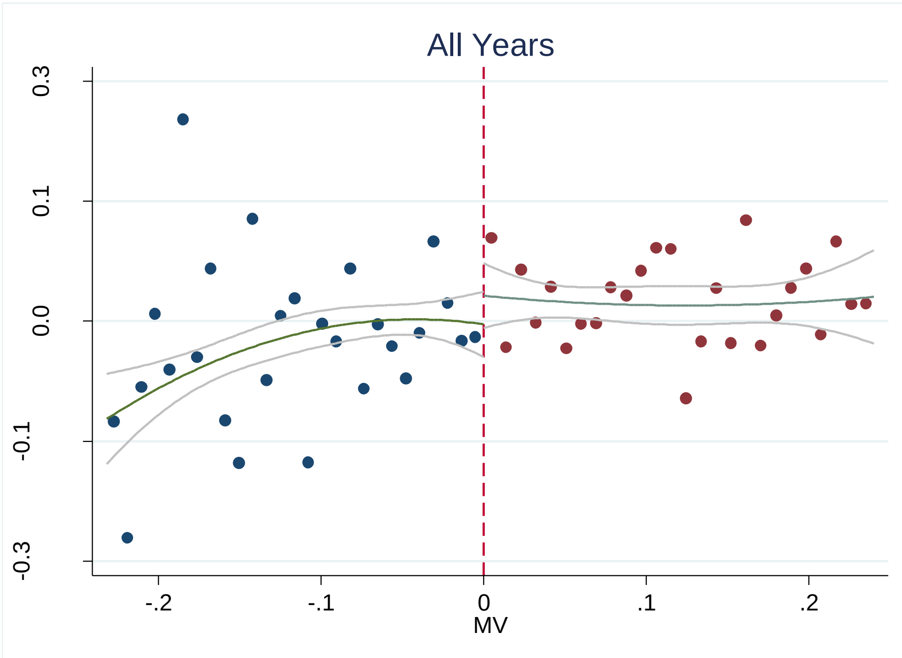
i) Linear Fit (p=1) in a small bandwidth of Victory Margin

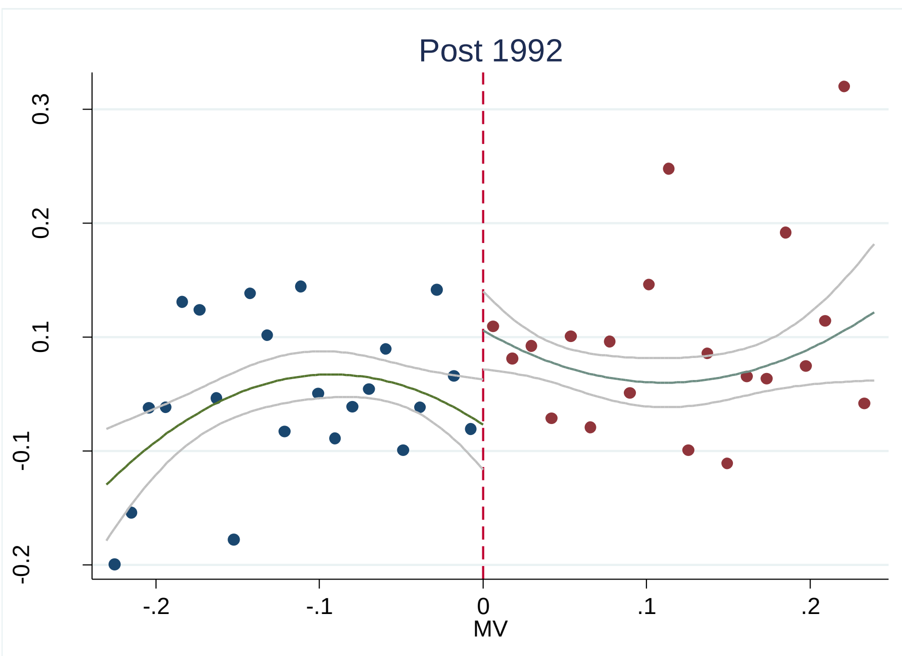




NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log of environmental patent per capita. The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. A linear fit is used for the bandwidth of victory margin of 14%. The diagrams on the left indicate results from the full sample of all years. The diagrams on the rights indicate the results from a sub-sample of post 1992 years.

ii) Quadratic Fit (p=2) in a larger bandwidth of Victory Margin





NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. A quadratic fit is used for the bandwidth of victory margin of 24%. The diagrams on the left indicate results from the full sample of all years. The diagrams on the rights indicate the results from a sub-sample of post 1992 years.

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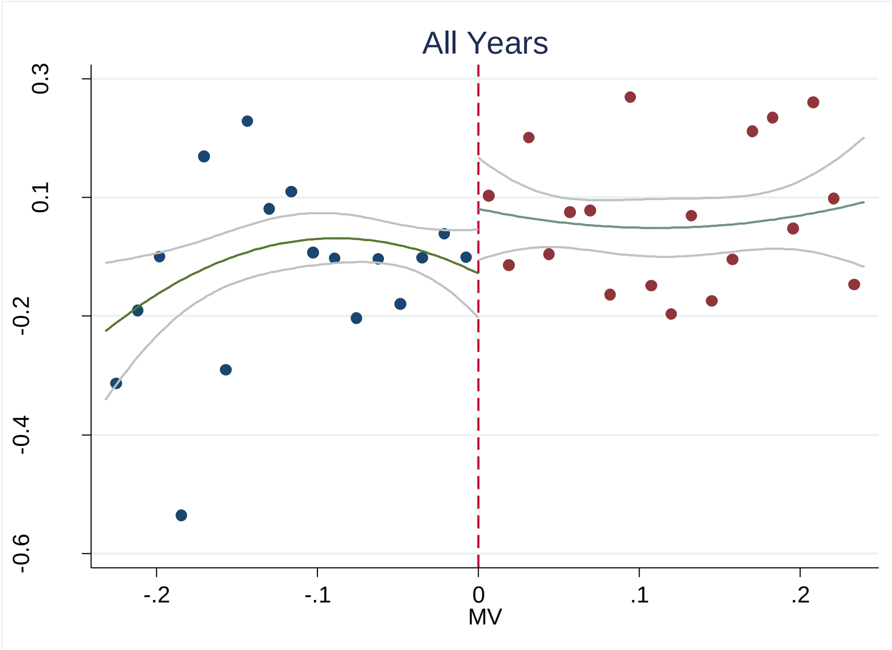
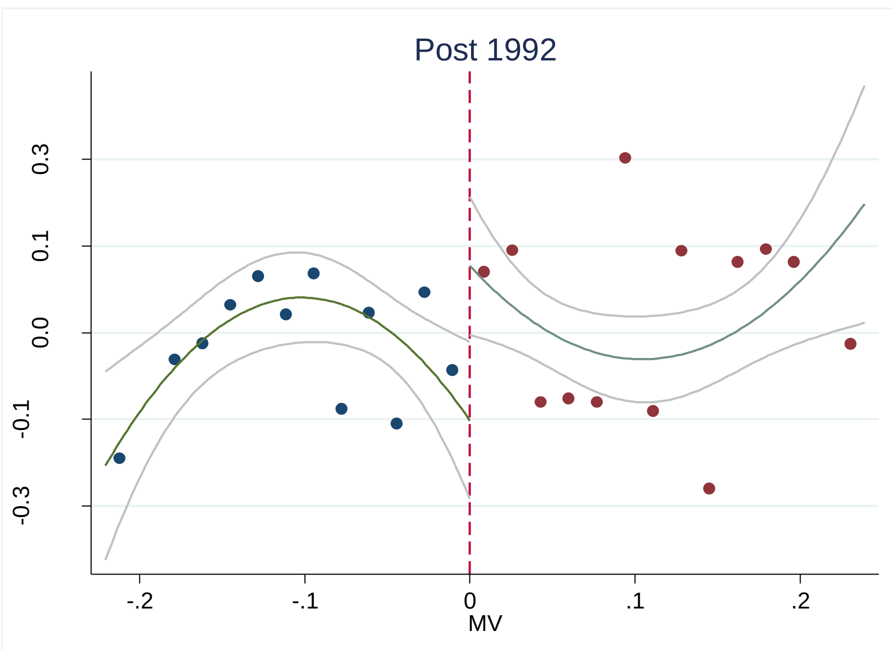
iii) Quadratic Fit (p=2) in a larger bandwidth of victory margin in a trifecta

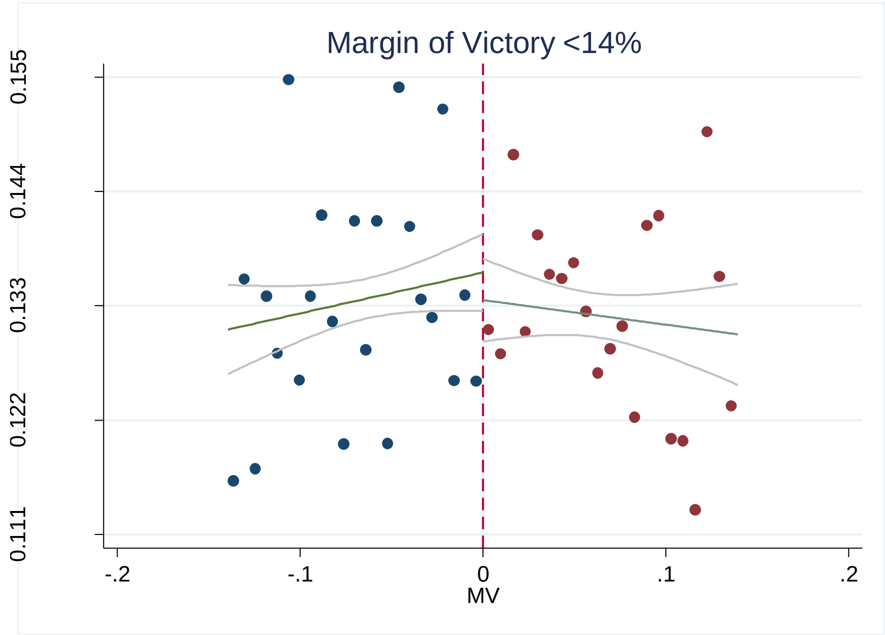


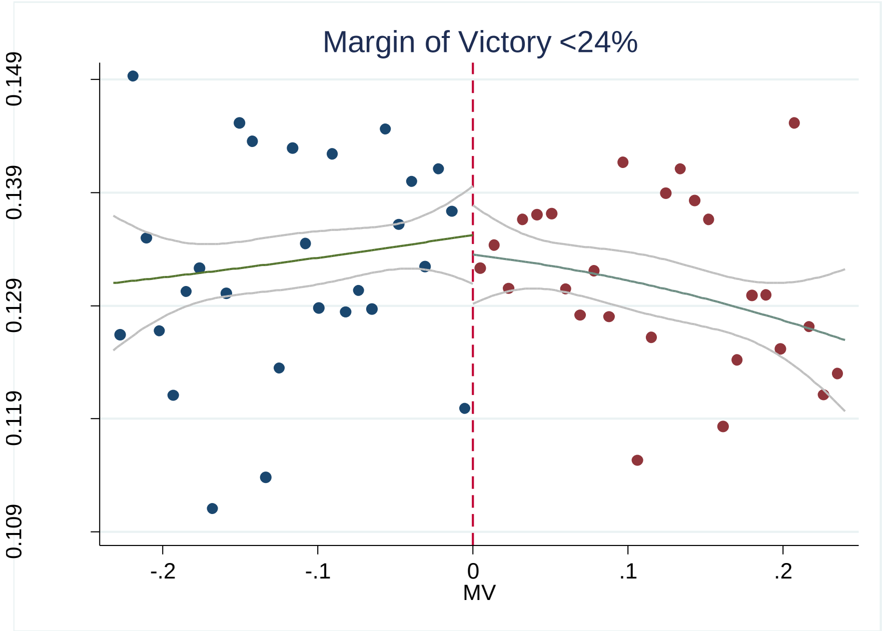


NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor with trifecta on log environmental patent per capita. The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. A quadratic fit is used for the bandwidth of victory margin of 24%. The diagrams on the left indicate results from the full sample of all years. The diagrams on the rights indicate the results from a sub-sample of post 1992 years.

Figure 7: Baseline covariates around the cut-off

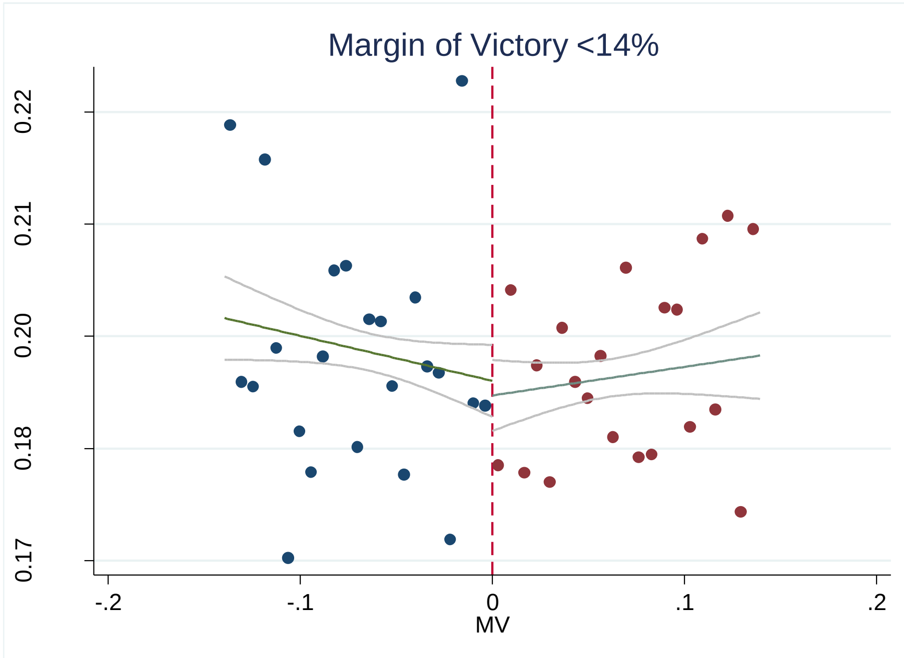
i. Population above 65 years (%)

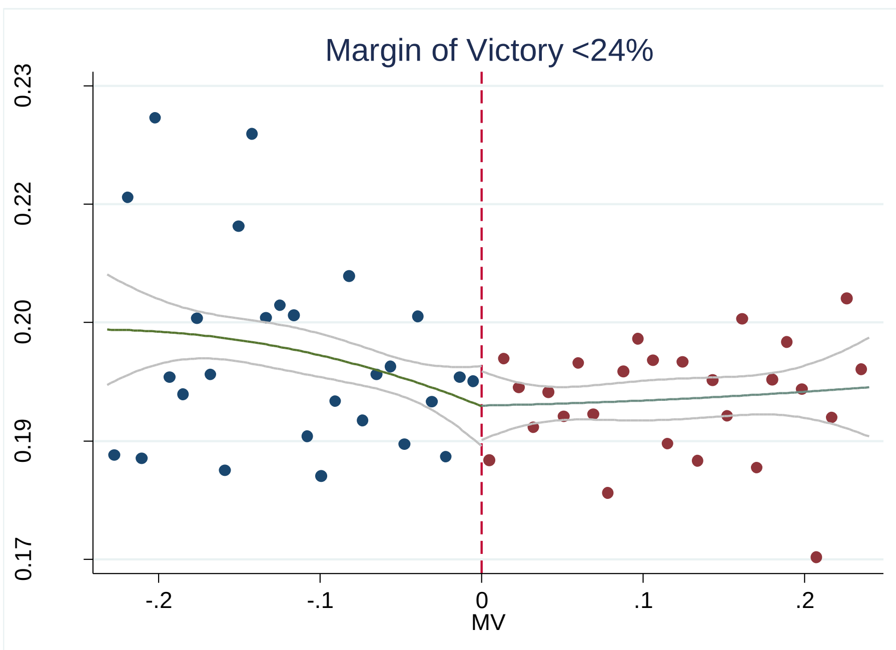




NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on the covariates used in the regression, that is, population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

ii. Population below 17 years (%)





NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on the covariates used in the regression, that is, population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

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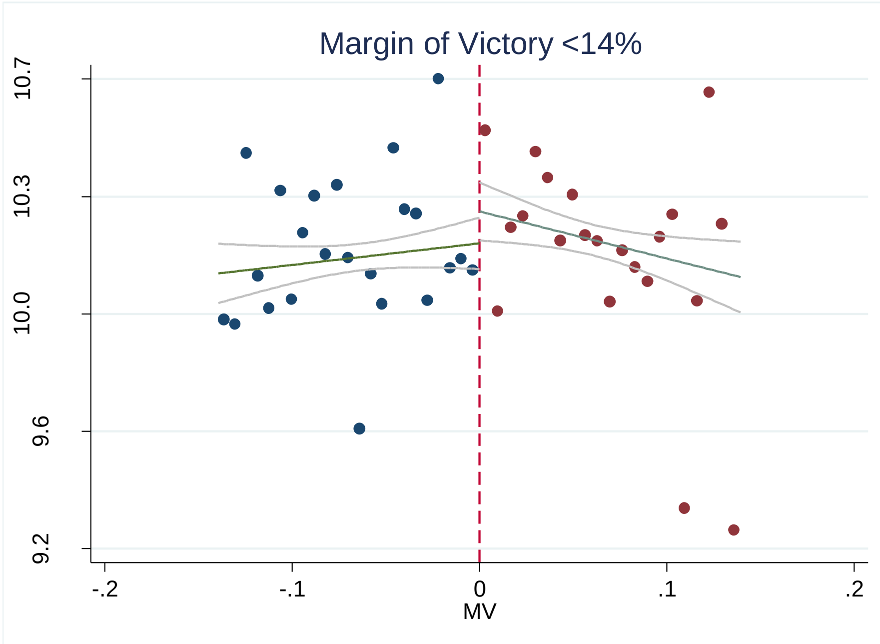
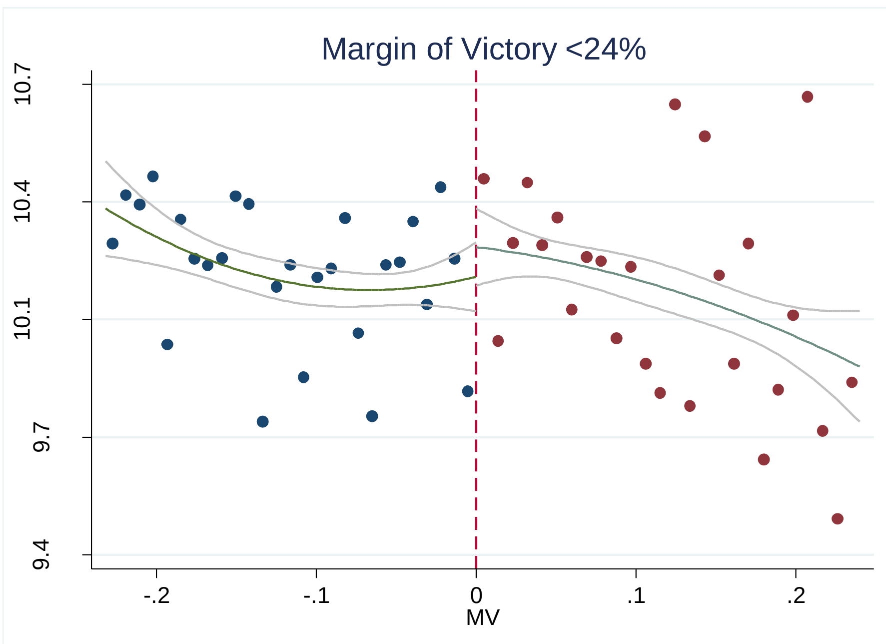
iii. Log of per capita personal income

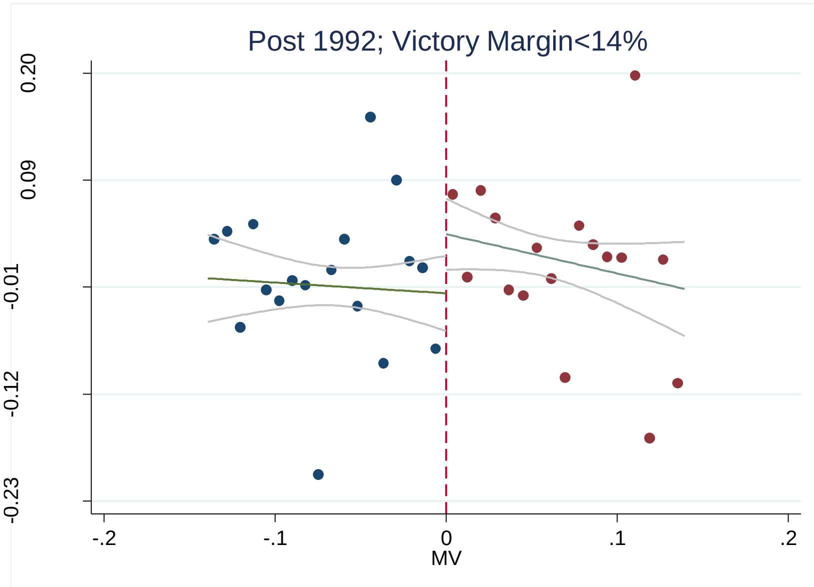




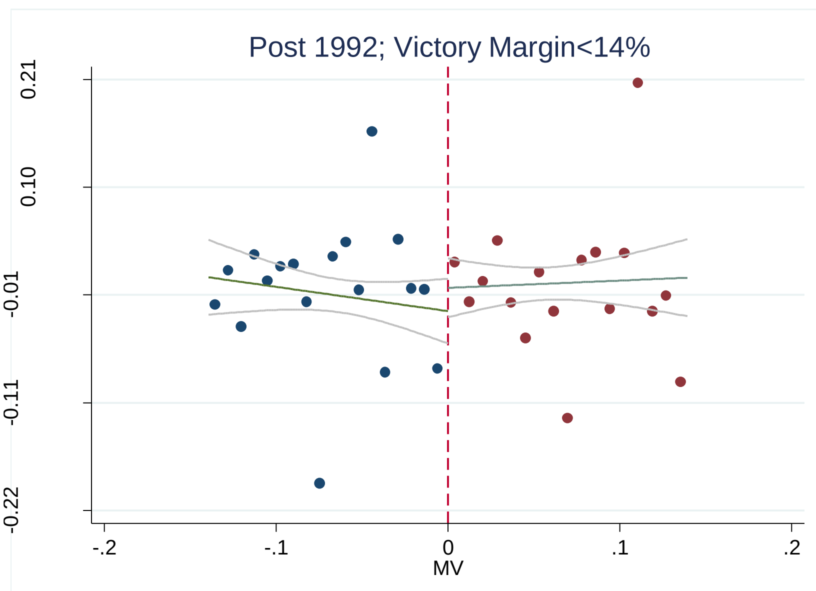
NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on the covariates used in the regression, that is, population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

Figure 8: Influence of democratic governors on current vs lagged environmental patent applications

i) Current environmental patent applications (Linear Fit)



ii) Lagged environmental patent applications (Linear Fit)



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on current and lagged terms of log environmental patent per capita. The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%.

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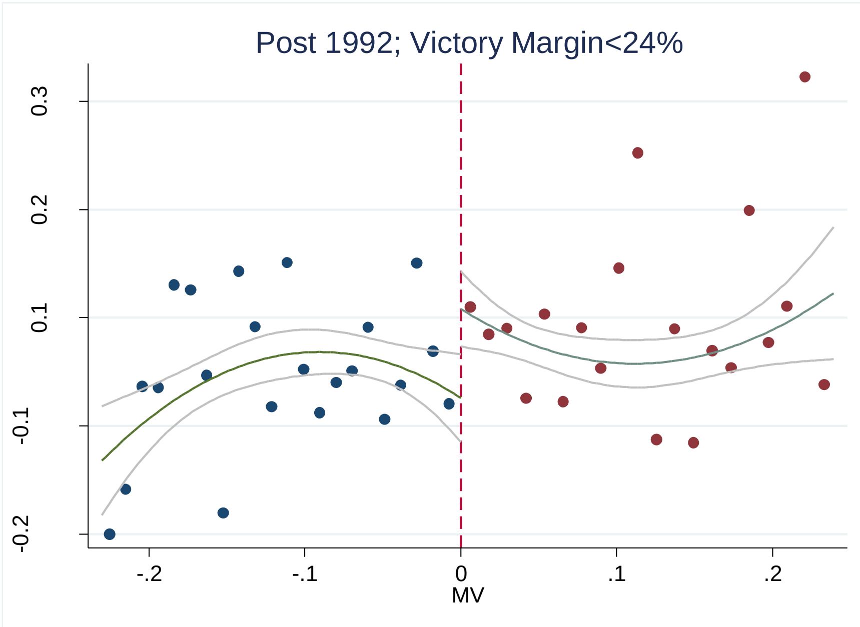
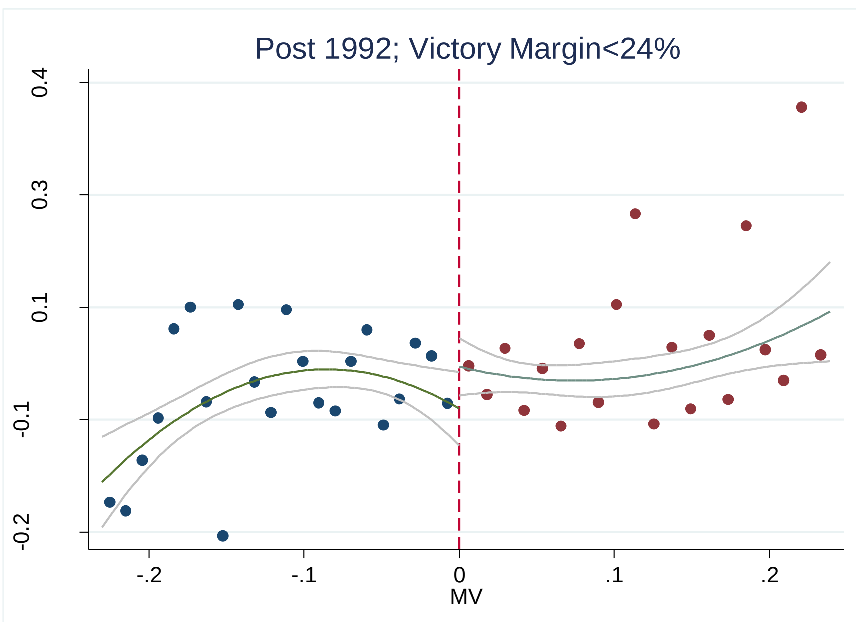
iii) Current environmental patent applications (Quadratic Fit)



iv) Lagged environmental patent applications (Quadratic Fit)

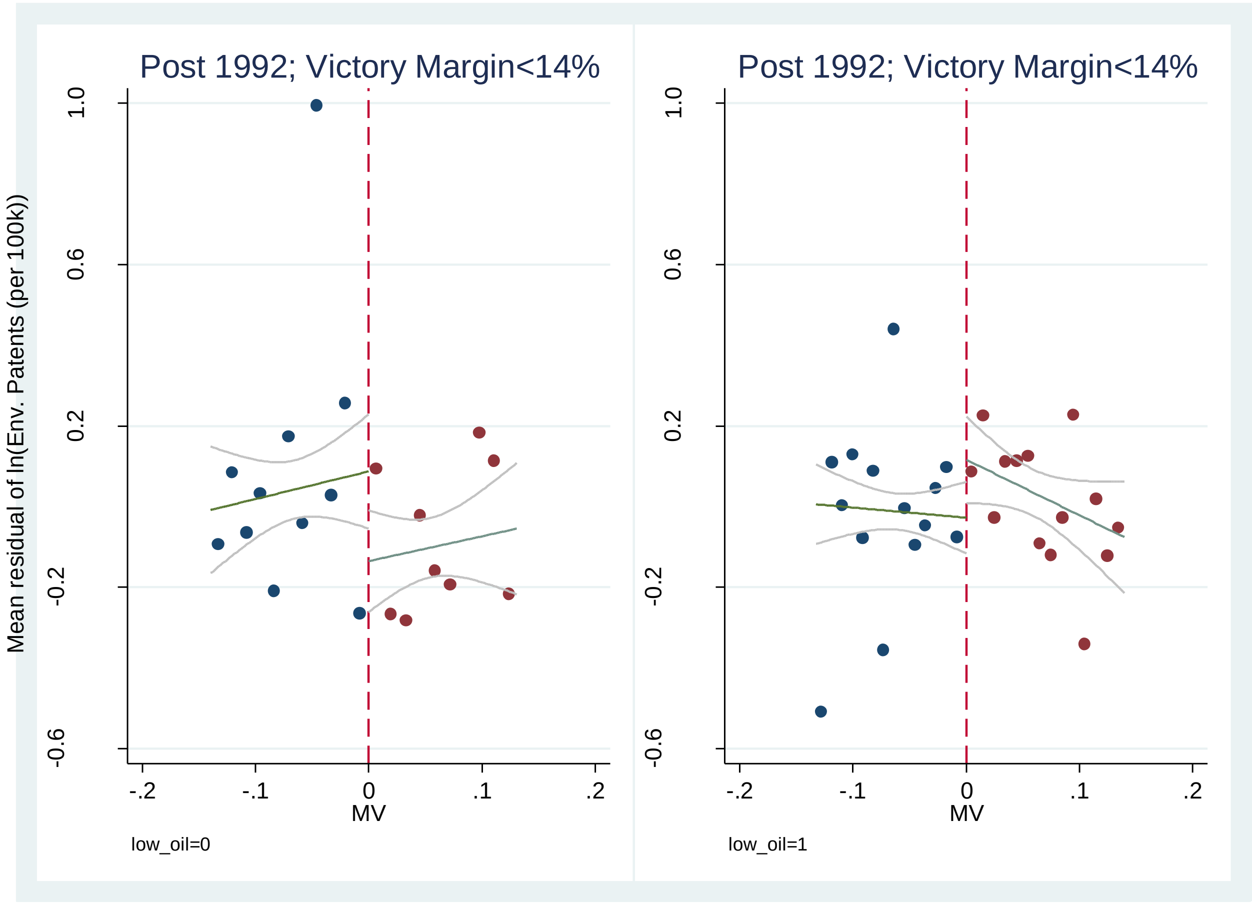


NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on current and lagged terms of log environmental patent per capita. The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. For a larger bandwidth of 24%, I use a quadratic fit.

Figure 9: Influence of Democratic governors on environmental patent applications in states with differing environmental sentiment

i) Comparing the effect in states with oil production per 100,000 resident > median (low_oil=0) vs < median (low_oil=1)

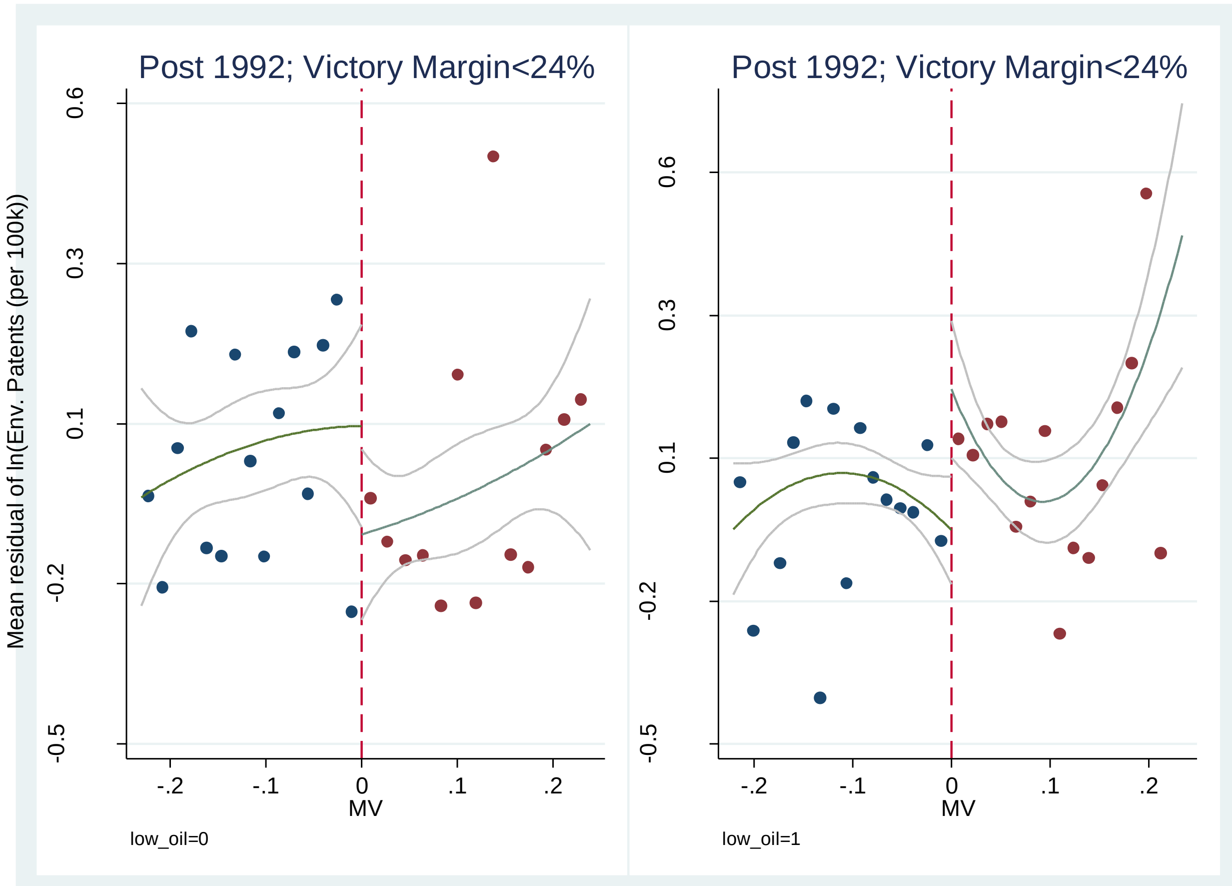
States with Oil production > Median | *States with Oil production < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states with oil production per 100,000 resident > median (low_oil=0) verses < median (low_oil=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

ii) Comparing the effect in states with oil production per 100,000 resident > median (low_oil=0) vs < median (low_oil=1)

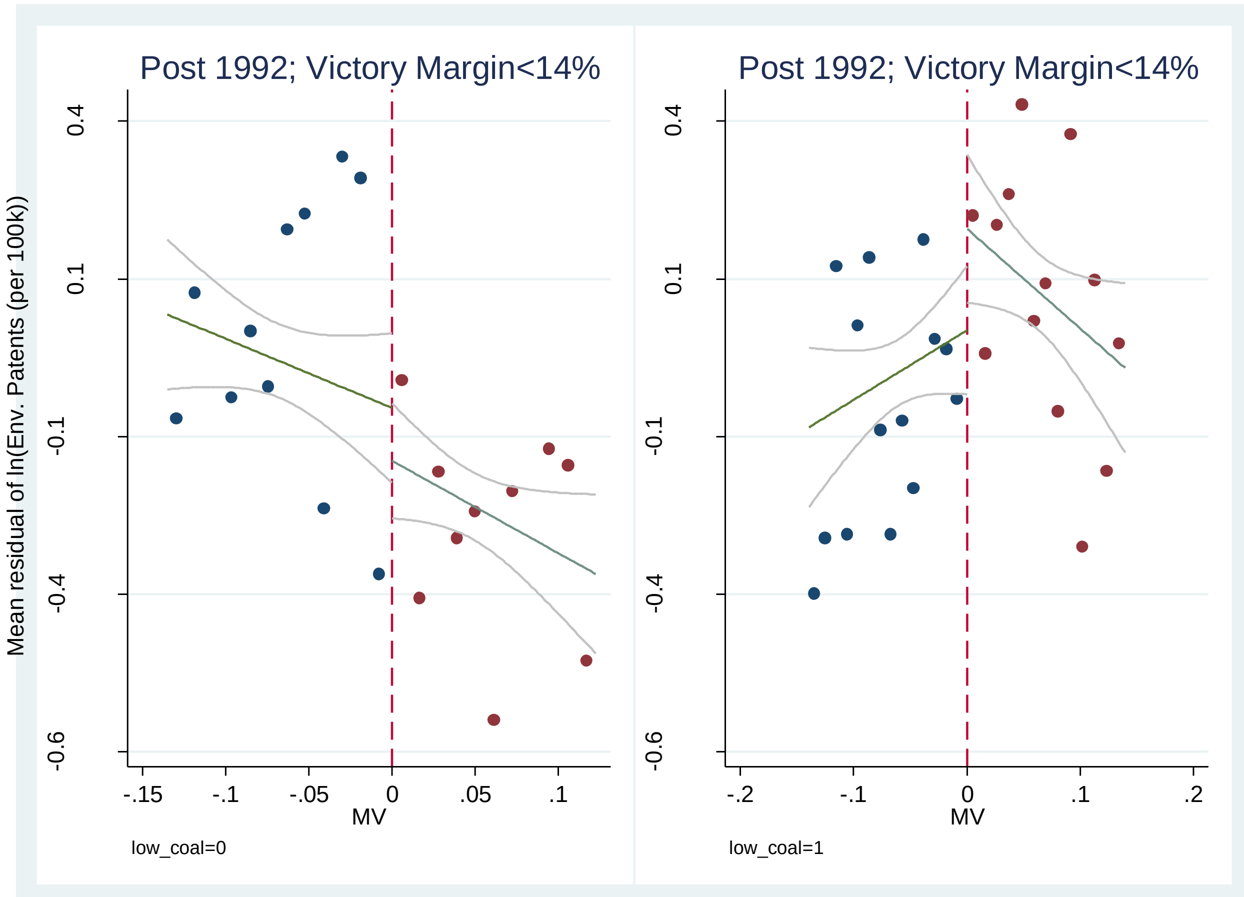
States with Oil production > Median *States with Oil production < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states with oil production per 100,000 resident > median (low_oil=0) verses < median (low_oil=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

iii) Comparing the effect in states with coal production per 100,000 resident > median (low_coal=0) vs < median (low_coal=1)

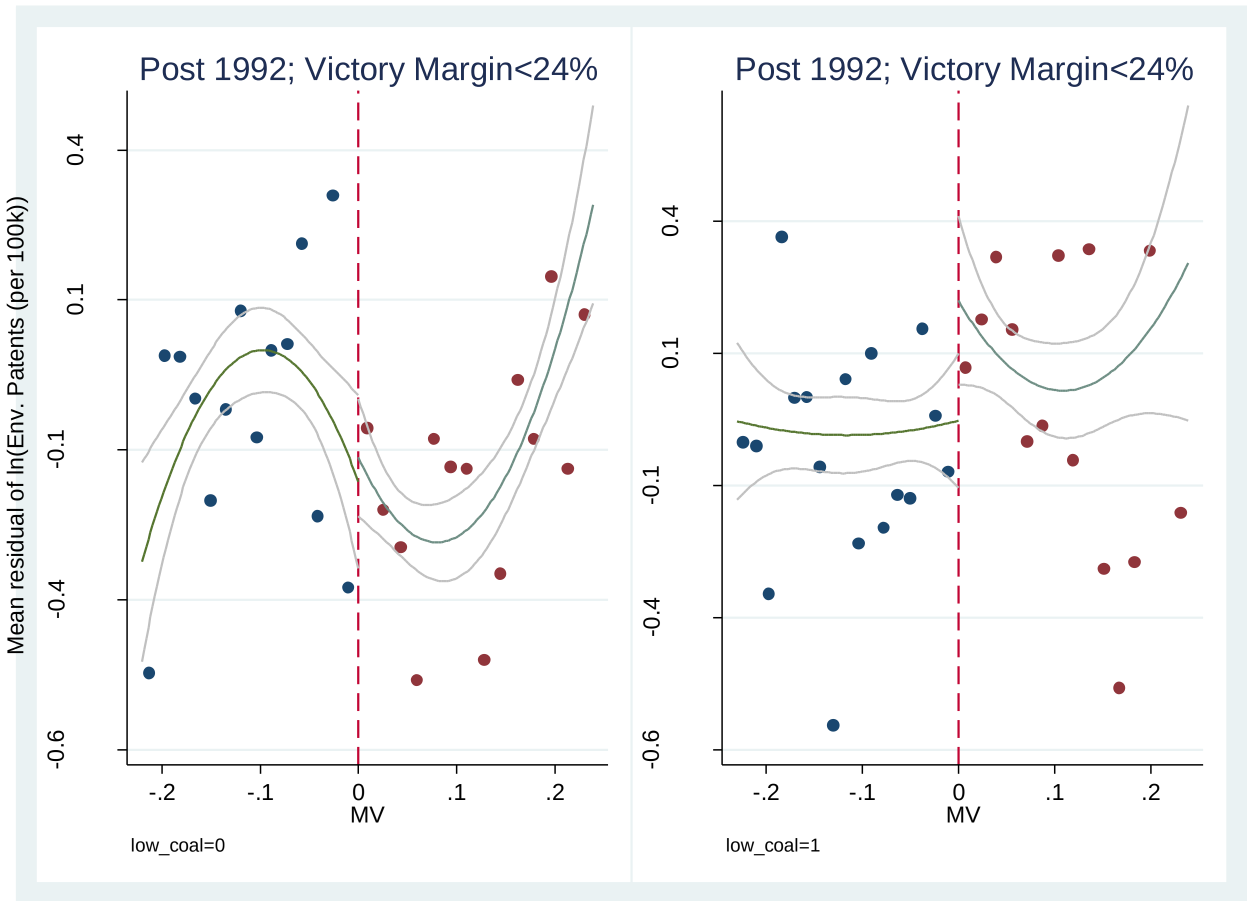
States with Coal production > Median *States with Coal production < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states with coal production per 100,000 resident > median (low_coal=0) verses < median (low_coal=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

iv) Comparing the effect in states with coal production per 100,000 resident > median (low_coal=0) vs < median (low_coal=1)

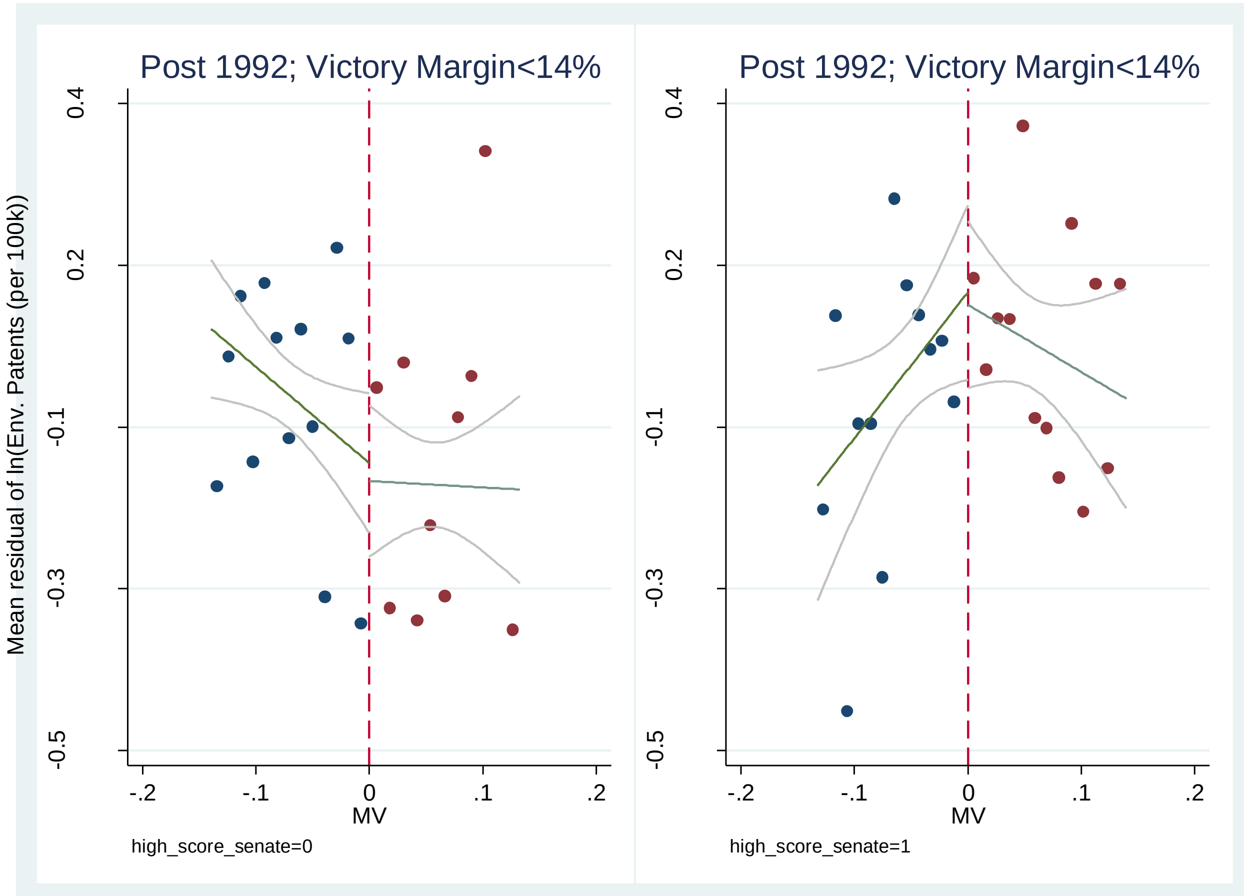
States with Coal production > Median *States with Coal production < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states with coal production per 100,000 resident > median (low_coal=0) verses < median (low_coal=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

v) Comparing the effect in states with Senate EVS score > median (high_score_senate=1) vs < median (high_score_senate=0)

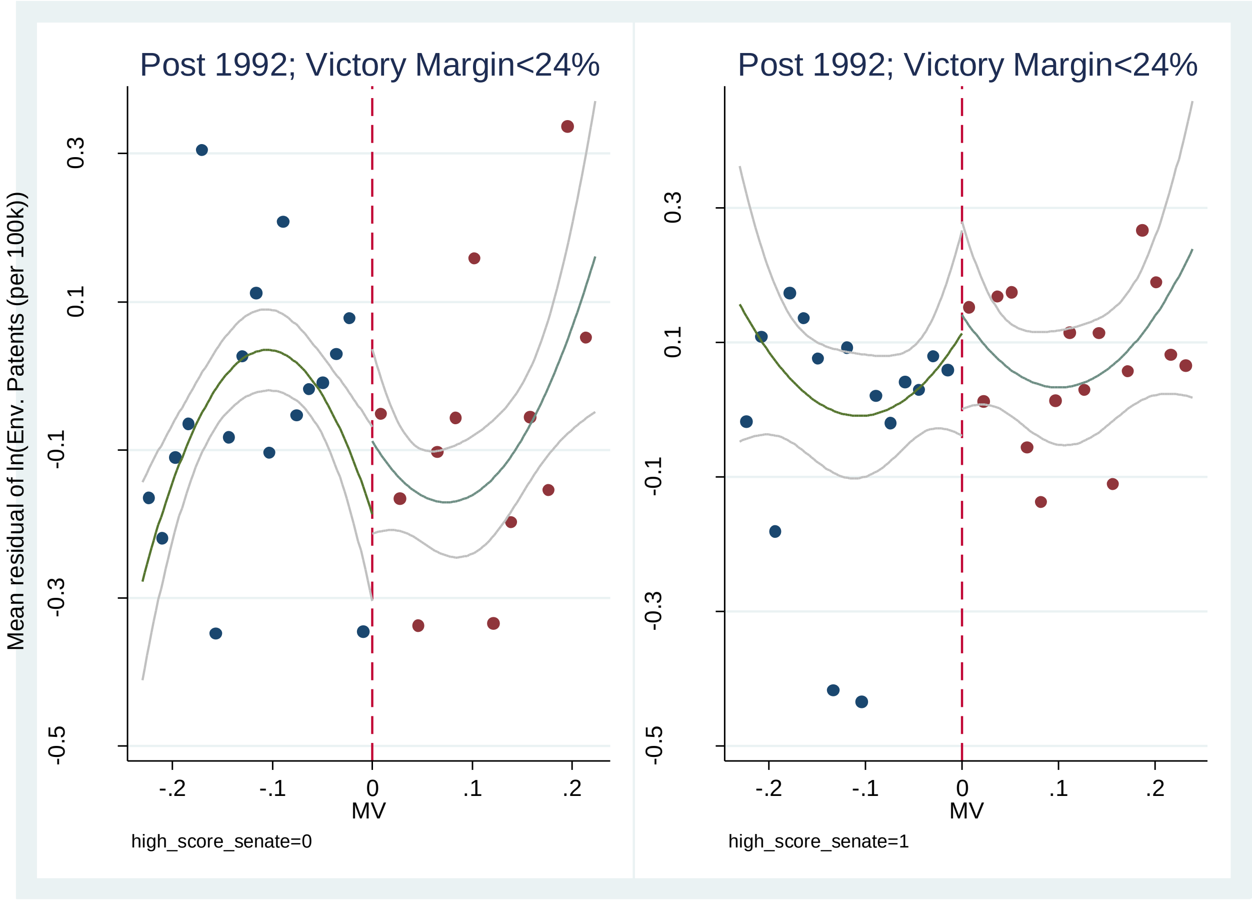
States with Senate EVS > Median *States with Senate EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states where environmental voting score of the senators from that state > median (high_score_senate=1) verses < median (high_score_senate=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

vi) Comparing the effect in states with Senate EVS score > median (high_score_senate=1) vs < median (high_score_senate=0)

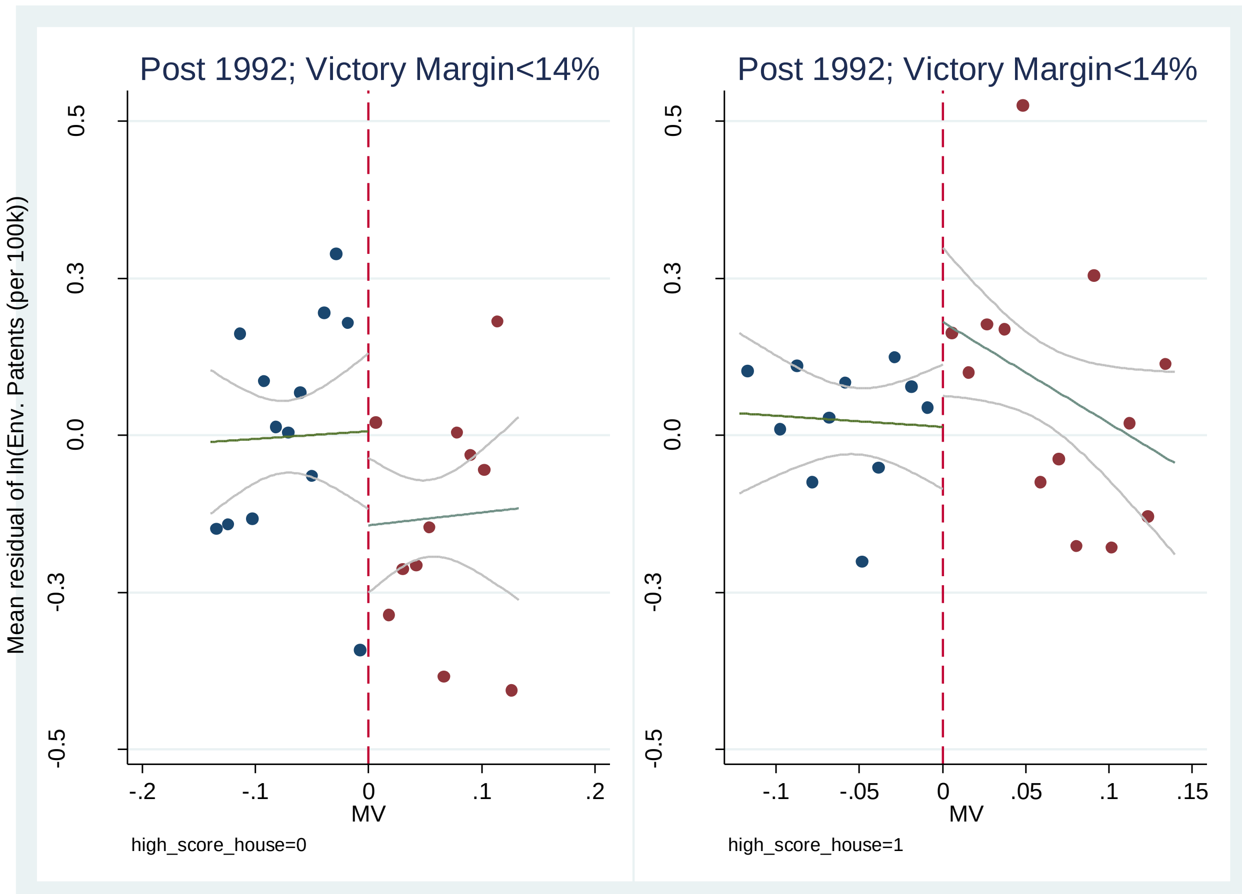
States with Senate EVS > Median *States with Senate EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states where environmental voting score of the senators from that state > median (high_score_senate=1) verses < median (high_score_senate=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

vii) Comparing the effect in states with House EVS score > median (high_score_house=1) vs < median (high_score_house=0)

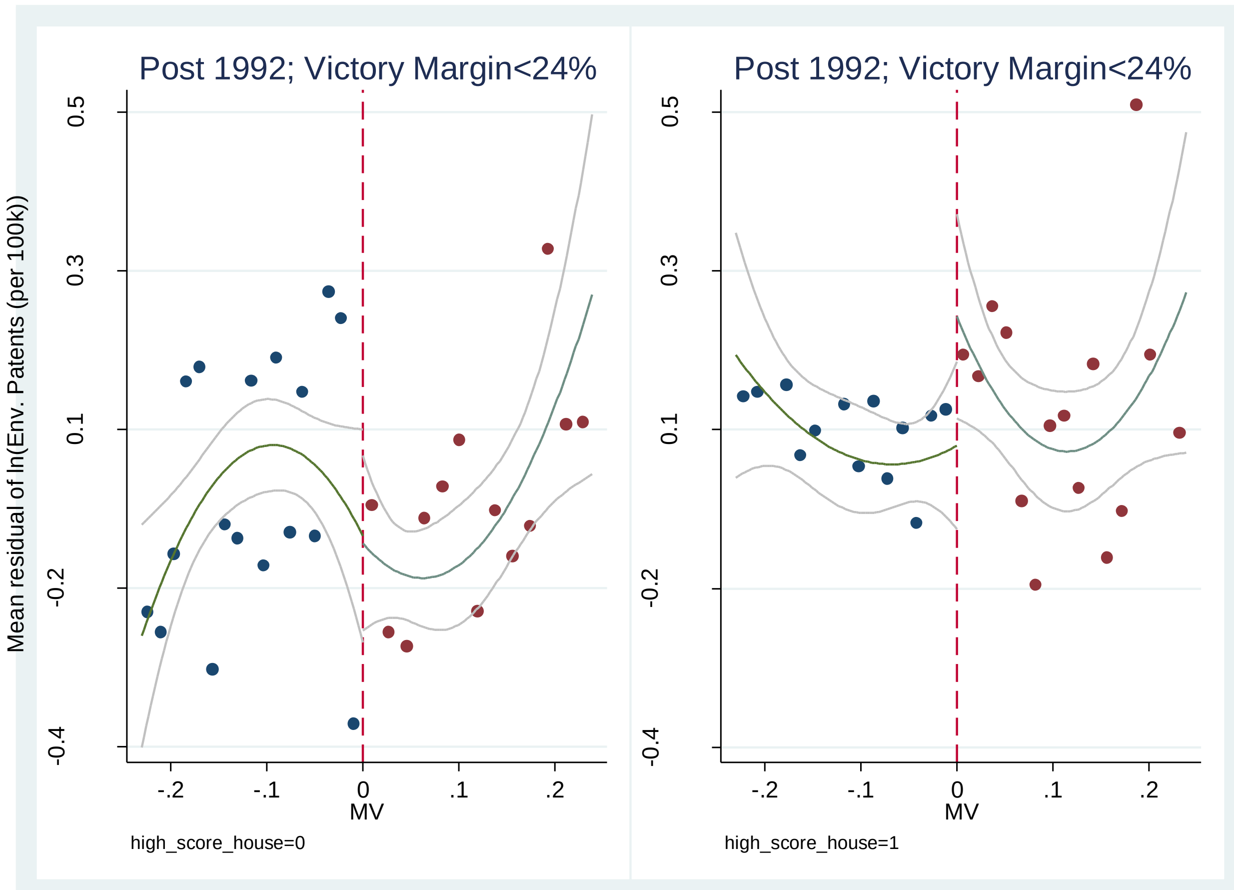
States with House EVS > Median *States with House EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states where environmental voting score of the House representatives from that state > median (high_score_house=1) verses < median (high_score_house=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

viii)   Comparing the effect in states with House EVS score > median (high_score_house=1) vs < median (high_score_house=0)

States with House EVS > Median   *States with House EVS < Median*

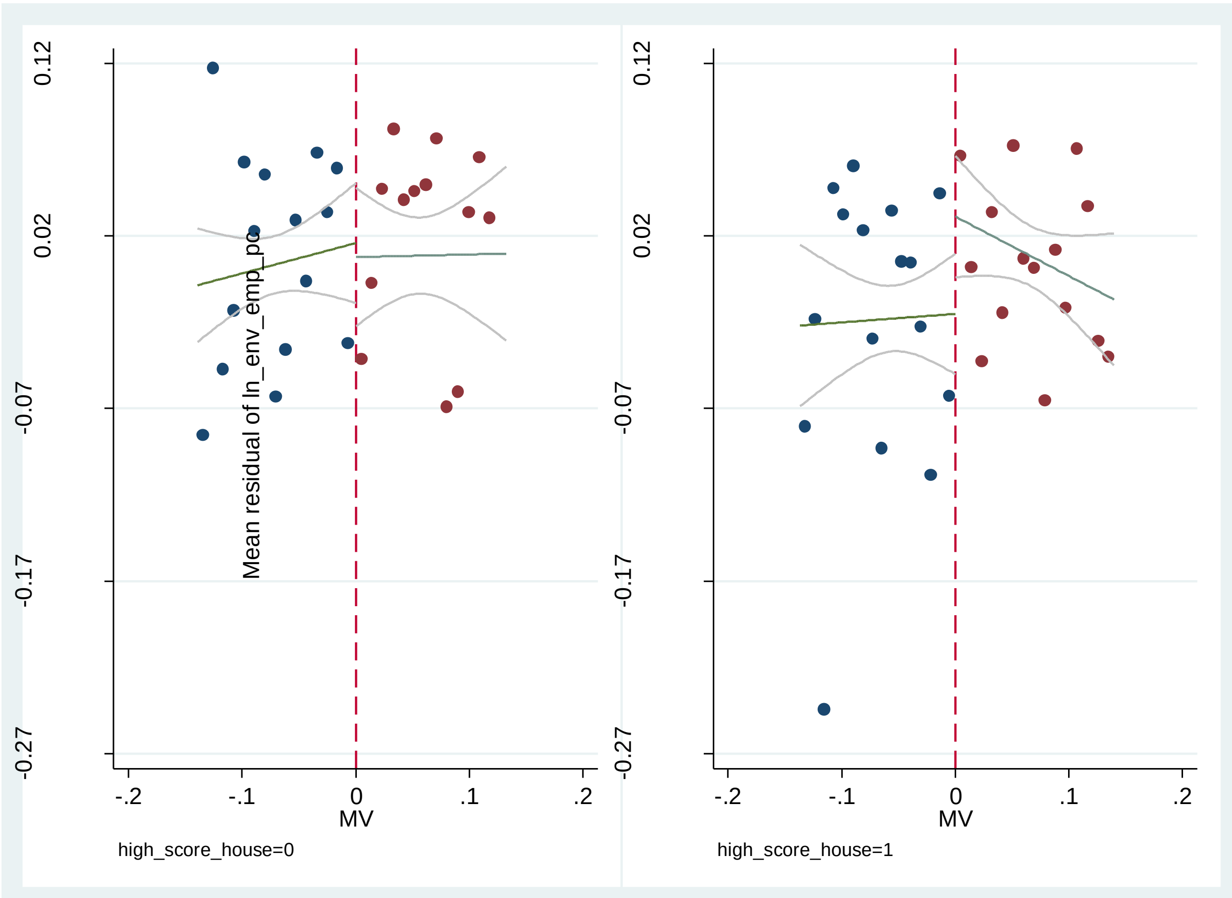


NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental patent per capita. The two panels compare the effect in states where environmental voting score of the House representatives from that state > median (high_score_house=1) verses < median (high_score_house=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

Figure 10: Influence Of Democratic Governors On Environmental Employment

i) Comparing the effect in states with House EVS score > median (high_score_house=1) vs < median (high_score_house=0)

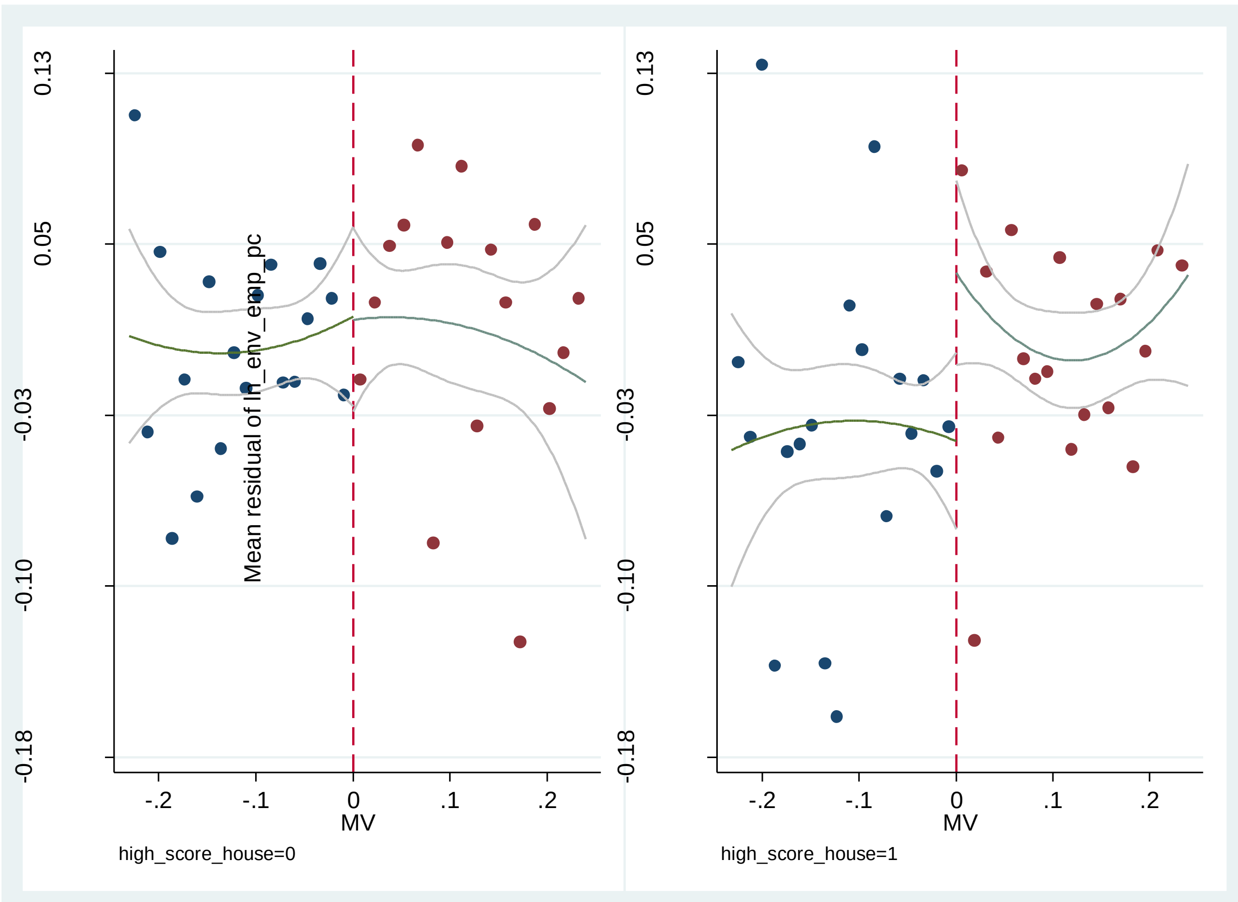
States with House EVS > Median *States with House EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states where environmental voting score of the House representatives from that state > median (high_score_house=1) verses < median (high_score_house=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

ii) *Comparing the effect in states with House EVS score > median (high_score_house=1) vs < median (high_score_house=0)*

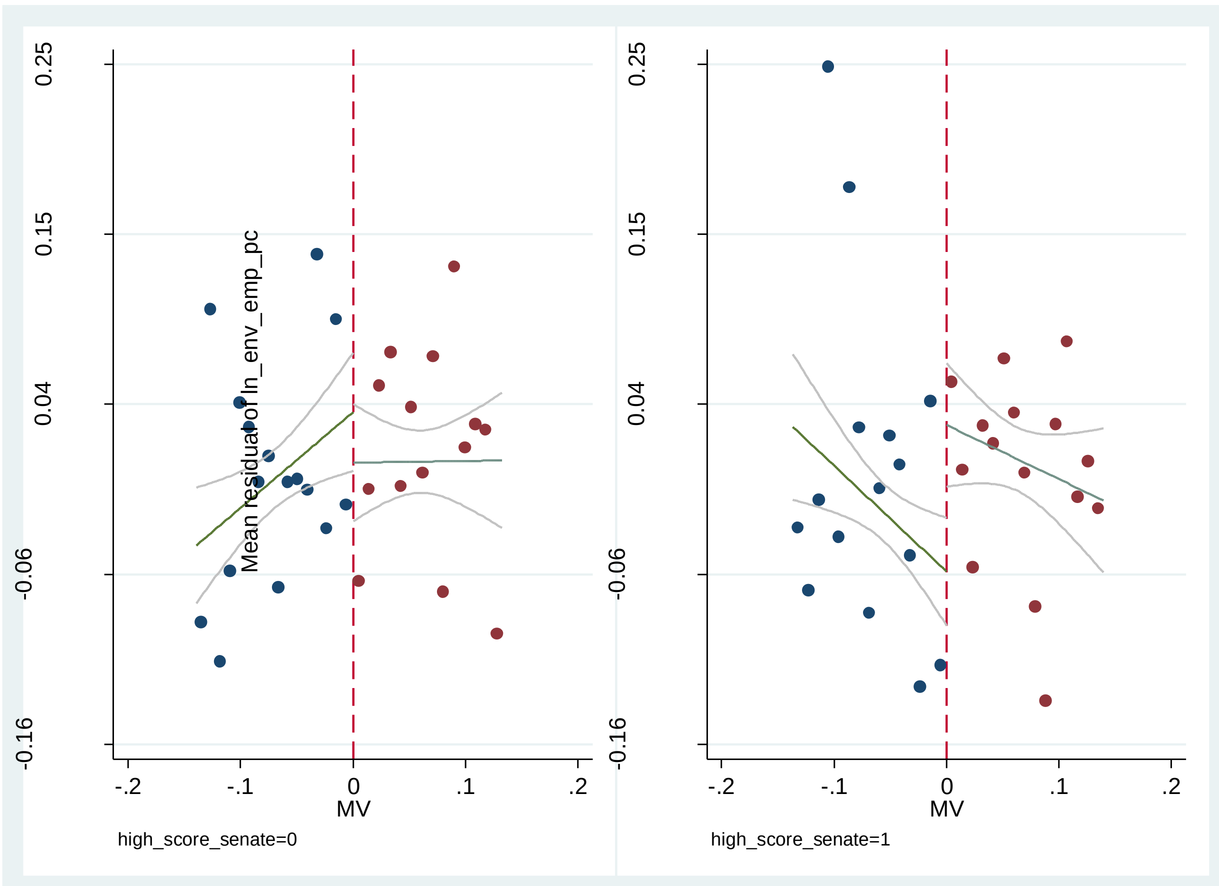
States with House EVS > Median *States with House EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states where environmental voting score of the House representatives from that state > median (high_score_house=1) verses < median (high_score_house=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

iii) Comparing the effect in states with Senate EVS score > median (high_score_senate=1) vs < median (high_score_senate=0)

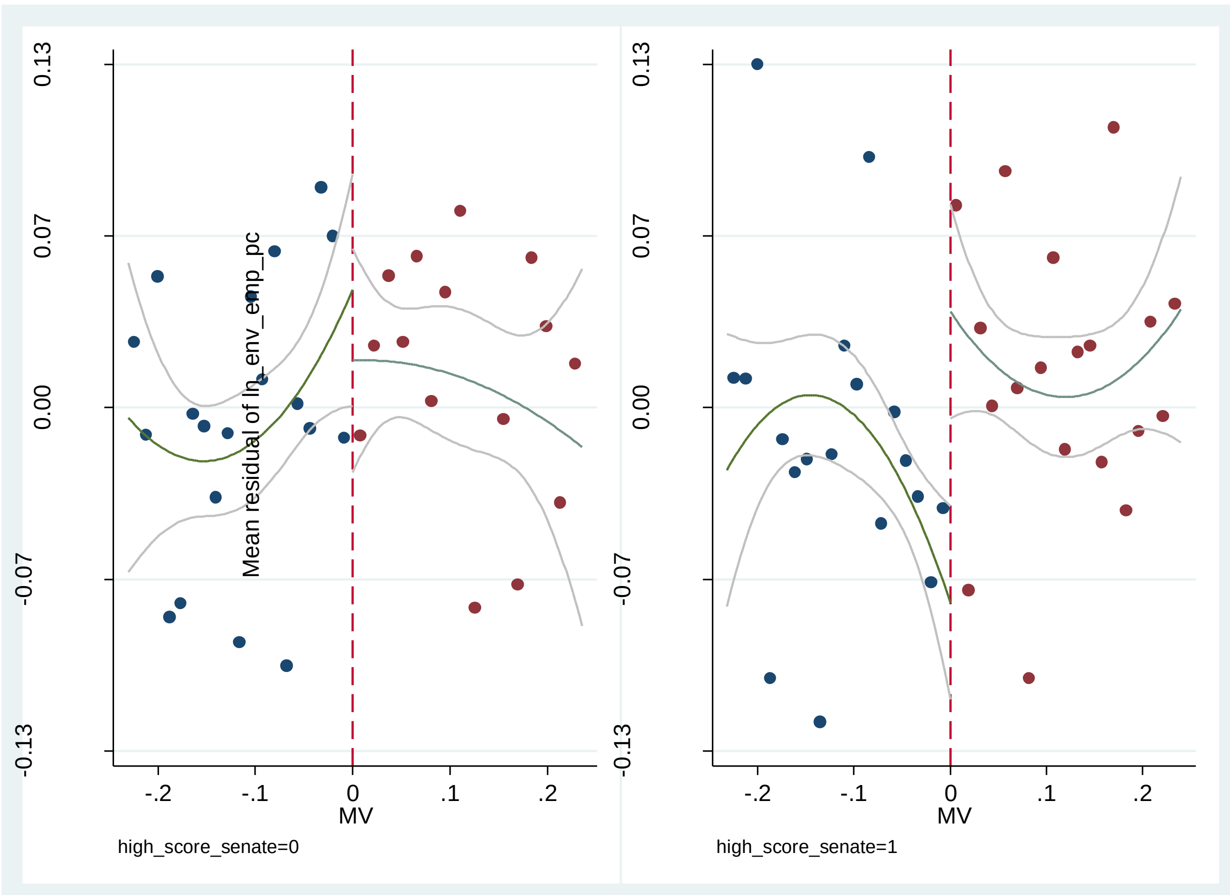
States with Senate EVS > Median *States with Senate EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states where environmental voting score of the senators from that state > median (high_score_senate=1) verses < median (high_score_senate=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

iv) Comparing the effect in states with Senate EVS score > median (high_score_senate=1) vs < median (high_score_senate=0)

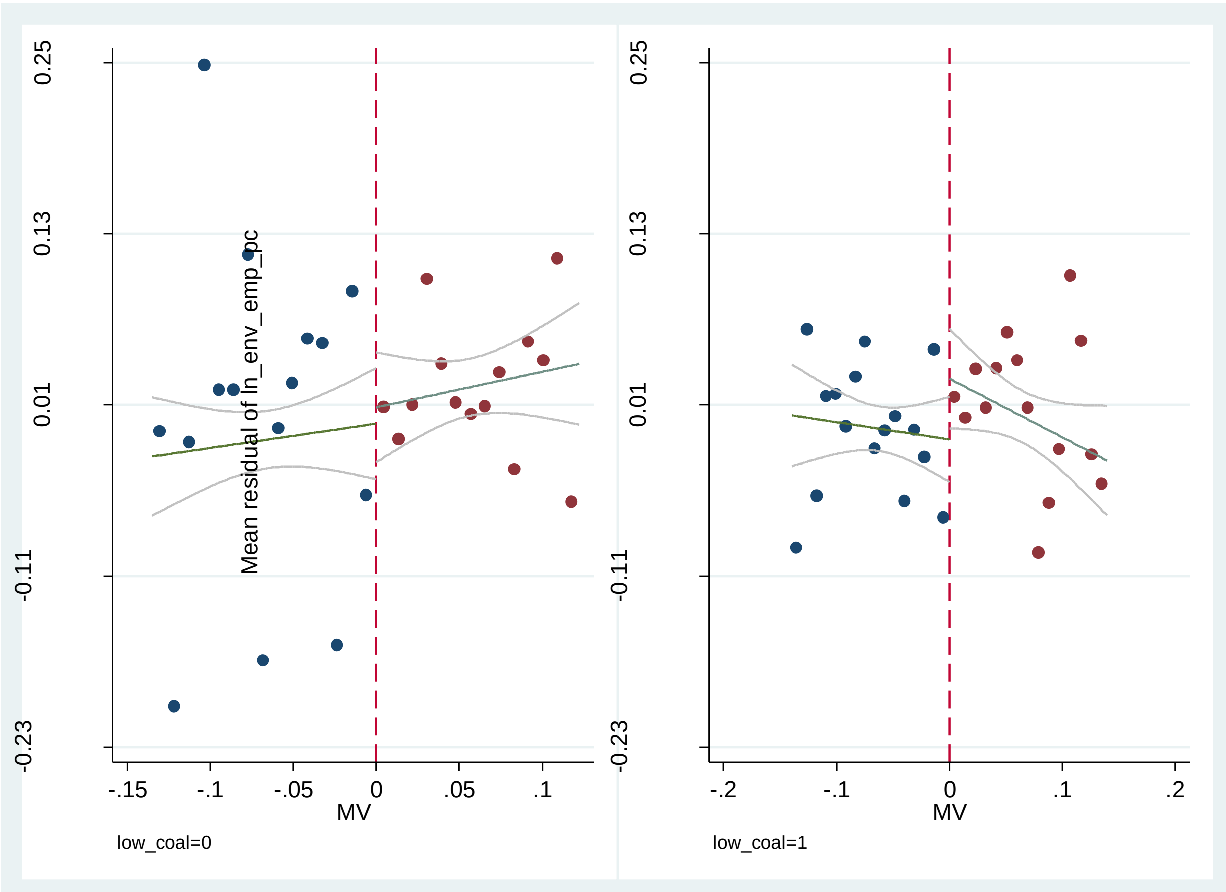
States with Senate EVS > Median *States with Senate EVS < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states where environmental voting score of the senators from that state > median (high_score_senate=1) verses < median (high_score_senate=0). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

v) *Comparing the effect in states with coal production per 100,000 resident > median (low_coal=0) vs < median (low_coal=1)*

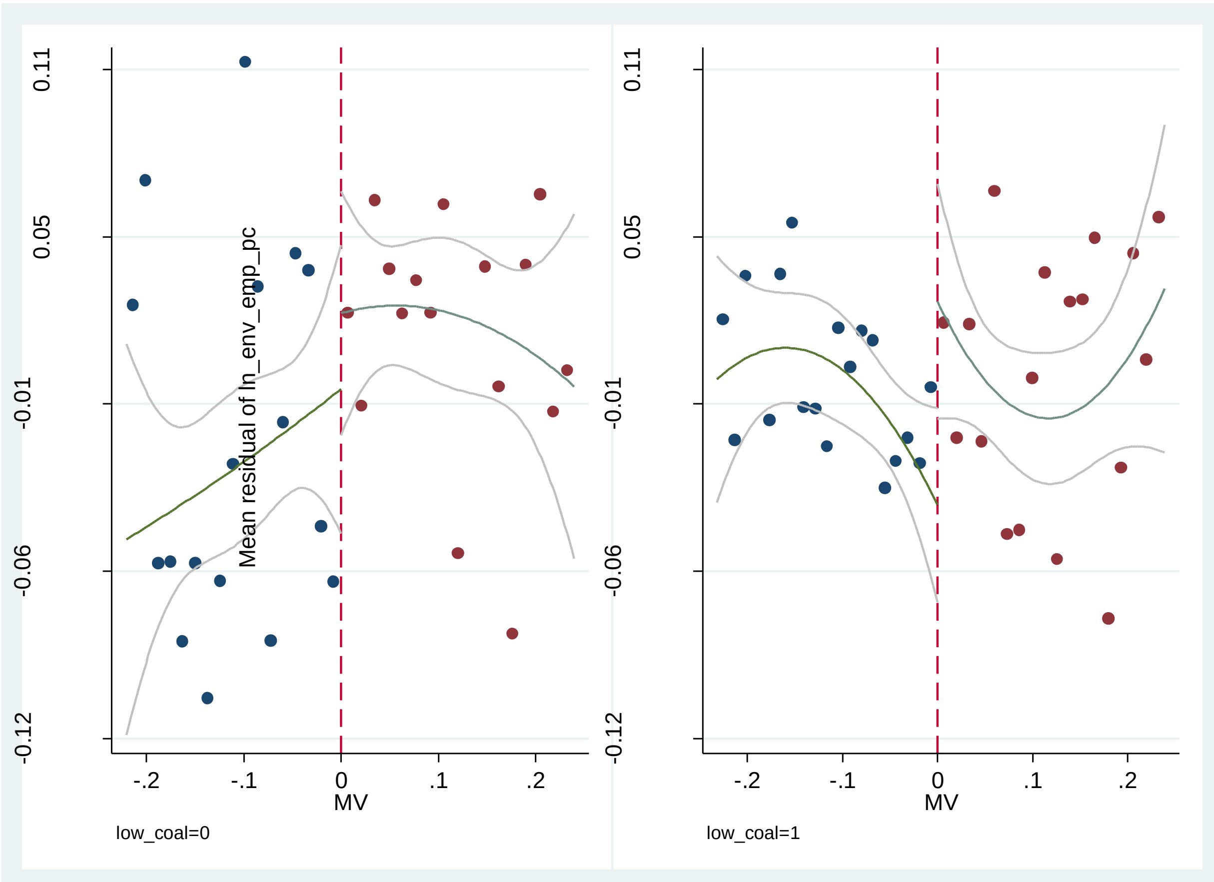
States with Coal production > Median *States with Coal production < Median*



NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states with coal production per 100,000 resident > median (low_coal=0) verses < median (low_coal=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

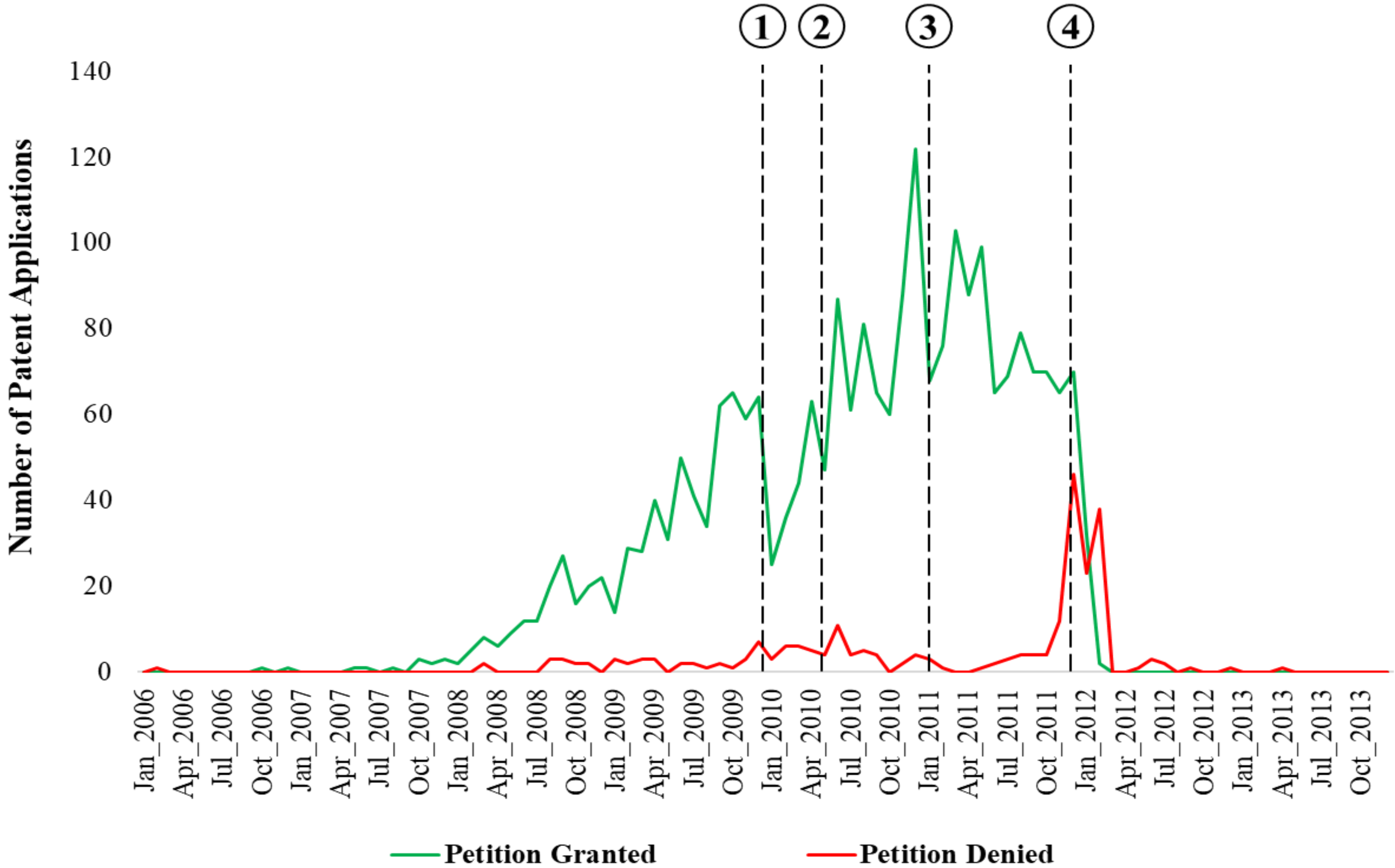
vi) Comparing the effect in states with coal production per 100,000 resident > median (low_coal=0) vs < median (low_coal=1)

States with Coal production > Median *States with Coal production < Median*



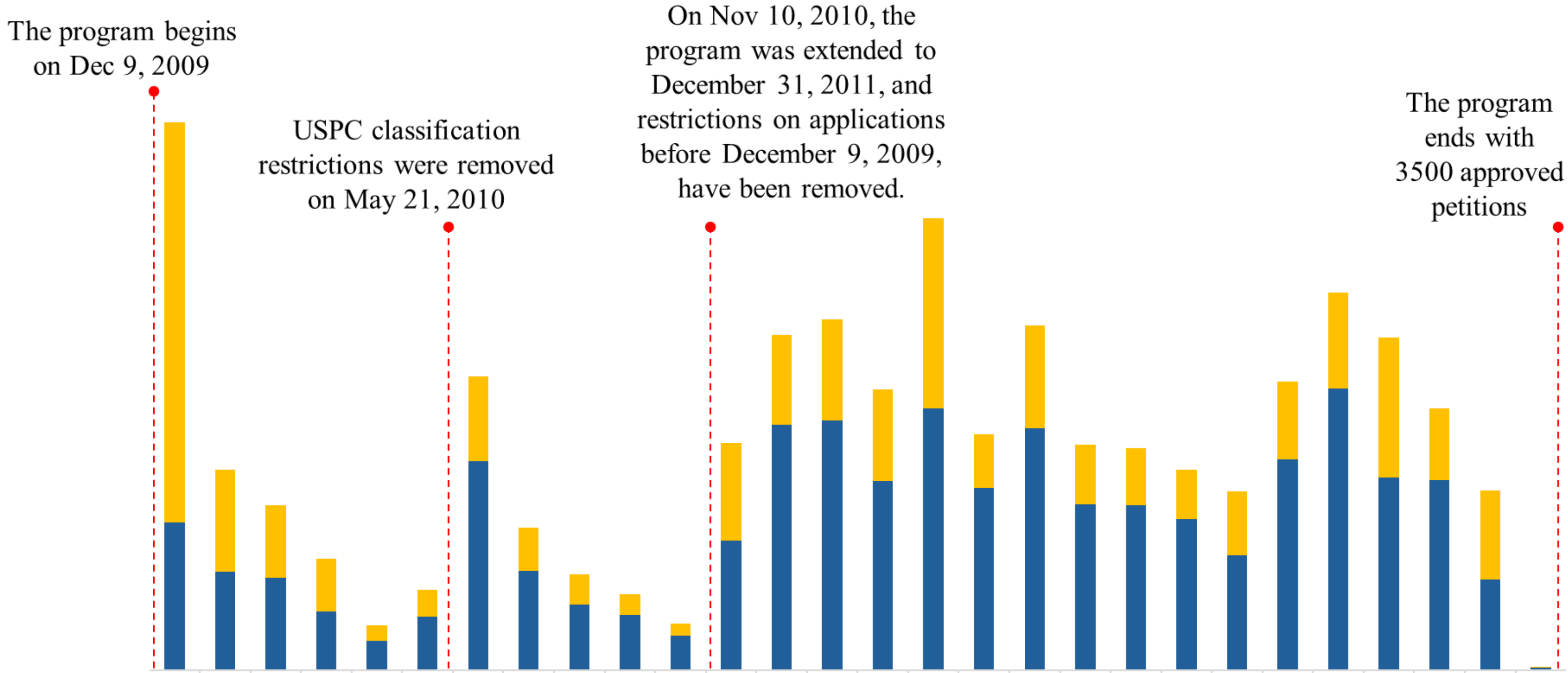
NOTE: The diagrams represent non-parametric RDD estimates of the effect of Democratic governor on log environmental employment per capita. The two panels compare the effect in states with coal production per 100,000 resident > median (low_coal=0) verses < median (low_coal=1). The estimations include covariates like population above 65 years, population below 17 years, and the log of per capita personal income. State and year fixed effects are included. I use a linear fit when the bandwidth of victory margin used is 14%. For a larger bandwidth of 24%, I use a quadratic fit.

Figure 11: Influence Petition Applications and Decision according to Patent Application Dates



NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The figure represents the number of patent applications which participated in the GTPP, and whether it was eventually granted or denied. The dates represent the patent application dates. The numbered dotted lines mark key event dates associated with the GTPP. Line 1 indicates the start of the program, line 2 indicates the removal of the environmental classification codes requirement, line 3 indicates the extension of the program into the second year and removal of the patent application requirement, and finally, line 4 indicates the stipulated end of the program in December 2011. Line 1 to Line is referred to as Phase 1, Line 2 to Line 3 is referred to as Phase 2 and Line 3 to Line 4 is referred to as Phase 3.

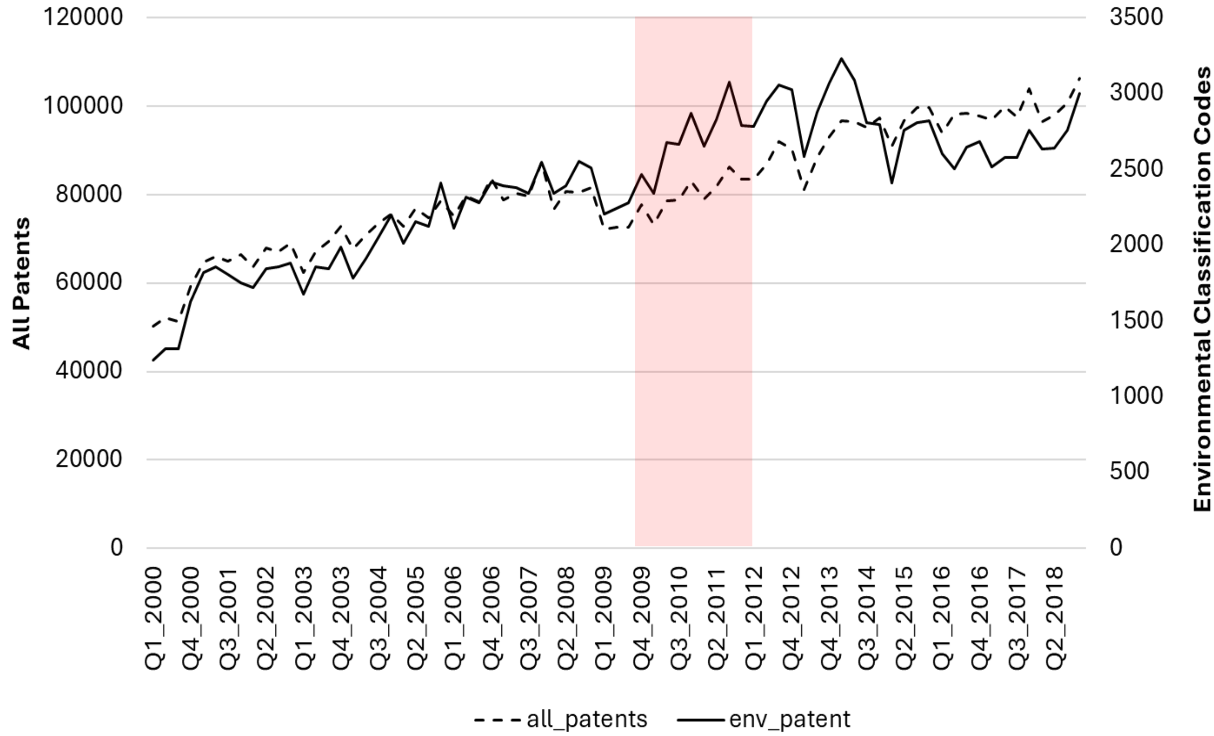
Figure 12: Key Events and Timeline of Petition Applications and Grants



	Dec_ 2009	Jan_ 2010	Feb_ 2010	Mar_ 2010	Apr_ 2010	May_ 2010	Jun_ 2010	Jul_ 2010	Aug_ 2010	Sep_ 2010	Oct_ 2010	Nov_ 2010	Dec_ 2010	Jan_ 2011	Feb_ 2011	Mar_ 2011	Apr_ 2011	May_ 2011	Jun_ 2011	Jul_ 2011	Aug_ 2011	Sep_ 2011	Oct_ 2011	Nov_ 2011	Dec_ 2011	Jan_ 2012	Feb_ 2012	Mar_ 2012
Petition not Granted	349	89	63	46	13	23	74	37	27	18	11	85	78	88	80	166	47	90	52	50	43	56	68	83	122	62	78	1
Petition Granted	129	86	81	51	26	47	182	87	57	48	30	113	214	218	165	228	159	211	145	144	132	100	184	246	168	166	79	2

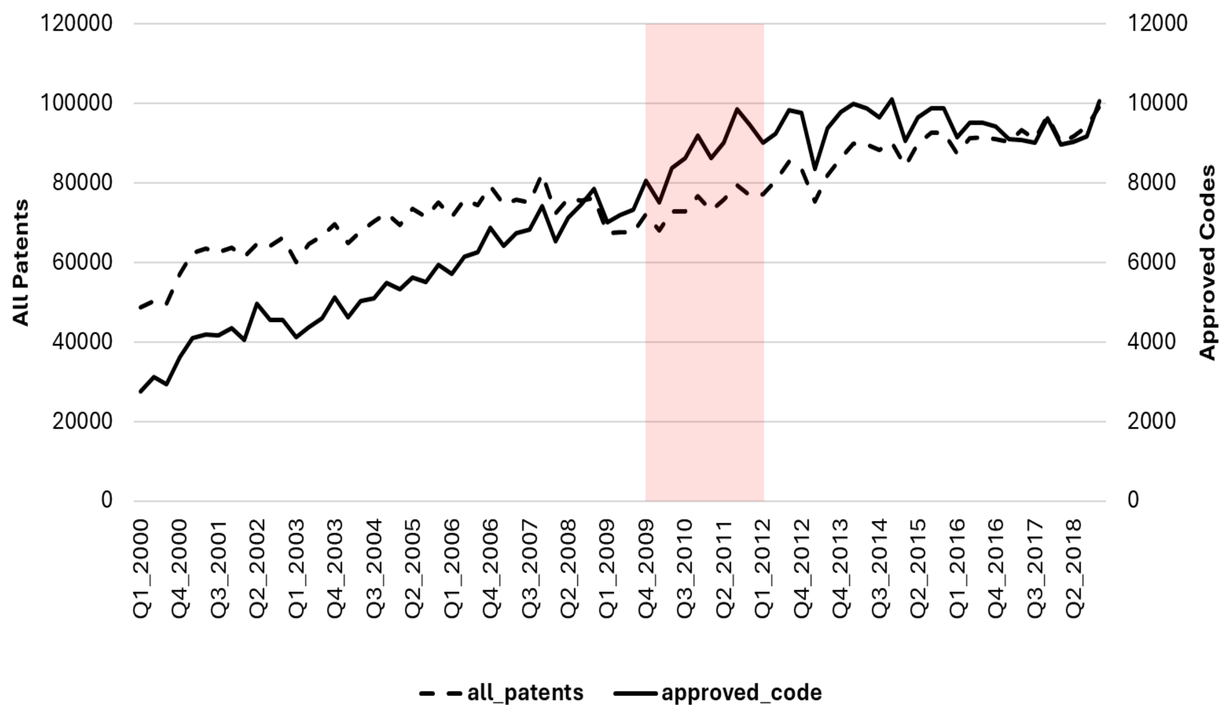
NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The height of the columns counts the total petitions in each month. The Yellow shade represents petitions which were not granted whereas the blue shade represents petitions granted. The counts are tabulated below each column. The red dotted lines mark important event dates as described.

Figure 13: Application Trends of Listed Code patents



NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The dotted line represents all patent applications whereas the solid line represents patent applications with classification codes listed in the initial announcement of the GTPP. The red patch indicates the program phase.

Figure 14: Application Trends of Approved Code patents

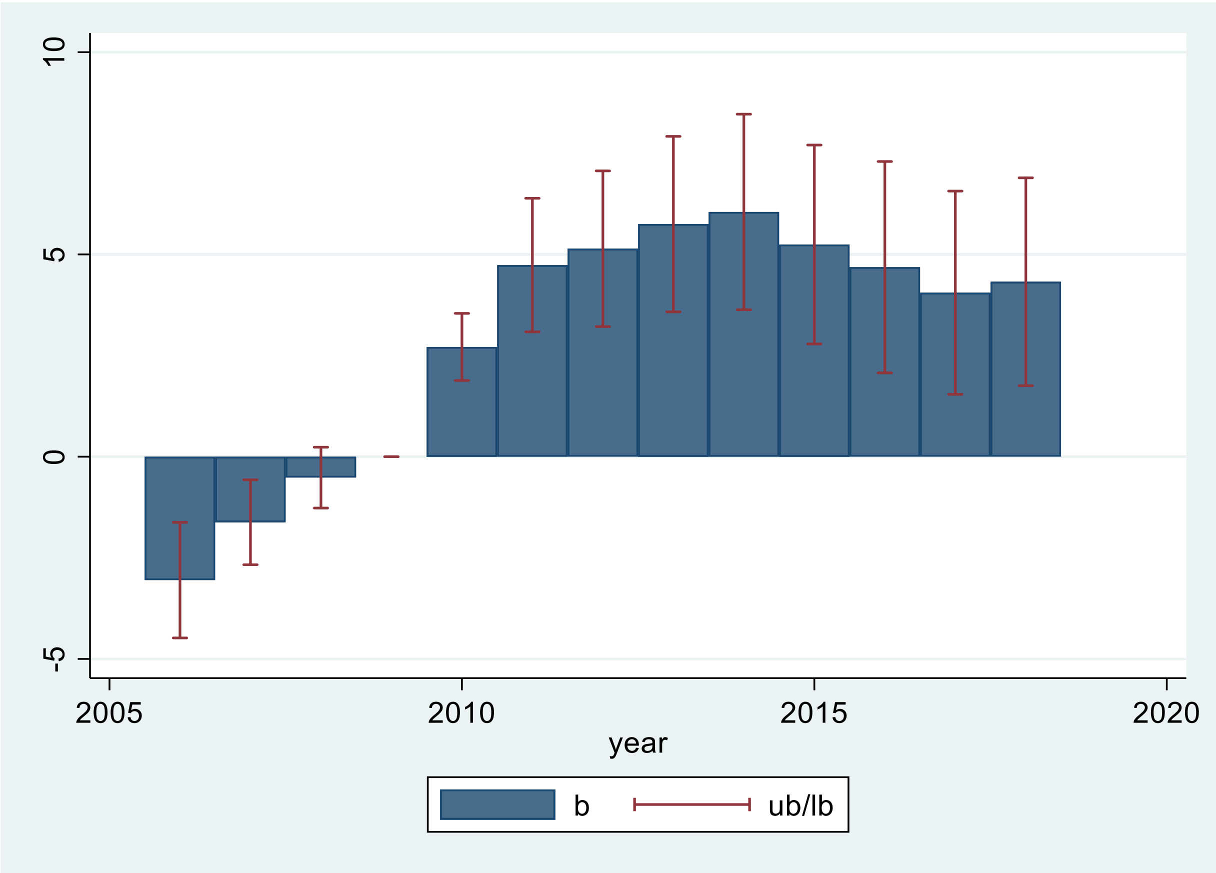


NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The dotted line represents all patent applications whereas the solid line represents patent applications with approved codes. The red patch indicates the program phase.

Figure 15: Event Study - Effect of GTPP on Listed Code Patent applications

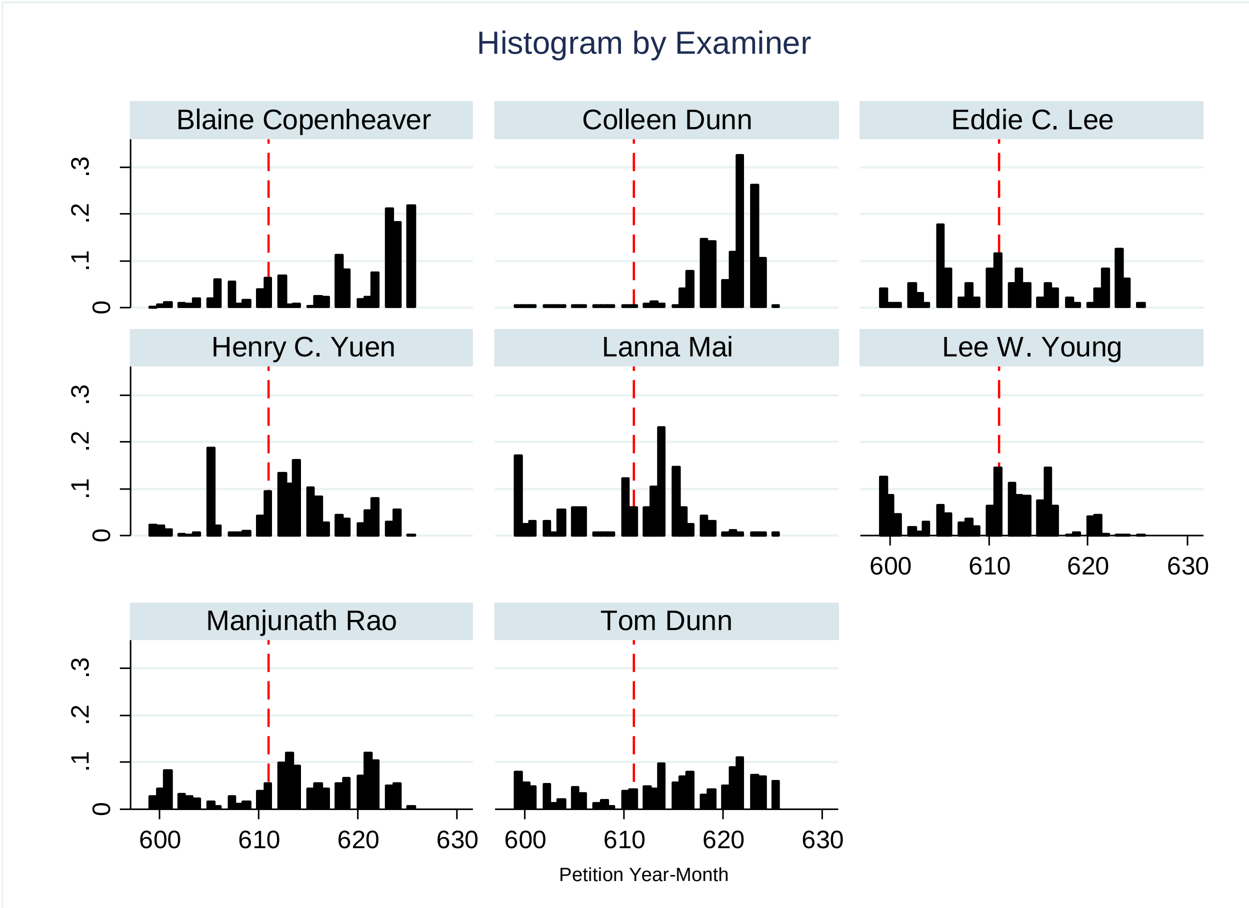
NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The baseline year is 2009. The figure represents the event study results of the listed codes on all other patent applications.

Figure 16: Event Study - Effect of GTPP on Approved Code Patent applications



NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). The baseline year is 2009. The figure represents the event study results of the approved codes on all other patent applications.

Figure 17: Distribution of Deskload per Month during GTPP by Examiner



NOTE: The data for this figure comes from the USPTO's Patent Examination Research Dataset (PatEx). Each figure represents the distribution of petitions per month at the desk of an individual petition examiner at the USPTO during the GTPP. The red dotted line represents December 2010 which marks the beginning of Phase 3 of the GTPP.

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